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Solar Photovoltaic Power Generation Forecasting Models and Techniques

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The various forms of solar energy - solar heat, solar photovoltaic, solar thermal electricity, and solar fuels offer a clean, climate-friendly, very abundant and in-exhaustive energy resource to mankind. Solar power is the conversion of sun light into electricity, directly using photovoltaic (PV). The forecasting of energy Demands have become concerns for facility managers, and predicting energy generation plays a critical role in power-system management, scheduling, and dispatch operations. A reliable energy supply forecast helps to prevent unexpected loads and provides vital information for decisions made on energy generation and purchase. However, study of energy generation prediction by the photovoltaic (PV) system has been limited over the years, especially concerning short-term predictions. This study will helps in providing the details on different type of models and techniques of solar power forecasting.

Keywords: *Solar forecasting; Forecasting models; Forecasting techniques*.

1.0 INTRODUCTION

Photovoltaic (PV) for electricity generation are the fastest-growing energy technology since 2002, experiencing an average annual increase of 48% [1-2]. The cumulative global installed capacity reaches 15200 MW, of which the majority is grid-connected systems [3]. In some power systems, like in the case of islands, PV penetration reaches already high levels and the management of the PV production is becoming an issue for the system operators. Therefore, the solar PV power generation forecasting will become more and more important for utilities, which have to integrate increasing amounts of solar power, especially for developing countries. In India the installed photo voltaic (PV) power amounts to more than 2 GW. In India, Gujarat is a maximum PV installed capacity and Rajasthan is second. Rajasthan is blessed with two critical resources that are essential to solar power production: high level of solar radiation per square inch and large amounts of contiguous, relatively flat, undeveloped land. The main challenge of PV power is its variability. Conventional power sources, apart from occasional technical failures, are easily dispatchable in the sense that future production can be precisely planned beforehand. This is not the case with Photovoltaic power generation, which closely depends on the weather conditions [4-5]. Forecasts of the solar power production can be useful to estimate reserves, for scheduling the power system, for congestion management, for coordinating renewable with storage, or for trading in the electricity markets. As in a solar panel at a fixed temperature, the power production is close linear depended on global irradiance [6], then predicting solar irradiance is not expected to be very different from predicting PV power.

In this paper we present further developments of a model and techniques to forecast the Photovoltaic power generation. A focus will be on further elaboration of the forecast of ensemble power generation for PV-Systems.

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2.0 CONVENTIONAL MODELS

In this early stage of development of PV power forecasting technology there are a number of competing technologies and methodologies. Some of the key differences amongst the competitors are time horizon, geographical area covered, accuracy (both absolute and over time), and cost

TABLE 1

TYPES OF IRRADIANCE FORECASTING TECHNOLOG IES

Technology	**Time Horizon**	**Cover-age**	**Remarks**
Satellite	12 hr to 7 days	Global	Error associate with satellite-based weather are greatest over short time period [7]
Mesoscale	12 hrs to months	global	All GFS-based models, including NDFD, havesimilar accuracies asquantified by RSME and MAE, but European or Canadian global weather simulations tend to deliver better RSME results. [8]
Aggregated Ground Based	1 hrs to 3 hrs	regional	Nationwide coverage ofhigher accuracy groundsensors make better shortterm prediction based onnetwork sensor impact onlocal sensor or local prediction.
Sky Imager	30 min to 3 hrs 2 to 10 km	radius	For 30-sec forecast a 50-60% reduction in forecasterror compared to persistence was found.[9]
Array Scale	1 to 30 minutes	Array size	This method shows the impact of cloud speed onthe complete array and also shows the impact of largerand smaller clouds on the PV production depending on the length of time averaging. [10]

Table 1 broadly summarizes most of the approaches currently in research and development. Modeling of solar power forecasting the input variables are solar radiance, air mass, ambient temperature, wind velocity, module temperature, etc. and these input variable parameters are measured by following conventional models such as clear sky models, clear sky and clearness indices, persistence forecasts, and a metric for the evaluation of solar forecasting skill.These conventional models are covered in the following sections.

