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Artificial intelligence based forecast models for predicting solar power generation

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Abstract

Carbon discharges from monetary movement proceed to rise and India is the third-biggest emitter among individual nations. The Renewable Energy is the way forward and the problems in harvesting it should surmount through policy and technical approaches. The prime disadvantage with most of the Renewable Energy resources is their susceptibility to the whim and vagaries of nature and becoming a variable random source of power. Predicting the power from these variable power sources define and determine the operation of the system. In this paper, ANN and ANFIS based forecast model for predicting the PV Generation are presented. The designed forecast model is trained using historical data. The results of the proposed model are validated and compared by considering data set of PV power generating station. A simulation model of proposed system is developed in MATLAB to evaluate the system performance.

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*Keywords:*Energy,Forecasting, Photovoltaic, Artificial Neural Network, Adaptive Neuro -Fuzzy Inference System

1. Introduction

Energy is basic, specifically or by implication, in the completetechnique of advancement, expansion and existence of all living being and it shows a fundamental part in the monetaryprogress and human prosperity of a nation. Energy has come to be known as a vital produce and any liabilityaround its source can weaken the operational of the economy, specifically in emerging economies.

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Realizing energy safety in this important sense is of essential prominence to India's monetaryprogress as well as for the socialprogress destinations that go for the mitigation of neediness, unemployment and meeting the Millennium Development Goals [1].Because of thepresent situation of energy utilization, India is progressively moving the attention towards its renewable energy sources. The launch of Jawaharlal Nehru National Solar Mission (JNNSM)has made a considerable measure of enthusiasm for the India solar segment. To make arequest and draw in interest in the part, the government is giving different impetuses.

India's solar photovoltaic market has developed by 75% in 2010 and a half in 2011. India has tremendous potential for sunlight based PV and with the right arrangement support from the Indian Government; India can turn into a noteworthy player in the solar market all around. One of the primary components of the Mission is to make India a worldwide pioneer in solar power generation and the mission predicts an installed solar power generation limit of 20 GW by 2022. This could really be much bigger because of private activities [2]. India is blessed with affluent solar energy resources. Due to its position between the Tropic of Cancer and the Equator, India has a normal yearly temperature that extent from 250C – 27.50C. Being a tropical nation, India has immense potential for PV power generation. The usual intensity of solar radiation in India is 200 MW/km^{2}through 250–300 sunshiny days in a year. According to government guesses, India gets 5,000tn kWh every year, with maximum parts of the nation getting 4-7 kWh per square meter every day [3].According to IEA projection,India will need 327 GW power generation capacities in 2020.

Predicting the output of these renewable sources is a critical issue for electricity departments to alter dispatch arranging in time, increase the reliability and reduce spinning reserve capacity of generation systems[4, 5]. In the existing literature; solar powerpredicting has been widely studied. Short-term power prediction methods for solar power plants primarilycomprise two classes: physical methods and statistical methods. Physical methods imply that a physical equation is established for prediction rendering to the solar power generationprocedure and system characteristics and in combination with forecast weather data [6, 7]. Statistical methods intention to summarize inherent laws to predict the solar power based on historical power data [8, 9, 10, 11, 12 and 13]. The above methods have their respective advantages, but the non-stationary characteristics of solar power output have asignificanteffect on the convergence and properties of the above methods.

From the time when solar irradiance got at a site on the Earth's surface shows periodicity and non-stationary characteristics because of the impact of Earth's rotation and revolution, output power data of solar plants indicates one-day periodicity. As it were, the output power shows a rising pattern before twelve and presents a declining pattern evening. If an effective method to decrease the non-stationary characteristics of solar output power is not implemented, Traditional solar power prediction methods cannot promise the exactness of forecasting outcomes or even the convergence of the method [14].

