

# A Review on Short term and Long Term PV Power Generation Techniques

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**Abstract:** With the increasing need for clean sources of energy, solar energy has been on the forefront. Photovoltaic (PV) can be effectively used to provide power to both domestic and industrial applications. However, intermittent nature of solar irradiation makes it challenging to deploy PV cells for large scale industrial applications with high reliability. One of the most effective ways to predict PV power is to estimate the solar irradiation on the PV cells which typically vary to month, day, time, temperature and other variables. It thus becomes necessary to forecast in advance the amount of PV output that can be generated from PV cells. This paper presents a comprehensive review on the forecasting techniques used in prevalence along with their salient features.

**Keywords:** Short Term Forecasting, Long Term Forecasting, Machine Learning, Photovoltaic (PV) output Prediction.

## I. INTRODUCTION

The current era sees that, the solar technology has been one of the most sought after renewable sources of energy attributing to its hassle free and flexible utility. The growing demands of the worlds at large can be fulfilled using the solar renewable power. Though there are many reasons to harness

the great energy potential of solar energy yet there is a flipside to it. Uncertainty lurks in the amount of solar energy that can be obtained from solar power. It is due to the reality that there are many random fluctuations in the solar energy levels unlike other renewable sources like the tidal energy, wind energy etc. So because of this intermittent fluctuating nature of the solar energy power, it creates difficulty in determining and harnessing the solar power properly. [6]

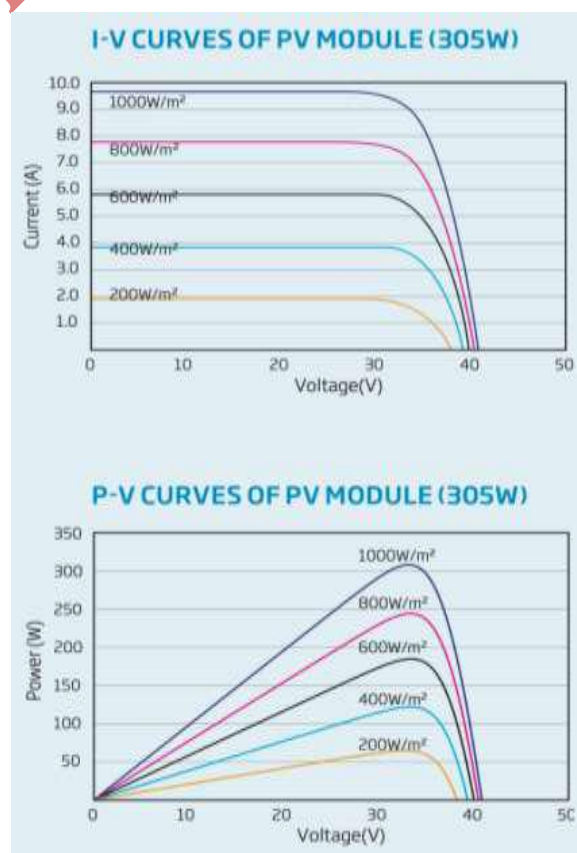


Fig.1 Typical VI-Curves for Solar PV Cells

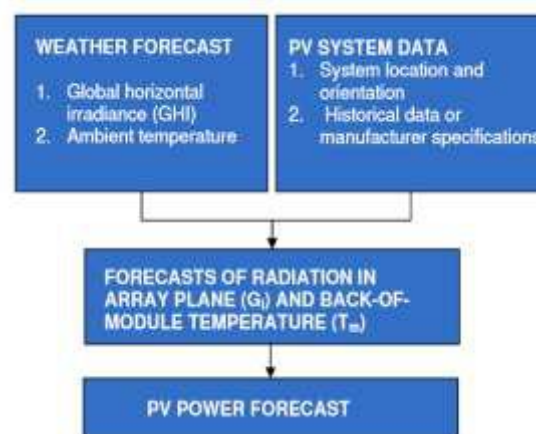
The solar irradiation and hence PV output is intermittent in nature. Due to this, the measure of solar power energy that can be obtained at given time is hard to be determined. The reasons for the same can be attributed to various natural phenomenon. When the apt solar energy measure cannot be determined in a proper way, there is no point in harnessing power from it as it would be non productive and irrelevant . It can result in weaker stability of the system unit, low power quality, and poor sustainability. Several other problems linked to power may also surface due to it. The repeated fluctuations in the solar irradiation power might produce unreliable and incorrect outcomes. [5]. Solar PV outputs are high solar irradiation dependent and intermittent in nature. Hence it becomes challenging to predict solar PV outputs.