A. Satellite Imagery

Satellite imagery is an established means of estimating groundlevel irradiance for photovoltaic system performance assessment. More recently satellite cloud motion data are beginning to be used as a means of generating short-term forecasts (hours ahead to days ahead) of ground level irradiance. Predictions of ground level irradiance are then extended to forecasts of PV production.

B. Mesoscale Weather Model Forecasts

Numerical weather prediction (NWP) models are being usedby a number of practitioners in the field of irradiance and PV power forecasting. The models simulate cloud fraction whichis then extended to ground level irradiance and, further, to PV power production forecasts. These models typically have effective forecast windows between one half a days to a week.

C. Aggregated Ground Based Solar Measurements

By one account the India has over 51 publically accessible C-Wet ground based measurement sites which report hourly and daily observations. Centre for Wind Energy Technology (C-WET), Chennai is implementing the project by installing a network of 51 Solar Radiation Resource Assessment (SRRA) station in the first phase in different States using high quality, high resolution equipment / instruments.

D. Sky Imager Technology

In recent years researchers at the University of California SanDiego and at commercial utility scale installations have developed a method of intra-hour, sub-kilometer forecasting using a device known as a "Sky Imager." Reflected images of loud motion are translated into estimates of ground level irradiance and, by extension, PV production.

E. Array Scale Irradiance Sensor Networks

Instrumentation such as silicon pyranometers and thermopile pyrheliometers are routinely installed in utility scale PV arrays providing high granularity global horizontal irradiance (GHI) and plane of array irradiance (POA).

3.0 METHODS FOR PHOTOVOLTAIC PLANT OUTPUT MEASUREMENT

3.1 Analytical Methods

Solar PV Nominal Power Output:

Nominal rated maximum (kW_p) power output of a solar array of n modules, each with maximum power of W_p at STC is given:

$$E_{p,o} = n * W_p * 1000 \quad \text{....(1)}$$

Where:

kW_p - nominal peak power, kW

W_p - peak power of a single module, W

Solar PV Power Output:

Solar PV system Output(kW_p) of a solar array of n modules, each with PV panel capacity ofW_p and (η) Balance of system at STC is given

$$E_{p,o} = n * W_p * (\eta)\ B.O.S. * 1000 \quad \text{....(2)}$$

Where:

$E_{p,o}$ = Solar PV Power Output

n = Number of modules

W_p = Peak power of a single module, W

η = Efficiency (Balance) of system

Estimated PV System Peak EnergyOutput:

The available solar radiation (E_{ma}) varies depending on the time of the year and weather conditions. However, based on the average annual radiation for a location and taking into account the efficiency (η) of the cell, we can estimate an average PV system energy

$$E_{e,o} = n * W_p * (\eta)\ B.O.S. * 1000 \quad \text{....(3)}$$

Where:

n = Number of modules

W_p = peak power of a single module, W

η = efficiency (Balance) of system

$E_{e,o}$ = estimated peak energy delivered, kWh

B.O.S = balance of system

Solar PV System Energy Yield

The final yield of the plants is defined as the daily, monthly and yearly net AC energy output of the plant divided by the theoretical power of installed photovoltaic array at standard test conditions (STC). It is related to the system quality, and allows the comparison between installations in different locations and orientations.

$$y_{f,d} = \frac{E_{ac,d}}{P_{pv,rated}} = \frac{kWh}{kWp} \quad ....(4)$$

$Y_{f,d}$ = Daily Energy Yield

$E_{ac,d}$ = Daily Energy output

$P_{pv,rated}$ = Rated Capacity of a PV system

3.2 PV System Monitoring Method

Monitoring and control of photovoltaic systems is essential for reliable functioning and maximum yield of any solar electric system. The simplest monitoring of an inverter can be performed by reading values on display - display (usually LCD) is part of almost each grid-connected inverter. Most important inverter and grid related parameters are available on LCD screen. Following parameter are usually measured by PV monitoring device is shown in Table 2.