Artificial intelligence techniques have been viewed as a convenient way to forecast solar power generation. In this work a comprehensive model to predict the solar power output based on historical data is presented. The work explores the option of using Artificial intelligence based methods like Artificial Neural Networks (ANN) and an Adaptive Neuro-Fuzzy Inference System (ANFIS) for predicting the power output. Artificial intelligence based methods are naturally flexible and capable of dealing with non-linearity. They do not need any previousmodelingknowledge and the workingproceduresinevitablycategorize the input data and associate it with the respective output values. They are ‘black box’ kindapparatuses and to a great extent do not agree for comprisinginformation of physical relationsamong model constituents.

2. Determination of input variables for the power forecasting model

Normally, adequatelyexact solar irradiance data can be input into a formula to derive predicted output power. Predicting power output from renewable energies is closely connected to weather forecast predictions. To predict the amount of solar irradiance or power generated, various environmental factors, such as solar irradiance, cloud cover, atmospheric pressure, and temperature, along with the conversion efficiency of PV panels, installation angles, dust on a PV panel, and other random factors must be considered. All these factors affect PV system output. Hence, in choosing input variables for a prediction model, one should consider deterministic factors strongly correlated with power generation. Additionally, time-series data for PV power generation are strongly autocorrelated and therefore these historical data should be the input data of the forecasting model.

To build up a precise and consistent output power forecast model for a solar power plant, it is important to analyzethe impact variables for the solar power plant output. In the physical sense, worldwide sun irradiance got on the ground is a direct impacting element on the voltage impact of solar cells. The Pearson product-moment correlation coefficient, otherwise called r, can measure the direction and quality of the straight relationship between two variables, which is a strategy to measure thenon-deterministic relationship. The estimation of PPMCC extents between - 1 to +1, where 1 is an aggregate positive connection, 0 is no relationship, and − 1 is an aggregate negative relationship.Table 1 provides the Pearson product-moment correlation coefficient between PV output and environmental factors under typical weather conditions.

It can be realized from Table 1that the correlation coefficient among the solar power output and solar irradiance is more than 0.8, which means they are extremely correlated, whereas the correlation coefficient between solar power output and thetemperature is more than 0.3, which means these variables are positively and low-level correlated.The correlation coefficient of humidity specifies a low but negative correlation. The correlation between solar power generation and wind speed is small.

Table 1Pearson product-moment correlation coefficient between solar output and environmental factors

Weather Condition	Pearson Product-Moment Correlation Coefficient			
	Irradiance	Temperature	Humidity	Wind Speed
Clear	0.966	0.322	-0.527	-0.229
Cloudy	0.891	0.441	-0.511	-0.025
Overcast	0.987	0.409	-0.478	0.125
Rainy	0.923	0.410	0.039	-0.178

3. Description of the proposed forecastingsystem

In this work, both ANN and ANFIS forecast models areemployed to predict the power for asolarpower plant using historical data set.

An Artificial Neural Network (ANN) comprises acollection of inputs, outputs, network topology and weighed connection of node. Input features will properlyreplicate the characteristics of the problem [15]. Additionalmain work of the ANN design is to choose network topology. This is done experimentally over a recurrent process to optimize the number of hidden layers and nodes rendering to training and forecast accuracy. In this work 9 Environmental Parameters namely;Global Horizontal Irradiance, Global DiffusedIrradiance, Ambient Temperature, Precipitation, Wind Speed, Air pressure, Sunshine Duration, Relative Humidity and Surface Temperature. Another network is designed by considering 4 inputs like Global Horizontal Irradiance; Global Diffused Irradiance, Ambient Temperature, and Surface Temperature.The Feed – Forward Back Propagation algorithm is applied to theneural network used in this work. A TRAINLM along with LEARNGDM functions are used for training and adaptation of the neural network. The performance measure is computed by using Mean Square Error (MSE). The neural network used in this work includes of two numbers of layerswith layer one having 9 neurons and TANSIG transfer function used to calculate theoutput.

