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A Prospective Study on Improvements and Developments on Photovoltaic Solar Generation Forecasting

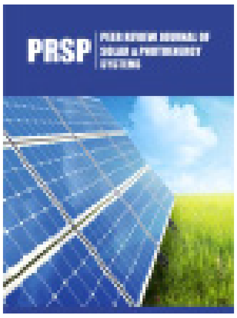
Hermes José Loschi*, Yuzo Iano and Douglas Aguiar do Nascimento

Department of Communications (DECOM), State University of Campinas (UNICAMP), Brazil

Abstract

The photovoltaic solar generation has been facing major challenges for its implementation worldwide. In most cases, hybridization aims to rationalize or make reliable forecast output and yield higher projection accuracy. One possible way to overcome the weaknesses of particular methods is to develop hybrid methodologies (hardware and Software) that capitalize on both approaches' strengths so that the end result is a forecasting system that is robust, flexible, and accurate. This paper intends a prospective study on improvements and developments to propose the structure of a methodology of photovoltaic solar generation prediction system, composed of communication and sensing infrastructure and a virtual environment for application and development of forecasting's CI methods.

Keywords: Energy planning models; Solar forecasting; Photovoltaics systems



***Corresponding author:** Hermes José Loschi, Department of Communications (DECOM), Faculty of Electrical and Computer Engineering (FEEC), State University of Campinas (UNICAMP), Brazil

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Introduction

Over the last decade, the photovoltaic solar generation has been facing major challenges for its implementation worldwide, almost always linked to issues intrinsic to the Power markets, applications and environmental impacts in Power systems, challenges to control methods for smart-grids and big data of green applications (i.e., solar radiation dataset). Methods of solar forecasting have been used to mitigate these challenges. Their range from physical to stochastic depends on available data inputs and resources and, to a large degree, forecasting time horizons of interest.

Forecasting involves the predictions of the future based on the analysis of trends of the present and past data, comprising three major components: input variables (past and present data), forecasting/estimation methods (analysis of trends), and output variables (future predictions). One possible way to overcome the weaknesses of individual methods is to develop hybrid methodologies (hardware and Software) that capitalize on both approaches' strengths so that the end result is a forecasting system that is robust, flexible, and accurate.

Computational intelligence methods were widely utilized than statistical ones. The accuracy of CI methods for forecasting was better than that of statistical ones. A significant number of forecasting models utilized multiple stand-alone methods to develop a hybrid approach because they yielded higher accuracy than that of stand-alone ones in most models. In the case of the incomplete dataset, some CI methods such as fuzzy logic and grey prediction, with the aid of stochastic model switching (i.e., Markov model), outperformed other stand-alone ones.

It is intended in this paper to perform a prospective analysis to propose the structure of a methodology to develop a photovoltaic solar generation prediction system composed of communication and sensing infrastructure and a virtual environment for application and development of methods forecasting's computational intelligence.

Motivation Roles, Challenges and Approaches

The pressing need to decarbonize energy systems poses multiple policy challenges - high among them, developing and maintaining a support package for low carbon technological innovation. In defining such policy support, multiple technical, economic, political, and societal forces have to be taken into account to deliver a balanced energy technology strategy and enable emerging technologies to progress along the 'innovation chain' from R&D to large scale deployment. A crucial element in such a challenge is a robust assessment of emerging energy technologies' cost-competitiveness, particularly by accounting for their possible future cost and performance trajectories. Indeed, a successful energy technology strategy must balance the need to set a stable long-term vision for innovation as part of overall energy system change while also being responsive to more immediate (and perhaps unexpected) changes in technology cost and performance [1].

This challenge is here considered and discussed in the context of solar photovoltaics (PV). Solar PV is a technology that has shown decades-long learning (in terms of reduced manufacturing costs and improved performance), under the benefit of sustained policy support; as such, it is seen a prime exemplar (along with wind) of renewable energy technology learning curve [1]. When we analyze the Power market, a tremendous challenge for photovoltaic solar generation is to meet the supply limits established by the contracts that are usually carried out (i.e., Day-Ahead Market (DAM), Term Ahead Market (TAM), and Renewable Energy Certificates (RECs)), that provides a variety of options to permitting partakers to buy/sell electrical power on a term basis, i.e., TAM provides a term basis from intraday weekly, i.e., up to 11 of days ahead. In this context, accurately anticipating weather conditions ensures plant owners and operators get the most out of their facilities. System operators need to know how much energy a photovoltaic solar plant can deliver, and traders strive to get the best price for every megawatt-hour and meet the Power market conditions [1].