TABLE 2

MEASURED PARAMETERS

Array voltage	V_{DC}	V
Grid voltage	V_{AC}	V
Array current	I_{DC}	A
Grid current	I_{AC}	A
Array power	P_{DC}	W
Grid power	P_{AC}	W
Module temperature	T_{mod}	°C
Ambient temperature	T_{amb}	°C
Global irradiance [1]	G	W/m^2
Global irradiation [2]	H	J/m^2
Wind speed	v	m/s

So we can directly collect the data from monitoring device and use for forecasting modeling.

4.0 CLASSICAL APPROCHES FOR FORECASTING MODELLING

Forecasting is simply a systematic procedure for quantitatively defining future solar power generation. Depending on the time period of interest, a specific forecasting procedure may be classified as a short term, intermediate or long term technique.

Because system planning is our basic concern and because planning for the flow generation, transmission and distribution facilities must begin 4 - 10 year in advance of the actual in service data, we shall be concerned with the methodology of intermediate-range forecasting.

Forecasting techniques may be divided into 3 broad classes. Techniques may be used on extrapolation or correlation or a combination of both. Techniques may be further classified as deterministic, probabilistic, or stochastic and soft computing.

4.1 Extrapolation

Extrapolation techniques involve fitting trend curves to basic historical data adjusted to reflect the growth. It produces reasonable results in many cases.

Such a technique is to be classified as a deterministic extrapolation, since no attempt is made to account for random errors in the data or in the analytical model. Some standard analytical functions are used in trend curves fitting, including:

1. Straight line $\bar{Y} = x_1 + x_2 t$
2. Parabola $\bar{Y} = x + x_1 t + x_2 t^2$

The most common curve - fitting technique for finding coefficients of function in a given forecast is the method of least squares as will be discussed later

4.2 Correlation

Correlation techniques are used to relate solar power generation to various deterministic and stochastic parameters. This approach has an advantage of forcing the forecast to understand clearly the interrelationship between PV power generation patterns and other measurable factors. The most obvious disadvantage, however results from the need to forecast dependent variable, which can be more difficult than forecasting PV power generation. Typically, these factors may be Solar radiation, Ambient temperature, Wind velocity, Cloud images, Rain and other important meteorological parameters

4.3 Method of Calculation: Mathematical Approaches

4.3.1 Simple Regression

Regression in general is a relationship between the variable we want to forecast (dependent) and another variable (independent).

Or, we can say

Y = f (x)

If the independent variable is time, then we call it simple time-series regression, and simple refers to a single independent variable.

In a simple regression the relationship is assumed linear, i.e.

$Y = x_1 + x_2\, t$

The principle of regression theory is that, any function $\hat{Y}$ = f (x) can be fitted to a set of data points so as to minimize the sum of errors squared at each data point and this type of fitting is called least square fit in which the objective is to:

$$\sum_{i=1}^{n}[Y_i - f(x_i)]^2 = \text{Minimum} \qquad \text{....(5)}$$

Where n is the number of data points

4.3.2. Linear Regression

$$Y = f(x)$$

$$\bar{Y} = x_1 + x_2 t$$

$$e^2 = \sum_{i=0}^{n}(Y - \bar{Y})^2$$

$$e^2 = \sum_{i=0}^{n}[Y - (x_1 + x_2 t)]^2$$

$$\frac{\partial e^2}{\partial a} = 2\sum_{i=0}^{n}[Y - (x_1 + x_2 t)](-1) = 0$$

$$\sum_{i=0}^{n} Y = \sum_{i=0}^{n} x_1 + \sum_{i=0}^{n} x_2 t \qquad \text{....(6)}$$