The figure below shows the solar radiation spectrum. The spectrum comprises of the infrared, visible and ultra violet regions of the spectrum. In the proposed work, a system is put forward that can accurately determine the maximum power point tracking of solar PV Cells by proper and accurate prediction of the solar irradiance. The two main challenges to high penetration rates of PV systems are variability and uncertainty, i.e. the fact that PV output exhibits variability at all timescales (from seconds to years) and the fact that this variability itself is difficult to predict. The proposed work addresses the second issue, uncertainty, and the method used to address it: photovoltaic forecasting.

## II. PV Forecasting and its Link to Solar Irradiation

The different uses of PV forecasts require different types of forecasts. Forecasts may apply to a single PV system, or refer to the aggregation of large numbers of systems spread over an extended

geographic area. Forecasts may focus on the output power of systems or on its rate of change (also known as the ramp rate). Accordingly, different forecasting methods are used. Forecasting methods also depend on the tools and information available to forecasters, such as data from weather stations and satellites, PV system data and outputs from numerical weather prediction (NWP) models.



**Fig.2 Model for PV Forecasting**

Forecasting methods can be broadly characterized as physical or statistical. The physical approach uses solar and PV models to generate PV forecasts, whereas the statistical approach relies primarily on past data to ‘train’ models, with little or no reliance on solar and PV models. The PV forecast is typically a function of relevant weather variables and PV system characteristics. The main variables influencing PV output power are the irradiance in the plane of the PV array and the temperature at the back of the PV modules or cells. Typically, the predications are categorized into 3 groups:

- 1) Short Term
- 2) Mid Term
- 3) Long Term

The intermittent nature of solar energy makes the short term prediction the most effective for PV applications.

### III. Previous Work

This section presents the various approaches to predict solar PV output with precision.

M. Monfared et al. in [1] proposed a new generalized technique for very short-term prediction of PV power generation from the lagged power generation data using fuzzy techniques. A preprocessor extracts relevant statistical features from the PV data which are fed to the fuzzy predictor. A modified version of Wang-Mendel training algorithm is employed to directly extract the fuzzy rules from the training data pairs. This methodology exploits the limited training data more efficiently. In addition, an online additive learning routine is proposed, which enables the predictor to learn from new data while running the predictions. So, the prediction accuracy increases over time and the predictor updates to account for long-term changing conditions of weather and PV system performance and its surroundings.

M. Torabi et al. in [4] proposed a Cluster-Based Approach (CBA) that utilizes the support vector machine (SVM) and an artificial neural network (ANN) to estimate and predict the daily horizontal global solar radiation. In the proposed CBA-ANN-SVM approach, authors first conduct clustering analysis and divided the global solar radiation data into clusters, according to the calendar months. Our approach aims at maximizing the homogeneity of data within the clusters, and the heterogeneity between the clusters. The proposed CBA-ANN-SVM approach is validated and the precision is compared with ANN and SVM techniques. The mean absolute percentage error (MAPE) for the proposed approach was reported lower than those of ANN and SVM.