In the present days, system operators in regions with significant penetration of photovoltaic systems typically have their forecasts, sometimes multiple forecasts for improved accuracy, provide prediction information, and to guide their decision-making processes, such as [1]:

A. Maintenance schedule during periods of low-prediction photovoltaic solar generation.

B. Scheduling to real-time dispatch and

C. Determined how many operating reserves are required to maintain system reliability based on historical forecast errors.

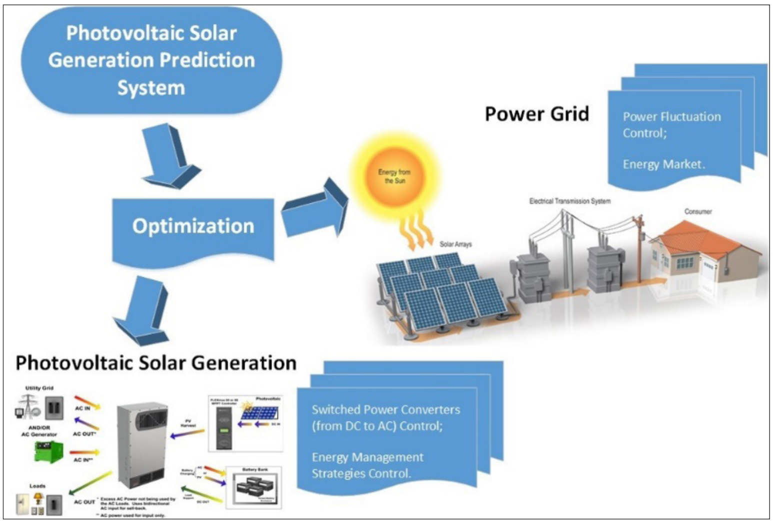

Figure 1: Who will benefit from de prediction information.

Figure 1 illustrating who will benefit from de prediction information. The prediction information can be useful by Power grid to Power fluctuation control and Power market, and photovoltaic solar generation to switched Power converts control and energy management strategies control. The prediction information can also be useful and contribute to higher forecast accuracy and improve the reliability of this systems in local sites where there is an extended amount of solarimetric dates and clouds patterns information [2-6].

Since so many different aspects can influence the forecasting of photovoltaic solar generation, mainly for this forecasting does an intermediate step of global solar irradiance forecasting, the probabilistic forecasting is increasingly used to deal with global solar irradiance dependence of the dynamics atmospheric and presence and level of clouds. Solutions with wireless sensors networks (WSN) integrated with the probabilistic forecasting systems have a solution to optimize the devices' performance and energy efficiency associated with the photovoltaic solar generation and produce prediction information, mainly if compared with statistical approach [7-10].

One way to add value to prediction information, thus increasing its reliability, is to use environments to generate and communicate this prediction information through virtual devices. Virtual devices have no physical counterpart - they only exist within the cloud, exactly like a real IO (Input/Output) device. Unlike real devices, their IO dates originate from sensors, and control actuators can represent information from the specific cloud service. Given this system design, it is possible, for example, to obtain weather information from the internet and make it available to the control system via the virtual device. This function can generate added value in a photovoltaic solar generation because it also allows for precise yield forecasts, among other things. Therefore, it is intended in this paper examination to propose the structure of a methodology to develop a photovoltaic solar generation prediction system composed of communication and sensing infrastructure and a virtual environment for the application and development of CI methods.

Methods and Evaluation Metrics

The choice of solar-forecasting method depends strongly on the timescales involved, which can vary from horizons of a few seconds or minutes (intrahour), a few hours (intraday), or a few days ahead (DA) (intraweek). Different time horizons are relevant according to the forecast application. In summary, intraday forecasts are currently of smaller economic value than are DA forecasts; however, with increasing solar penetration and the expected accuracy improvement of intraday compared to DA forecasts, substantial market opportunities will likely materialize. The type of solar resource to be forecast depends on the technology (Table 1) [10,11].

Table 1: Solar resource technology [10,11].

Forecast Variable	Application	Primary Determinants	Importance to Market	Current Forecast Skill
GI	PV	Clouds, solar geometry	High	Medium
Cell temperature	PV	GI, air temperature, wind	Low	High

For non-concentrating systems (i.e., most PV systems), primarily global irradiance

GI= diffuse + direct

on a tilted surface is required, which is less sensitive to errors in direct normal irradiance (DNI) since a reduction in clear-sky DNI usually results in an increase in diffuse irradiance. For higher accuracy, forecasts of PV-panel temperature are needed to account for the (weak) dependence of solar-conversion efficiency on PV-panel temperature (Table 2) [11].