Or

$$\sum_{i=0}^{n} Y = n x_1 + \sum_{i=0}^{n} x_2 t$$

$$\frac{\partial e^2}{\partial b} = 2\sum_{i=0}^{n}[Y - (x_1 + x_2 t)](-1) = 0$$

$$\sum_{i=0}^{n} tY = \sum_{i=0}^{n} x_1 t + \sum_{i=0}^{n} x_2 t^2$$

$$\begin{pmatrix} n & \sum_{i=0}^{n} t \\ \sum_{i=0}^{n} t & \sum_{i=0}^{n} t^2 \end{pmatrix} \cdot \begin{pmatrix} x_1 \\ x_2 \end{pmatrix} = \begin{pmatrix} \sum_{i=0}^{n} Y \\ \sum_{i=0}^{n} tY \end{pmatrix} \qquad \text{....(7)}$$

4.3.3 Quadratic Regression

$$Y = f(x)$$

$$\bar{Y} = x_1 + x_2 t + x_3 t^2$$

$$e^2 = \sum_{i=0}^{n}(Y - \bar{Y})^2$$

$$e^2 = \sum_{i=0}^{n}[Y - (x_1 + x_2 t + x_3 t^2)]^2$$

$$\frac{\partial e^2}{\partial a} = 2\sum_{i=0}^{n}[Y - (x_1 + x_2 t + x_3 t^2)](-1) = 0$$

$$\sum_{i=0}^{n} Y = \sum_{i=0}^{n} x_1 + x_2 t + x_3 t^2$$

$$\sum_{i=0}^{n} Y = n x_1 + x_2 \sum_{i=0}^{n} t + x_3 \sum_{i=0}^{n} t^2$$

$$\frac{\partial e^2}{\partial b} = 2\sum_{i=0}^{n}[Y - (x_1 + x_2 t + x_3 t^2)](-t) = 0$$

$$\sum_{i=0}^{n} tY = x_1 \sum_{i=0}^{n} t + x_2 \sum_{i=0}^{n} t^2 + x_3 \sum_{i=0}^{n} t^3$$

$$\frac{\partial e^2}{\partial c} = 2\sum_{i=0}^{n}[Y - (x_1 + x_2 t + x_3 t^2)](-t^2) = 0$$

$$\sum_{i=0}^{n} t^2 Y = x_1 \sum_{i=0}^{n} t^2 + x_2 \sum_{i=0}^{n} t^3 + x_3 \sum_{i=0}^{n} t^4 \qquad \text{....(8)}$$

$$\begin{pmatrix} n & \sum_{i=o}^{n} t & \sum_{i=0}^{n} t^2 \\ \sum_{i=0}^{n} t & \sum_{i=0}^{n} t^2 & \sum_{i=0}^{n} t^3 \\ \sum_{i=0}^{n} t^2 & \sum_{i=0}^{n} t^3 & \sum_{i=0}^{n} t^4 \end{pmatrix} \cdot \begin{pmatrix} x_1 \\ x_2 \\ x_3 \end{pmatrix} = \begin{pmatrix} \sum_{i=0}^{n} Y \\ \sum_{i=0}^{n} tY \\ \sum_{i=0}^{n} t^2 Y \end{pmatrix} \quad ....(9)$$

4.3.4 Polynomial Regression

$$Y = f(x)$$

$$\bar{Y} = x_1 + x_2 t + x_3 t^2 + x_4 t^3$$

$$e^2 = \sum_{i=0}^{n} (Y - \hat{Y})^2$$

$$e^2 = \sum_{i=0}^{n} [Y - (x_1 + x_2 t + x_3 t^2 + x_4 t^3)]^2$$

$$\frac{\partial e^2}{\partial a} = 2\sum_{i=0}^{n} [Y - (x_1 + x_2 t + x_3 t^2 + x_4 t^3)](-1) = 0$$

$$\sum_{i=0}^{n} Y = \sum_{i=0}^{n} x_1 + x_2 t + x_3 t^2 + x_4 t^3$$

$$\sum_{i=0}^{n} Y = n x_1 + x_2 \sum_{i=0}^{n} t + x_3 \sum_{i=0}^{n} t^2 + x_4 \sum_{i=0}^{n} t^3$$

