Review Paper:

Artificial Intelligence Methods for Solar Forecasting for optimum Sizing of PV systems: A Review

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Abstract

Solar photovoltaic (PV) system includes PV array/modules connected in series or parallel, converter, battery and inverter with their capacity to cater load in an efficient, economic and reliable manner. The proper sizing of these components is very much crucial for stable and efficient output generation. PV plants performance, being governed by the weather parameters like, solar irradiance, sky conditions etc., number of modelling and estimation techniques for their availability were developed. In this paper, a comprehensive forecasting techniques and were introduced and discussed about the intelligent techniques which are dominant and accurate in extracting high level features from big data and environmental variability.

This study summarized the artificial intelligent(AI) techniques for solar irradiance to estimate PV systems power output and also presented hybrid techniques in forecasting. It is envisioned that the material collected in this paper will be a reference for the academicians/researchers provide a direction for future research.

Keywords: PV system, Solar irradiance, optimum sizing, forecasting techniques, artificial intelligence, hybrid techniques.

Introduction

PV generation mostly relies upon the measure of global solar irradiation incident on photovoltaic panels, whereas that global solar irradiation isn't uniform at all times. The most critical challenges in integrating the solar PV system to grid and maintaining the grid stable are the solar resource variability and its improbability. These issues need to be tackled. These uncertainties are also governed by the Earth's rotation around sun and can be accurately deduced by different equations. Nevertheless, there likewise occurs unforeseen variations in the measure of global solar radiation landing on Earth's surface, mostly got by mists nearness, which stochastically obstruct the Sun's beams and award PV power measuring a specific degree of vulnerability.

An exact conjecture isn't valuable for framework administrators since it diminishes expenses and vulnerabilities, yet additionally for PV plant maintainers, as they keep away from potential financial punishments that are brought about because of deviations among anticipated and created vitality.

The significance of the issue has supported the improvement of numerous examinations worldwide to forecast exact figures of solar radiation and power generation from photovoltaic plants. Atmospheric occurrences: movements of air mass, the existence of cloud cover, pollutants and dirt in the air mass etc. have a pivotal influence on the value of the flux density of solar radiation[1]. Ground reflectivity, visibility, atmospheric albedo etc. are the regional atmospheric data.

Position of sun can be estimated using astronomical equations and hence, solar radiation can be predicted based on regional atmospheric data, weather and sun's position[2].

Solar photovoltaic modules exhibit non-linear current–voltage characteristics because of the load, solar irradiance and module cell temperature influences[3].In the nations, having poor number of solar observation sites, the global solar radiation (GSR) amounts are generally made available at few specific locations, probably not be the same as the real site of solar photovoltaic power generation and utilization, for predicting actual site specific solar irradiance.

Therefore, long term measurements from the nearby observation site will be used[4].Noteworthy investigations were carried out regarding solar energy predictionusing artificial neural network(ANN) methods.

Several meteorological and site specific variables which includes temperature, relative humidity, sunshine hours, cloud cover, latitude, longitude and altitude were used to develop ANN models for solar forecast[5].

Enhancement in accuracy of prediction of solar PV power can optimize the total power generation and forecasting is a requisite and solar power prediction or forecasting will still be an requisite tool in future tool[6].

Material and Methods

Indirect forecasting and direct forecasting are two principle forecasting approaches. Indirect forecasts first estimates solar radiation and followed by the photovoltaic power production by using performance model of the photovoltaic plant. Then again, direct forecast straightforwardly computes the power yield of the plant.[7]

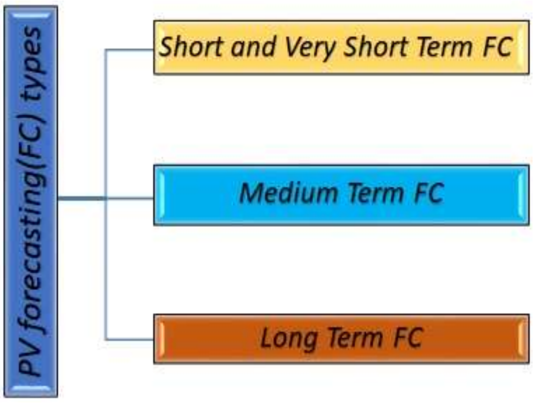

Fig. 1: Time horizon based PV forecasting classifications

According to time horizons, the PV output forecasts are classified in to three main classes, namely very short term, short term, medium term and long term PV output forecast.[8]

1. Very short-term forecast (1 min to several min ahead) and Short term forecast (1 h or several hours ahead to 1 day or 1 week ahead).
2. Medium term forecast (1 month to 1 year ahead).
3. Long term forecast (1–10 year ahead).