Table 2: Characteristics of and inputs for solar-forecasting techniques [11].

Technique	Sampling Rate	Spatial Resolution	Spatial Extent	Suitable Forecast Horizon	Application
Persistence	High	1 point	1 point	Minutes	Baseline
Total-sky imagery	30s	10 -100m	2-5m radius	Tens of minutes	Short-term ramps
GOES satellite imagery	15min	1km	Country	5 hours	Load following
Weathers Models	1 hour	12km	Country	10 days	Unit commitment

For relatively longer time horizons of the order of 6h or more, physics-based models are typically employed. In the 2-6h time horizons, a combination of methods is used that relies on observations or predictions of clouds through numerical weather predication (NWP) models, especially those in "rapid-refresh" mode, and satellite images with cloud optical depth and cloud-motion vector information. For the very short term (<3 min), a number of techniques based on ground-to-sky imagers have been developed for both global horizon irradiance (GHI) and DNI by converting the cloud-positioning information into deterministic models. At shorter time horizons (<2 h), forecasting applications tend to rely more on statistical approaches, such as autoregressive integrated moving averages (ARIMA) and artificial neural network (ANN) modeling. For example, at shorter forecast horizons, ANN time series-based forecasts are competitive in terms of overall error with satellite-based models. Ultimately, statistical post-processing that includes stochastic-learning techniques to dynamically assemble or correct different input forecasts typically improves forecast accuracy. For example, to improve site-specific forecast accuracy, forecasts derived from NWP models can be corrected using model output statistics (MOS) [9-11].

Time series-based methods, including regression methods such as ARIMA and nonlinear model approximates such as ANNs, are categorized as stochastic. When developing these approaches, it is postulated that a function exists that can be used to forecast future values based on previous values of the time series under consideration and/or other time-series variables. The stochastic class of solar-forecasting methods includes data-driven approaches that are developed by fitting the parameters of the model function in a training phase with input and target data. Ideally, each forecasting model derived from the different inputs is optimized through stochastic-learning techniques that remove bias and learnable errors from the deterministic models as data collection and forecasting assessments progress [9-11].

Forecasting inaccuracies have different economic consequences depending on the time horizon and application. It is therefore important to develop forecasting metrics that are applicable to each (or all) forecasting time horizon involved and that reflect appropriate measures of forecasting skill according to readily computable quantities. Moreover, to intercorporate forecasting approaches that are typically applied to different locations or at least to different time periods, the ideal forecasting-skill metrics should be independent of the specific meteorological or climatological characteristics of the site under consideration [9-11].

In general, stochastic approaches can more easily incorporate information about phenomena at various timescales; thus, a time-horizon limitation mostly depends on the available historical data for the training stages, but also depends on the temporal autocorrelation function of the input variables. Stochastic methods for solar irradiance may make use of any one or several of the following as input variables: clear-sky irradiance models, solar-geotemporal variables, NWP-derived cloud cover and other meteorological fields, satellite data, sky imagers, historical solar-irradiance values, and other ground-measured meteorological data. Because stochastic methods do not necessarily rely on a closed-form model, the ability to select relevant inputs for inclusion in the model is a critical point [9-11].

Physically based (PB) forecasting approaches is one side of the modeling spectrum, where the model is deterministic and reasonably complex, but limited in its ability to cover all the nonlinear and chaotic relationships that characterize atmospheric phenomena. At the other end of the spectrum lie the purely stochastic methods, in which there is no physical model per se (only nonlinear interactions between variables). However, the mathematical approach is flexible enough to cover a statistically significant portion of the solution space in an auto-corrective process that can represent the complexity of the physical processes but may not necessarily yield an explicit model for all of the relationships involved (complex algebraic expressions are typically all that is available) [9-11].

Because stochastic-learning methods need to learn from the process, good-quality historical data (or a communication and sensing infrastructure with a virtual environmental for data processing) are required for comparatively long periods, as compared to less need for historical data for most explicit, deterministic PB models. Between these two extremes, there is room for hybrid models that take advantage of the strengths of both by minimizing the effects of their shortcomings, as discussed in the item 1, In case of incomplete dataset, some CI methods such as fuzzy logic and grey prediction, with the aid of stochastic model switching (i.e., Markov model) can be applicate.