$$\frac{\partial e^2}{\partial b} = 2\sum_{i=0}^{n} [Y - (x_1 + x_2 t + x_3 t^2 + x_4 t^3)](-t) = 0$$

$$\sum_{i=0}^{n} tY = x_1 \sum_{i=0}^{n} t + x_2 \sum_{i=0}^{n} t^2 + x_3 \sum_{i=0}^{n} t^3 + x_4 \sum_{i=0}^{n} t^4$$

$$\frac{\partial e^2}{\partial c} = 2\sum_{i=0}^{n} [Y - (x_1 + x_2 t + x_3 t^2 + x_4 t^3)](-t^2) = 0$$

$$\sum_{i=0}^{n} t^2 Y = x_1 \sum_{i=0}^{n} t^2 + x_2 \sum_{i=0}^{n} t^3 + x_3 \sum_{i=0}^{n} t^4 + x_4 \sum_{i=0}^{n} t^5$$

$$\frac{\partial e^2}{\partial d} = 2\sum_{i=0}^{n} [Y - (x_1 + x_2 t + x_3 t^2 + x_4 t^3)](-t^3)$$

$$\sum_{i=0}^{n} t^3 Y = x_1 \sum_{i=0}^{n} t^3 + x_2 \sum_{i=0}^{n} t^4 + x_3 \sum_{i=0}^{n} t^5 + x_4 \sum_{i=0}^{n} t^6 \quad ....(10)$$

$$\begin{pmatrix} n & \sum_{i=o}^{n} t & \sum_{i=0}^{n} t^2 & \sum_{i=0}^{n} t^3 \\ \sum_{i=0}^{n} t & \sum_{i=0}^{n} t^2 & \sum_{i=0}^{n} t^3 & \sum_{i=0}^{n} t^4 \\ \sum_{i=0}^{n} t^2 & \sum_{i=0}^{n} t^3 & \sum_{i=0}^{n} t^4 & \sum_{i=0}^{n} t^5 \\ \sum_{i=0}^{n} t^3 & \sum_{i=0}^{n} t^4 & \sum_{i=0}^{n} t^5 & \sum_{i=0}^{n} t^6 \end{pmatrix} \cdot \begin{pmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{pmatrix} = \begin{pmatrix} \sum_{i=0}^{n} Y \\ \sum_{i=0}^{n} tY \\ \sum_{i=0}^{n} t^2 Y \\ \sum_{i=0}^{n} t^3 Y \end{pmatrix} \quad ....(11)$$

5.0 ADVANCE APPROACHES

Given the limitations of the basic models seen above, in the last years much research has been devoted to nonlinear models. Different studies show that nonlinear and non-stationary models aremore flexible in capturing the characteristics of data and that, in some cases, are better in terms of estimation and forecasting. These advances do not rule out linear models at all, since these models are a first approach which can be of great help to further estimate some of the parameters [11].

5.1 Neural networks

A neural network (NN) is a mathematical model that is inspired by biological neural networks, like the human brain shown in Figure 1. Neural network usually used to model complex relationships between inputs and outputs or to find patterns indata [12-13]. The ANN consists of layers, the first layer has input neurons, which send data via synapses to the second layer of neurons (hidden layer) and then via more synapses to the third layer, which include the output neurons shown in Figure 2. More complex systems have more hidden layers with increased number of input and output neurons. The synapses store parameter scalled "weights" that manipulate the data in the calculations [14].

