Short-Term PV Power Forecasting Using Generalized Neural Network and Weather-Type Classification

Priyanka Chaudhary and M. Rizwan

Abstract Generation of electricity from solar energy is gaining huge attention because of advancement in the solar photovoltaic technology. Power from solar energy is intermittent in nature and requires a good forecasting method for efficient and reliable operation of smart grid systems. A large number of forecasting approaches are available in the literature. Due to intermittent nature of power obtained from sun, the results obtained from mathematical models for solar PV power prediction are not found satisfactory. An intelligent approach based on generalized neural network (GNN) is proposed and applied for the short-term solar PV power forecasting. Short-term forecasting for an hour to day ahead has applications in energy storage optimization, electricity pricing, etc. Keeping in mind aforesaid, 15 min ahead, short-term solar energy forecasting has been done and presented in this work for smart grid applications. The developed model requires an input of historical data set for PV output power, i.e. solar irradiance, temperature and the relative humidity of the site where solar PV is installed. The performance of the developed PV power forecasting model is evaluated with respect to the accuracy of the developed model for a 1 kWp practical system. Further, the evaluation of proposed method has been performed on the basis of root mean square error (RMSE) and mean absolute error (MAE).

Keywords Generalized neural network · Grid-integrated solar PV systems · Solar PV forecasting · Smart grid systems

1 Introduction

Solar photovoltaic (SPV) systems are playing important role in moving toward low-carbon energy resources. Output of solar photovoltaic depends on availability of solar

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irradiance and other meteorological parameters. Output power forecasting of SPV plant helps in controlling of variables in advance and optimize the capacity of energy storage system. A reliable and efficient forecasting model helps in improving grid-integrated operations, advance planning and maintenance. Prediction of solar energy becomes utmost important from the utilities point of view to balance the supply and demand for an efficient operation. Intermittent nature of power from solar energy becomes significant challenge for successful and economically efficient integration of solar power generating plants into utility grid. Hence, the prediction of SPV power output plays a significant role in sustainable power generation, power system operation and control. A large number of mathematical models for prediction of solar PV output power for cloudless sky conditions are available in the literature [1, 2]. Broad classification of short-term solar PV forecasting approaches is available in two categories, namely statistical methods and artificial intelligence methods. Some of statistical models are multiple linear regression, stochastic time series, autoregressive integrated moving average with exogenous variables (ARIMAX) and general exponential smoothing, state-space model and support vector regression (SVR). Intelligent models like artificial neural network, fuzzy inference systems, etc., are also available in the literature. The solar PV power output prediction using statistical models was not satisfactory subjected to the cloudy sky constraints. Further, fuzzy logic, neural network-based models are proposed by researchers to estimate the solar irradiance to deal with large uncertainties associated with the weather conditions [3]. In this paper, a generalized neural network (GNN)-based model for 15 min ahead solar PV output power forecasting has been developed and presented. Proposed model has the advantage of fast convergence and stronger training and learning ability. The developed model has been compared with the artificial neural network (ANN)-based model for results validation. Further, the evaluation of proposed method has been performed on the basis of root mean square error (RMSE) and mean absolute error (MAE).

2 Forecasting Model

2.1 Data Collection and Weather Classification

Data for global solar irradiance, ambient temperature, average relative humidity and past data for PV output power has been collected from Jamia Millia Islamia (JMI), National Institute of Solar Energy (NISE) and Ministry of New and Renewable Energy (MNRE), Government of India for New Delhi location at 15 min time interval and used as input for short-term solar PV output power forecasting. According to Indian weather scenario, seasonal classification of available solar power generation data is done as summer, winter and rainy seasons to achieve more granularity can be achieved to perform clustering on available historical data set. Input and output variables from the data set are not of the same order of magnitude. So, it is necessary to

Table 1 Neural network structure

Parameters	Value
Input parameter	4
Output	1
Input layer	1
Output layer	1
Hidden layer	1
Hidden layer neurons	3

normalize the data sets and convert it in the same order of magnitude. Normalization of the data within the range of (0.1–0.9) is used to convert actual monthly data, and this is done to improve convergence and learning process and given below:

$$L_s = \frac{Y_{\max} - Y_{\min}}{L_{\max} - L_{\min}}\left(L - L_{\min}\right) + Y_{\min} \tag{1}$$

where L is the actual solar irradiance data, L_s is the scaled solar irradiance data being used as input to the GNN model, $L_{\max}$ is maximum value of solar irradiance data in a particular column, $L_{\min}$ is minimum value of solar irradiance data in a particular column, $Y_{\max}$ is normalization upper range (0.9) and $Y_{\min}$ is normalization lower range (0.1).

2.2 ANN Model

The nonlinearity and complexity are the problems can be easily handled with the neural network [4, 5]. The neural network takes past data as feedback and generalizes the set of equations from previous calculations to the new ones. ANN does not require any physical link between solar power output and input parameters. Inputs to the model are global solar irradiance, ambient temperature, average relative humidity and previous PV output power. Parameters of structure of ANN are provided in Table 1. ANN model for short-term solar PV power output forecasting can be developed using the steps: input parameter selection; neural network architecture selection; training algorithm; training parameter selection. Backpropagation training algorithm for training of ANN has been used which helps in adjustment of the weight and threshold coefficients. NN training parameters are shown in Table 2. A single layer ANN structure has been used to develop the ANN-based solar PV output power forecasting model.