Solar-Forecasting Consideration

According discussed in the section II and III, CI methods were widely utilized than that of statistical ones. The accuracy of CI methods for forecasting were better than that of statistical ones. There were significant number of forecasting models utilized multiple stand-alone methods to develop hybrid approach, because they yielded higher accuracy than that of stand-alone ones in most of the models. In case of incomplete dataset, some CI methods such as fuzzy logic and grey prediction, with the aid of stochastic model switching (i.e., Markov model) outperformed other stand-alone ones.

Methods of solar forecasting range from physical to stochastic depending on available data inputs and resources and, to a large degree, on the forecasting time horizons of interest. As discussed in the chapter III, both physical and stochastic approaches have significant strengths and weaknesses. One possible way to overcome the weaknesses of individual methods is to develop hybrid methodologies that capitalize on the strengths of both approaches so that the end result is a forecasting system that is robust, flexible, and accurate. Because solar-forecasting applications are developed and evaluated at different time periods and locations, and because of a lack of consensus on error metrics, judging the relative strengths or weaknesses of a given approach is generally difficult.

As interest grows in the impacts of high solar penetration, more robust metrics will be needed, with the aid of structure composed of a communication and sensing infrastructure and a virtual environment for application and development of forecasting's CI methods (The accuracy of CI methods for forecasting were better than that of statistical ones).

Through the analysis carried out, it can be concluded that a photovoltaic solar generation prediction system, must be provide a measure based on the variability of the solar resource, with the potential to become one of the benchmark metrics for solar-forecasting evaluations. This benchmark metric applied in a virtual environment, can generate added value in photovoltaic solar generation, because it also allows for precise yield forecasts and make possible the communicate of this prediction information through virtual devices.

Conclusion

Therefore, we are objectively destined to develop the photovoltaic solar generation prediction system on two fronts:

A. Communication and sensing infrastructure (i.e., wireless sensor network and controls systems for signal processing)

The definition of the use of a wireless sensor network (WSN) technology initially requires two initial investigations. First is the applicability analysis of sensors, sensor node and sensing methods for global solar irradiance (analysis of aspects like: Lux information, A/D converter, resolution, sensitivity, uncertainties, calibration, purchase specification, etc.). Second is the applicability analysis of wireless sensor network topology (analysis of aspects like: type of network (i.e Wi-Fi, Zigbee), transmission range, access points, network layout, connection between the sensor nodes, massage protocol, energy consumption, purchase specification, etc.).

After these two initial investigations, it would be possible to study the integration and optimization solutions for WSN infrastructure considering probabilities forecasting approaches.

From this point, considering that a prototype can be easily implemented a profound investigation into energy management schemes and hardware solutions in energy harvesting wireless sensor networks can be performed with the objective of providing an energy efficiency condition for the WSN.

B. Predictive analysis of the use of existing publically available solar databases

Initially, a profound investigation into sources of solar (panel and irradiance) data, Market data, Simulation data, Tools to manage big data (i.e. MongoDB, Cassandra, CouchDB), NoSQL and SQL for solar database (possible conclusion of this report is the lack and/or lost data) and forecasting's CI methods, should be developed with the objective of consolidating the predictive analytics model, that can be used to identify useful correlated patterns (considering the lack and/or lost data) to predict the global solar irradiance, or, photovoltaic solar generation based on past data.

The virtual work environment will be very important, it should allow the manipulation of analog signals, apply discretization techniques, and signal processing. It is believed that applying forecasting's CI methods may have better efficacy on already identified and processed signal patterns.

After that, the integration of these two fronts (A and B), can be accomplished by a cloud platform, preferably of an industrial and control level (i.e., PROFICLOUD Technology). One of the ways to add value to a prediction information, thus increasing its reliability, is to use environments that can generate and communicate this prediction information through virtual devices. Virtual devices have no physical counterpart - they only exist within the cloud, where they function exactly like a real IO (Input/Output) device. Unlike real devices, their IO dates do nor only originate from sensors and control actuators; instead, it can represent information from the specific cloud service. Given this system design, it is possible, for example, to obtain weather information from the internet and make it available to the control system via the virtual device. This function can generate added value in photovoltaic solar generation because it also allows for precise yield forecasts, among other things.

Among the main objectives for the development of a system of prediction of photovoltaic solar generation, which indicate its importance, include:

A. Alternative and original means to address the prediction issue of photovoltaic solar generation through time intervals of global solar irradiance through a wireless sensor network

B. Consolidate the mathematical method proposed as Software as a service (SaaS);

C. Development of a modular communication and sensing infrastructure with integration of a data analysis and processing tool

Option to optimize the control of the devices (from DC to AC) and control of energy management strategies, based on information from the prediction system of photovoltaic solar generation.

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