Likewise, numerous different investigations emphasis on the global solar irradiance, since it is the most complicated component to model and have different applications separated from solar PV forecasting.

A novel method of direct estimation and design of photovoltaic system and its generation, based on the Autoregressive Network with Exogenous Inputs(NARX) network accurately was presented in[9].

In[10], proposed a PV power forecasting method based on advanced learning algorithms for forecasting and required variables for it.

With rapid increasing interest and the evident reason for estimating solar irradiance for different solar based applications, it is required to consolidate all such works in a single reference and efforts in that direction are made in this paper. Its main objectives are to summarize different solar irradiance forecasting techniques available and their applicability based on different time horizons. Estimating the solar radiation is the first and foremost step in indirect solar PV generation technique.

Though it is very complex to assure standard of reference because of each individual researcher evaluates their algorithm on different photovoltaic system designated ratings, size and operating conditions. It is envisaged through this paper, the information presented in this review will provide a proper inclination for future research work of indirect forecasting Meager focus was given for selection of variable in estimating or forecasting in the earlier works on solar PV power forecasting. Proper variable selections lead to the enhanced accuracy, fast training and lesser complexity of the model prediction.

Very Short and Short Term Radiation Forecasting: PV installations largely affected by the solar radiation fluctuations caused by the passing clouds and other short term shading effects. This compels the power plant managers for proper planning and necessary load management through short term forecasting of solar radiation.

In[11] Linear and nonlinear models were paralleled, nonlinear models based on computational cleverness practices exhibit better results with a simple approach to get the model. The investigation of the total forecasting error, "weak points: low accuracy and actual historical data from the weather station located at the solar power plant site, which probably have the corresponding measurement mistake" were presented in [1] and found that removal of “weak points” with *statistically calculated numbers* minimized the short term forecast error. Major challenges in forecasting the radiation are accuracy and real time applications. Models like Artificial neural network (ANN), Numerical Weather Prediction (NWP) and Machine Learning methods: like Bayesian Approaches, Support Vector Regression and Hybrids models are used for prediction. Assuming, all other parameters constant except cloud movement, cloud cover, temperature and wind speed constant, the said models forecasted with high accuracy[12].

Fuzzy and statistics based cloud model with data mining techniques to achieve interrelationships between data was presented in[13]. Apriori algorithm was used for uncertainty prediction as the predicted results fluctuate under a threshold limit.

A hybrid approach, proposed by Hottel: clear sky model fed by the outcome of an algorithm driven by data was reported in [14] to compute key parameters through by exploring data base of solar radiation values.

With three input parameters like mean radiation, maximum temperature and time, for a time horizon of ten minutes [15] proposed a very short term forecasting technique centered on multi-layer artificial neural networks, with the Levenberg-Marquardt algorithm.

In [16]using meteorological data for a real time solar photovoltaic plant, day-ahead forecasting was done on hourly basis and with the help of regression modelling, the statistical importance of atmospheric parameters were analyzed and found that clustering approach improved accuracy of forecast.

Results from[17] suggested, inclusion of neighboring geographical location to the target location improves the forecasting accuracy of short and medium term forecasting horizon.

Forecasting 5 to 20 minutes in advance of global horizontal irradiance(GHI)was analyzed in[18] by three forecasting techniques namely 1) the persistence model, 2) the convolution neural network (CNN)approach using total-sky images and 3) the CNN approach using total-sky images and lagged global horizontal irradiance together and found that, later outperformed the former two with minimum root mean square error (RMSE).

In[19], the adaptive neuro-fuzzy inference systems(ANFIS) model was used to forecast photovoltaic power with one year historical data and results are appreciable with good accuracy of forecasting and minimum error.

In[20], power output of solar PV plant by support vector regression(SVR) with the parameters optimized by Cuckoo search(CS) and Differential evolution algorithms individually are compared and found that, support vector regression with Radial Basis function optimized by cuckoo search and differential evolution gave the utmost precise predictions.

A high-precision deep neural network model called PVP Net for 24-h probabilistic and deterministic forecasting of PV system output power was proposed in [21] and observed that it outperforms other standard models, meritoriously forecasts difficult time series with a notch of instability and indiscretion.

Due to the availability of big data, deep learning has taken new shapes and a novel technique for hourly, daily and solar radiation prediction for a year in advance using Long-Short Term Memory (LSTM) was proposed in [22].