A. Amaroa et al. in [5] proposed that solar energy is one of the most sought after renewable resources of today. As the non renewable sources are getting over fast, there is this urgent need to turn towards the renewable resources. Spatio-temporal solar forecasting is an area that has not been explored much. Hence in this work, the researchers tried to gauge the effect of network layout on such spatio-temporal prediction schemes. Network layout is an important feature that adds to the overall network lifetime and throughput of the system. Many different methods are employed based on the type of outcome that is anticipated. This approach yielded satisfactory outcomes for the particular type of solar prediction. It showed moderate results with all types of solar power forecasting.

Y. Wang et al. in [6] proposed that for optimum benefits, PV output has to be clubbed with accurate and effective methods that can increase the efficacy of the system. Large quantity of data is also the reason for going the data centric methods. In this approach proposed, the researchers come up with the idea of probabilistic net load prediction for specific PV domains. This system provided 95% accuracy and precision with the methods and the metrics were also quite improved and as per the requirements. The concept was data driven as the large pool of data was involved that was the main information store for all the executable methods.

H. Sheng et al. in [7] proposed a weighted Gaussian process is a relatively conventional method but coupling it with regression method improves the overall functionality of the procedure. Many different methods are employed based on the type of outcome that is anticipated. This approach yielded satisfactory outcomes for the particular type of solar prediction. The results showed moderate results with all types of solar power

forecasting. This variable nature of the solar irradiation quantity is due to many atmospheric conditions.

The challenges that exist for the method of solar irradiation prediction are listed as underneath:

1. Continuous variations in the solar irradiation due to conditions of atmosphere make it difficult to forecast it accurately.
2. Setting up solar panels and units for processing the solar power and tap it incur fair amount of cost.
3. Where the solar panels and the units are located is a major factor as only in abundance of sun rays, it shall be effective to tap the energy.
4. Also at night there is no availability of solar irradiation rendering zero value, so the irradiation is nil. So the night time renders unfruitful for tapping the solar energy forecasting.
5. The pattern and parameters for the forecasting is quite large and inter related. Often it is difficult to comprehend it and obtain the energy.
6. Data can be very big and complex to process and handle. Only some advanced technology or technique can be able to process it.

### III. PERFORMANCE METRICS

The Finally, the proposed system is to be evaluated in terms of prediction accuracy in terms of mean absolute percentage error (MAPE) and compared with previously existing techniques.

The final aim is to achieve low values of errors for the prediction problem. Since the errors can have

both negative and positive polarities which can cancel out, hence total or simple averages are not computed for the prediction errors. The commonly analyzed errors are:

The different Errors which are to be computed are:

The parameters which can be used to evaluate the performance of the ANN design for time series models is given by:

- 1) Mean Absolute Error (MAE)
- 2) Mean Absolute Percentage Error (MAPE)
- 3) Mean square error (MSE)

The above mentioned errors are mathematically expressed as:

$$MAE = \frac{1}{N} \sum_{t=1}^N |V_t - \hat{V}_t|$$

Or

$$MAE = \frac{1}{N} \sum_{t=1}^N |e_t|$$

$$MAPE = \frac{100}{N} \sum_{t=1}^N \frac{|V_t - \hat{V}_t|}{V_t}$$

$$MSE = \frac{1}{N} \sum_{t=1}^N e_t^2$$

$$RMSE = \sqrt{\frac{1}{N} \sum_{t=1}^N e_t^2}$$

Here,

N is the number of predicted samples

V is the predicted value

$\hat{V}_t$  is the actual value

e is the error value

The accuracy is generally computed as:

$$Accuracy = 100 - error(\%)$$

**Conclusion:** It can be concluded from the previous discussions that predicting Solar PV output has been shown to be extremely complex due to the nature of the irradiation. As it has been pointed out earlier, PV output prediction can be challenging because of the wide range variation of the parameters affecting irradiation on the PV cells. Off late machine learning approaches are being used to predict short, mid and long term PV output. The paper presents the salient features of prediction systems along with the contemporary work in the domain.

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