Adaptive Neuro-Fuzzy Inference System (ANFIS) is the combinations of ANN and Fuzzy System, generally, have the advantages of both systems.The hybrid learning algorithm is applied to recognize parameters of Sugeno-type fuzzy inference system[16]. It applies a combination of the least squares method and the back propagation gradient descent method for training FIS membership function parameters to emulate a given training data set. An ANFIS works [17] by applying neural learning rules to identify and tune the parameters and structure of a Fuzzy Inference System (FIS). There are several features of the ANFIS which enable it to achieve great success in a wide range of scientific applications. The attractive features of an ANFIS include easy to implement, fast and accurate learning, strong generalization abilities, excellent explanation facilities through fuzzy rules, and easy to incorporate both linguistic and numeric knowledge for problem-solving. According to the neuro-fuzzy approach, a neural network is proposed to implement the fuzzy system, so that structure and parameter identification of the fuzzy rule base are accomplished by defining, adapting and optimizing the topology and the parameters of the corresponding neuro-fuzzy network. The network can be regarded both as an adaptive fuzzy inference system with the capability of learning fuzzy rules from data and as a connectionist architecture provided with linguistic meaning.

Global horizontal irradiance; Global diffused irradiance, Ambient Temperature, and Surface Temperature are the input vectors for the network. In the proposed work both Backpropagation and Hybrid methods of optimization are employed.

4. Dataset used for the analysis

In this work 9 environmental parameters namely; Global Horizontal Irradiance, Global DiffusedIrradiance, Ambient Temperature, Precipitation, Wind Speed, Air Pressure, Sunshine Duration, Relative Humidity and Surface Temperature are considered as inputs to train the proposed forecast system. The Data pertains to 10 MW power plants in Kalipi, Andhra Pradesh, India. The model is scaled down to 10 KW for simplification of analysis. The Latitude of the site is: 13.9928873^0 and Longitude are: 77.4587239^0. The site is located at an altitude of 548 meters from the mean sea level. The Data format considered training the proposed model comprises of 3960 individual data sets pertaining to hourly data for 365 days .The data hour is considered from 7 am to 6 pm. Each individual data set comprises 9 data points pertaining to different parameters being employed in the forecast system. The sample data set used in the training of ANN PV forecast model is given in Table 2.

Table 2 Sample data set used in training the ANN forecast model

PV Parameters	SD1	SD2	SD3	SD4	SD5	SD6	SD7	SD8
G_Gh (Global Horizontal)	119	76	70	237	78	341	660	345
G_Dh (Global Diffused)	75	76	70	227	78	312	350	289
Ambient Temperature	24.5	24.7	24.7	25.5	25.4	26.3	27.8	28.2
Precipitation	0	0	0	0	0	0	0	0
Wind speed	1.5	0.8	3.3	1.8	1.5	1.8	2	1.3
Air pressure	940	940	940	940	940	940	940	940
Sunshine Duration	30	1	0	3	0	5	46	10
Relative Humidity	62	63	68	62	63	59	55	51
Surface Temp	25.2	24.9	24.8	27.3	25.6	29.1	33.9	31.3

In order to simplify the forecast system; again the considered data of PV generating station is scaled down to 10 KW systems. A total of 1440 data sets pertaining to hourly monitoring for a 60 day period is considered to train the forecast system. Table 3 summarizes the database of PV generating station used in this study for forecasting the PV energy systems.

Table 3 Database utilized in this study

Data Sources	Installed Capacity	Sampling Data	Measurement Item	Total number of data points
Kalipi solar power installation	10 MW	Average values for 60-minute	(i) PV generation (ii)Atmospheric temperature (iii) Solar irradiance (Global and Diffused) (W/m^2) (iv) PV module temperature (v) Ambient temperature (vi) Wind speed (vii) Precipitation (viii) Duration of sunshine (ix) Atmospheric Pressure	71280
Sotavento Galicia wind energy farm	17.56 MW	Average values for 60-minute	(i) Wind generation (ii) wind speed (iii) Wind Angle	2880

5. Forecasting results and discussions

The data points being considered for analysis of the PV system are given in table 4.