Optimum Sizing of a Photovoltaic System: Electrical loads to meet, the factor that determines the PV sizing is the least mean daily solar irradiance on the PV panel surface generally during winter season.

Utilization to the maximum available solar irradiance for cost reduction is based on three parameters: Proportions of the PV array, magnitude of the battery storage and inverter size are the main objectives in optimizing the overall sizing of PV system. Researchers reported that, one of the optimum elucidation is to reduce the size of PV array since, PV array itself takes the major share of initial cost and also observed that increment in battery size without increment in array size has no significant effect on performance of the system[23]. Optimizing the size of the PV systems are basically categorized in to four different approaches, namely, intuitive, numerical, analytical and intelligent approach[3].

a. **Intuitive Approaches:** Intuitive approaches are not accurate but gives a rough estimations and are simplest compared to the other.
b. **Analytical Approaches**: These approaches are very accurate and simple using empirical relations and mathematical modelling.
c. **Numerical Approaches**: These approaches are based on simulation programs and involves rigorous computations and big data. These are further classified in to two methods. Firstly, Stochastic numerical method and secondly deterministic numerical method.
d. **Intelligent Approaches**: These are also known as Artificial Intelligent(AI) Techniques(algorithms) which includes fuzzy logic(FL), genetic algorithm(GA), neural networks(NN), simulated annealing(SA), ant colony optimization (ACO), particle swarm optimization(PSO), Hybrid approaches (ANFIS)(GA-FL)(NN-FL)etc.,[24].

AI in PV Systems: PV systems being weather dependent, forecasting the output from solar PV plants plays a vital role in policy making for the governments and PV plant managers. Cloud positions and solar irradiance are the basic weather parameters that influence the performance of PV systems. Therefore, AI techniques can be employed in effectively estimating solar irradiance and output power from the PV panels[24].

Forecasting Solar irradiance: In[25], monthly mean global solar irradianceprediction was done, by transforming neural network to a multiple linear regression(MLR) problem with addition of hard edgeconsequence to minimize the total nodes present in hidden layer and employing bio inspired optimization techniques like cuckoo search algorithm and differential evolution algorithms which are two effective and innovative approaches.

In[26] artificial neural network (ANN) model was employed to predict the parameters of solar radiation. Effect of increasing quantity of input parameters were investigated on solar radiation and found that increment in input parameters resulted in effective estimation of future data on solar radiation.

With various inputs (e.g. day of the year, time, pressure, sky cover and wind speed),Nonlinear Autoregressive Network with Exogenous Inputs (NARX) approach was implemented to estimate *hourly solar irradiance*, in[27].

NARX neural network outperformed than the linear regression model.

In[28] two ANN models with four different algorithms were considered and based on minimum mean absolute error (MAE) and root mean square error (RMSE) and maximum linear correlation coefficient (R) it was found best suitable to estimate the mean monthly global radiation in order to design or examine solar PV installations.

Artificial neural network and random forest, are two forecasting methods used to forecast the three different components of solar irradiation (horizontal global, beam and diffuse) in[29] and found that the forecasting in spring and autumn is less trustworthy compared to winter and summer because of the in meteorological data fluctuations.

Support vector machine (SVM) for forecasting *daily and monthly global solar radiation* on horizontal surface was presented in[30].SVM centered models entail little simple parameters to get good accuracy.

Hybrid Solar Forecasting Techniques: In[31] Forecasting solar radiation based on fuzzy and neural networks technique was presented. Classifying the cloud and temperature data as different fuzzy sets and fuzzy rules together with neural network, the prediction was found effective. In[32], artificial neural networks (ANN), autoregressive moving average (ARMA), support vector machines (SVM) was employed and found lacking accuracy because of their inability to seize long-term scalable data. Deep recurrent neural networks (DRNNs) was used to estimate solar radiation. DRNNs add intricacy to the model no mention of what form to accept the variation and permit high-level feature extractions. For hourly solar radiation, a hybrid method with the combination of clustering technique and multilevel perception is presented in[33].Comparing results with other well-established predicting models reveal greater performance of the proposed hybrid method.

In [34] proposed a standard of supervised machine learning techniques (neural networks, Gaussian processes and support vector machines) to forecast the Global Horizontal Solar Irradiance (GHI). Machine learning techniques performed outstandingly for forecasting horizon greater than one hour.

Cloud imagery in combination with physical models along with machine learning techniques are the two major classification presented in[35].