Table 2 Neural network training

Parameters	Value
Epochs	900
Momentum factor	0.1
Learning rate	0.003
Error tolerance	0.001

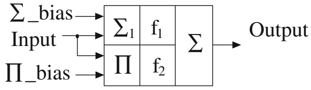

Fig. 1 Generalized neural network model

2.3 GNN Model

GNN is used to overcome problems associated with the performance, training and testing of ANN [6, 7]. It acts as a multi-layer feed-forward network in which each node performs a particular function on incoming signals as well as a set of parameters pertaining to this node. A common neuron structure has summation or product as the aggregation function with linear or nonlinear threshold function. A summation type GNN model is shown in Fig. 1, which shows the internal structure of GNN with summing up the outputs of the sigmoidal (f_1) and Gaussian (f_2) characteristic functions of product (Π) and summation (Σ_1) neuron [8].

The development of GNN model consisting of two phases: development phase and testing phase. The GNN model for solar PV power forecasting has been developed using same number of input and output variables as in ANN model. The output calculations can be divided into two parts: forward calculations and reverse calculations.

1. Forward calculations:

(i) Output of the Σ_A part with a sigmoidal characteristic function can be calculated as

$$O_\Sigma = \frac{1}{1 + e^{-\lambda s * s\_net}} \tag{2}$$

$s\_net = \Sigma W_{\Sigma i} X_i + X_{o\Sigma}$
$\lambda s =$ gain scale factor of $\Sigma_{A.}$

(ii) Output of the Π part with a sigmoidal characteristic function can be calculated as

$$O_\Pi = e^{-\lambda p * pi\_net^2} \tag{3}$$

$pi\_net = \Pi W_{\Pi i} X_i * X_{o\Pi}$ and λp is the gain scale factor of $\Pi_{A.}$

(iii) The output of the GNN is the function of two outputs and with the weights W and $(1 - W)$, respectively

$$O_{pk} = O_{\Pi} * (1 - W) + O_{\Sigma} W \tag{4}$$

2. Reverse calculations

(iv) After the calculation of output in forward mode, as in the feed-forward neural network, the output compared with the desired output to find the error. Back-propagation training algorithm is used here to train the GNN. Error of ith set of input for a single GNN is calculated by comparing the GNN output and desired output.

$$\text{Error } E_i = (Y_i - O_i) \tag{5}$$

(v) Sum squared error for the convergence of all the pattern is

$$E_p = 0.5 \sum Ei^2 \tag{6}$$

Multiplication factor of 0.5 has been taken to simplify the calculations.

vi) Weights associated with the Σ_A and Σ_B part of the summation type GN are:

$$W(k) = W(k-1) + \Delta W \tag{7}$$

$\Delta W = \eta \delta_k (O_{\Sigma} - O_{\Pi}) X_i + \alpha W(k-1)$
And $\delta_k = \sum (Y_i - O_i)$

(vii) Weights associated with the Σ_A part of the summation type GN are:

$$W \sum_i (k) = W \sum_i (k-1) + \sum W_{\Sigma i} \tag{8}$$

$\Delta W_{\Sigma i} = \eta \delta_{\Sigma i} X_i + \alpha W_{\Sigma i}(k-1)$
And $\delta_{\Sigma j} = \sum \delta_k W (1 - O_{\Sigma}) * O_{\Sigma}$
α momentum factor for better convergence and lies between 0 and 1
η learning rate and lies between 0 and 1

(viii) Weights associated with the Π part of the summation type GN are:

$$W \Pi_i (k) = W \Pi_i (k-1) + \Delta W_{\Pi i} \tag{9}$$

$\Delta W_{\Pi i} = \eta \delta_{\Pi i} X_i + \alpha W_{\Pi i}(k-1)$
And $\delta_{\Pi j} = \sum \delta_k (1 - W) * (-2 * pi\_net) * O_{\Pi}$

The output of summation part of generalized neural network can be obtained as:

$$O_{\Sigma} = f_1 \left(\sum W_{\Sigma i} X_i + X_{o\Sigma} \right) \tag{10}$$

The output of product part of generalized neural network can be obtained as:

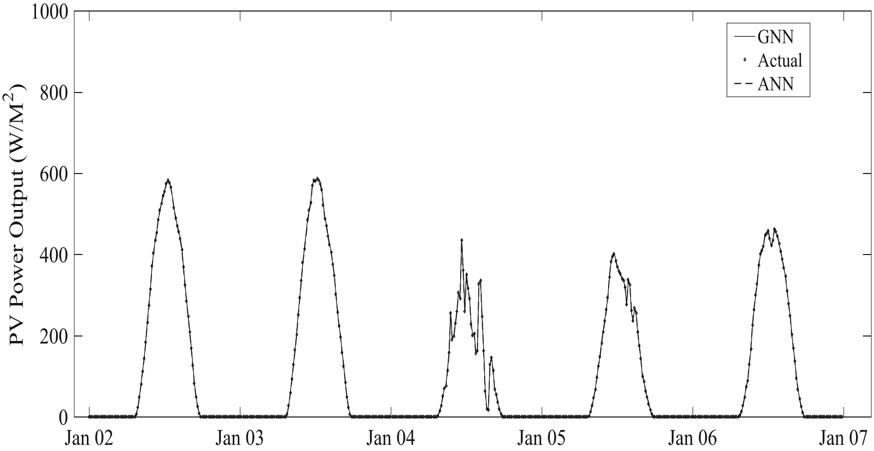

Fig. 2 Testing performance of ANN and GNN model for the winter season

$$O_{\Pi} = f_2(\Pi W_{\Pi i} X_i + X_{o\Pi}) \tag{11}$$

The final output of generalized neuron will be the sum of summation part and product part and can be mathematically written as:

$$O_i = O_{\Sigma} * W_{\Sigma} + O_{\Pi}(1 - W_{\Sigma}) \tag{12}$$

where O_{Σ} is output of the summation part of the neuron, O_{Π} is output of the product part of the neuron and W denotes weights.

3 Results and Discussions

The testing results for short-term solar power output forecasting using proposed GNN model are presented in this section and compared with ANN results. Data has been chosen and classified according to the three season types, namely summer, winter and rainy. Testing performances of developed models for winter season, summer season and rainy season are given in Figs. 2, 3 and 4, respectively. The average RMSE and percentage MAE for different seasons are given in Table 3. It is observed from Table 3 that the average values of RMSE and percentage MAE are less for GNN model as compared to ANN model. The average RMSE and percentage MAE are large for the rainy season because of the large uncertainties associated with the data.

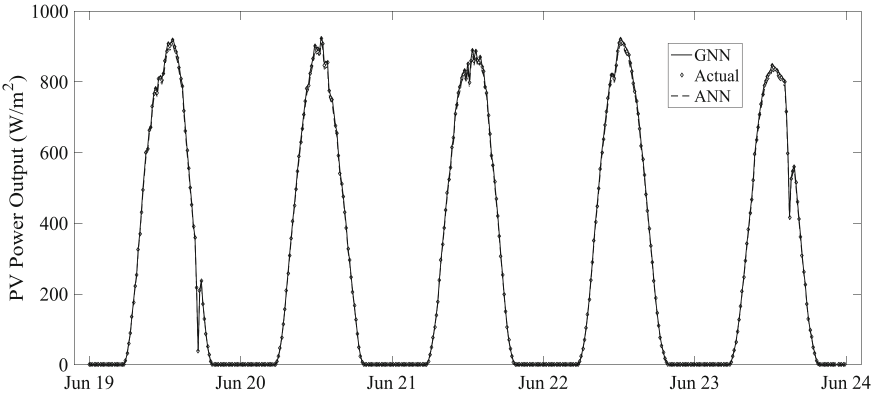

Fig. 3 Testing performance of ANN and GNN model for the summer season

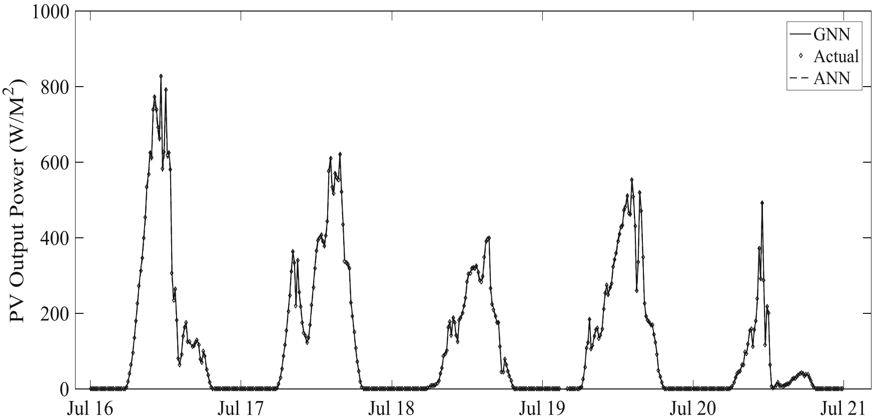

Fig. 4 Testing performance of ANN and GNN model for the rainy season

Table 3 Comparison of testing performances

Seasons	Model	RMSE(W)	MAE %
Summer	GNN	62.2	2.93
	ANN	72.8	3.34
Rainy	GNN	91.3	3.48
	ANN	104.2	4.42
Winter	GNN	69.2	3.05
	ANN	78.8	3.64

4 Conclusion

In this paper, 15 min ahead short-term solar PV output power forecasting models based on GNN has been developed and presented. The results of ANN and GNN are compared for solar power forecasting. The performance of the model is evaluated on the basis of statistical indicators such as MAE and RMSE. It is found that GNN performs better as compared to ANN in terms of learning time and convergence.

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