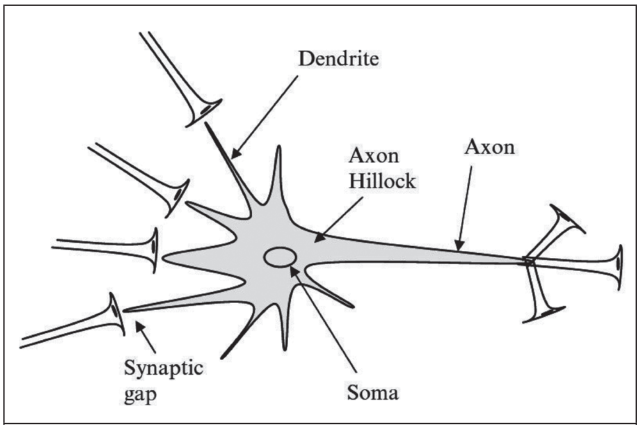

FIG. 1 STRUCTURE OF BIOLOGICAL NEURON

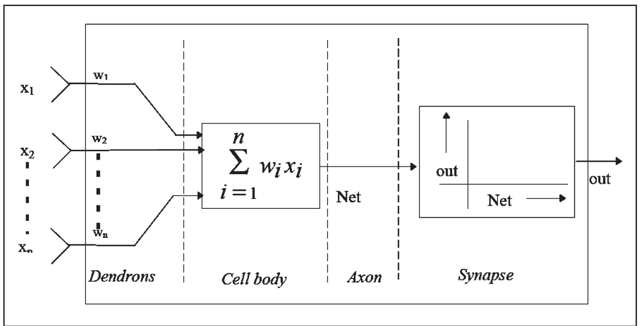

FIG. 2 AN ELECTRICAL EQUIVALENT OF THE BIOLOGICAL NEURON

The working of neural network is like a human brain [15-16]. In neural network, past data or events play an important role. Past data is very important for neural network. The non-linear and complex problem can easily handle with neural network. There is no need for any functional relationship between solar power and dependent. The neural network gets feedback from past data; generalize from previous examples to new ones, abstracts essential characteristics from input containing irrelevant data. The neural network helps in provide better and accurate results compared to statistical methods [4-6].

Following major steps are necessary to develop neural network:

a. Selection of input parameters

b. Selection of neural network

c. Selection of perfect training algorithm

d. Selection of training parameter

Neural Networks (NN) are a class of nonlinear functional forms which have been developed separately from standard regression techniques. Fitting the network involves training the model over known input and output values; the algorithm adjusts the hidden and output node weights until the output approximates the actual data within a given threshold. Training is accomplished using a back-propagation algorithm, which is analogous to the steepest descent algorithms used in nonlinear regression, except that the derivatives for each weight are adjusted separately. For this reason, the time involved in training can be considerable. Forecast studies with NN are found in [17-20].

5.2 Proposed Nature Inspired Hybrid Computing for Solar Forecasting Modeling

Nature Inspired Computing (NIC) is one that aims to develop new computing techniques after getting ideas by observing how nature behaves in various situations to solve complex problems like nonlinear, dynamic and complex in nature. Research on NIC has opened new branches such as:

a. Neural Networks,

b. Genetic Algorithms,

c. Power swarm intelligence,

d. Quantum computing.

It is well known that that all the Nature Inspired Computing methods have their strengths and drawbacks, since they are based on only certain phenomena in nature [21]. It is generally advantageous to apply them in combination instead of individually for example, Neural Network with Genetic Algorithm, PSO, and Quantum computing. Nature-inspired computationshave already achieved remarkable success [22].

7.0 CONCLUSION

In last few years various type of conventional forecasting techniques discussed in this paper. Compared to the vast amount of literature on linear forecast combination, the number of publications about nonlinear, nature-inspired methods appears small. The majority only use linear regression and nonlinear regression techniques. These methods offer many advantages over conventional forecasting approaches, including the ability to combine statistics and soft computing techniques of forecast. In certain circumstances, parallel executionand asynchronous communication can improve performance. Existing nature inspired systems may benefit parallel implementations and their self-organizing properties may address the problem of coordinating decentralized execution. These algorithms help in initiating and studying the way in which problem can make solutions, learn, take decisions or perceive others. We believe that further properties of natural environments are worth investigating, either because these properties are desirable for optimum results for new computing environments.

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