Table 4 Data points used in the validation for PV forecast

PV parameters	SD1	SD2	SD3	SD4	SD5
G_Gh (Global Horizontal)	34	98	532	836	973
G_Dh (Global Diffused)	34	52	134	147	101
Ambient Temperature	28.1	20.5	24.4	29.7	28.3
Precipitation	0	0	0	0	0
Wind speed	1.5	0.2	0.7	4.1	0.3
Air pressure	941	944	944	947	949
Sunshine Duration	2	17	55	59	60
Relative Humidity	54	78	63	35	40
Surface Temp	27.9	20.9	29.8	36.1	39
Actual Generation Scaled to 10 KW (KWh)	0.20574	1.175237	5.9933	8.8797	9.9185

In order to validate the results of the proposed work, the forecast model is tested against 5 data points of PV energy. The data points being considered for validation are sampled to represent high, medium and low values of the parameters being considered in the forecast model. The result of the forecast for the above data set is discussed in the following section; the results are being described through a series of tables

Table 5 Forecast for PV generation by ANN– forecast I

Data Point	SD1	SD2	SD3	SD4	SD5
Actual Value	0.20574	1.17524	5.9933	8.8797	9.9185
Predicted Value	0.35521	0.94286	6.106	8.75604	9.84484
% Error	-72.649	19.7729	-1.8804	1.39261	0.74265

Table 6 Forecast for PV generation by ANN – forecast II

Data Point	SD1	SD2	SD3	SD4	SD5
Actual Value	0.20574	1.17524	5.9933	8.8797	9.9185
Predicted Value	0.3688615	0.910558	5.35801	8.58571	10.0603
% Error	79.2853	22.52133	10.6	3.31081	-1.42965

Table 7 forecast for PV generation by ANFIS – forecast I

Data Point	SD1	SD2	SD3	SD4	SD5
Actual Value	0.20574	1.17524	5.9933	8.8797	9.9185
Predicted Value	0.364641	0.797184	5.31916	8.08136	10.7236
% Error	-77.2339	32.16824	11.24823	8.990619	-8.11715

Table 8 Forecast for PV generation by ANFIS – forecast II

Data Point	SD1	SD2	SD3	SD4	SD5
Actual Value	0.20574	1.17524	5.9933	8.8797	9.9185
Predicted Value	0.37844	0.78824	5.40998	8.10273	10.6893
% Error	-83.94	32.929	9.73287	8.74996	-7.7713

From the table 5, table 6, table 7 and table 8 following observations can be inferred

a) For very low insolation values all the forecast methods result in very high error percentage, this can be evident from the fact the least error percentage is 72.64 % being delivered by the forecast by ANN Forecast I (which considers all the 9 parameters for forecast)
b) As there is anincrease in the insolation values, there is asubstantial and appreciable increase in the prediction accuracy and subsequently a decrease in the error percentage. It can be observed that the error percentage stands at 19.79 for SD2 as predicted by ANN Forecast I
c) At higher insolation values the percentage of error drastically falls and the best forecast being delivered by ANN Forecast I. It has given a forecast for an error as less as 0 .74265 % for SD5.
d) When the comparison is inferred between different forecasting methods, between ANN and ANFIS, ANN delivers better results. In particular, the forecast delivered by ANN Forecast I which considers all the 9 parameters for theforecast is superlative.

There are several evaluation criteria for forecasting models, such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and others. In this work, the Normalized Root Mean Square Error (NRMSE) was utilized because it can provide the comparative analysis for different installed-capacity cases. It is defined as follows:

$$\boldsymbol{NRMSE = 100\sqrt{\frac{1}{N}\sum_{i=1}^{N}\frac{(P_a^i-P_j^i)^2}{P_{install}}}}\%(1)$$

Where $P_{install}$, P_a, P_f, indicate installed capacity, actual power output, and power forecast value, respectively, and N is the total number of samples.

6. Conclusion

As the search for clean energy continues to grow, solar power generation will be one of the most important contributors towards delivering the required energy. In this, we have implemented a forecast method based on ANN and ANFIS for predicting the output power with thehelp of ANN and ANFIS models trained using historical data. It can be inferred from the results that in regard to predicting the PV generation ANN based forecast delivers better results when compared to the ANFIS based forecast. The outputs of the forecast models have multiple applications including serving as inputs for energy management system for hybrid PV systems.

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