Comparison of AI Techniques: Stochastic meteorological parameters like solar radiation, influence PV performance, the results of inflation variance factor number of month (M), air temperature mean (T_{mean}), extraterrestrial radiation (R_a) and mean relative humidity (RH_{mean}) were extracted to be expressive instructive variables for prediction of solar irradiance. Different pairs of input parameters were divided employing ANFIS, MLR and ANN approaches and their precisions were compared and shown in table 3 and 4 [36].

Statistics revealed that, artificial neural network model (ANN model) performed better than other models.

In[37] 3 different Artificial Neural Network (ANN)methods namely Multilayer Perceptron (MLP), Radial Basis Neural Network (RBNN) and Generalized Regression Neural Network (GRNN) were used for estimating global solar radiation(H_g) using meteorological parameters as input parameters.

By considering the different parameters influencing solar radiation Bristow-Campbell model too was developed and found the following statistical comparative results shown in table 5[37] and suggested that Multilayer Perceptron and Radial Basis Neural Network models are accurate in predicting solar radiation at different climatic zones.

Table 1
Summary on Artificial Intelligence contribution in forecasting solar radiation

Author	Algorithm	Contribution
Jiang, et al[25]	CS-DE	Mean global solar radiation
Koca et al[26]	ANN	Effectiveness of input parameters
A. Alzahrani et al[27]	NARX	Hourly solar irradiance
Premalatha and Valan Arasu[28]	ANN	Monthly mean global radiation
Benali et al[29]	RF	GH, beam normal and diffuse horizontal
Belaid and Mellit[30]	SVM	Daily and monthly global solar radiation

Table 2
Summary on Hybrid approaches in forecasting solar irradiance

Author	Algorithm	Contribution
Chen et al[31]	FL-NN	smaller Mean Absolute Percentage Error (MAPE)
Ahmad Alzahrani et al[32]	SVM-DRNN	High level feature extraction
Azimi et al[33]	K-mean-MLPNN	Accurate multiple time horizon prediction
Lauret et al[34]	AR-Naïve model	Accurate forecasting for horizons greater than 1 h.
Voyant et al[35]	Cloud image-physical method	machine learning approach

Table 3
Criteria comparison for the best models during training

Best Models	Training Set				
	MAE	**MARE**	**RMSE**	**OI**	**R^2**
ANN	1.137	8.475	1.523	0.941	0.940
ANFIS	1.117	8.362	1.496	0.943	0.943
MLR	3.9353	37.412	4.631	0.826	0.826
Bahel equation	1.511	10.768	2.189	0.910	0.910

Table 4
Criteria comparison for the best models during testing

Best Models	Testing Set				
	MAE	**MARE**	**RMSE**	**OI**	**R^2**
ANN	1.253	9.319	1.650	0.941	0.930
ANFIS	1.292	9.676	1.691	0.929	0.926
MLR	4.017	38.853	4.745	0.815	0.810
Bahel equation	1.521	11.044	2.062	0.904	0.925

Table 5
Statistical Indices comparison

Models	**RMSE ($MJ\ m^{-2}\ day^{-1}$)**	**MAE ($MJ\ m^{-2}\ day^{-1}$)**	**R^2**
GRNN	2-3.29	1.58-2.34	0.72-0.90
IBC	3.13-4.58	2.32-3.41	0.53-0.77
MLP	1.94-3.27	1.53-2.21	0.73-0.90
RBNN	1.96-3.25	1.54-2.32	0.72-0.92

Conclusion

Environmental challenges to address as top priority, solar energy will continue to play dominating role in the coming future minimizing the dependence on conventional fuels. Photovoltaics are likely to be torch bearer for the development of new energy market along with back up service in emergency. This low maintenance free, clean PV energy is easy to generate but, its reliability and production costs have not taken the position that they completely replace the conventional energy sources. Therefore, to extract maximum possible from PV plants, they have to be designed optimally. Since, the performance of PV systems completely depending on the weather parameters like solar irradiance and sky conditions, accurate forecasting of weather parameters will help in optimum sizing of PV plants.

This work collected and summed up the current status of different AI techniques in forecasting weather parameters and hybrid techniques in particular. With the fast developments in computing capabilities, the interest in forecasting techniques seems to be increasing. It is believed that, this paper will be an informative source to academicians and scholars interested in employing AI weather forecasting.

Acknowledgement

The authors would like to thank (1) Karunya Institute of Technology, Coimbatore, Tamilnadu, India, (2) Anand Agricultural University, Godhra, Gujarat, India for providing facilities for the output in this paper form. Also, authors wish to thank the academicians/researchers whose works have been cited directly or indirectly in this paper.

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