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Short-term PV power forecasting based on sky-conditions using intelligent modelling techniques

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Abstract

The work in this paper involves intelligent modelling techniques i.e. fuzzy logic, Artificial Neural Network (ANN) and Adaptive Neural Fuzzy Inference System (ANFIS) methodologies for estimating the power in a solar photovoltaic (SPV) system. Since, the generation of power is subjective to environmental factors such as ambient temperature, variation in sky-conditions and solar insolation, therefore, an intelligent modelling techniques have been proposed for forecasting the power of a solar photovoltaic system employing 210 W Heterojunction with Intrinsic Thin layer (HIT) photovoltaic modules for different sky-conditions such as clear sky, hazy sky, partially foggy/cloudy sky and fully foggy/cloudy sky conditions respectively for composite climate zone and performance has been evaluated using statistical indicators.

Keywords: ANFIS (adaptive neural-fuzzy inference system); ANN (artificial neural network); forecasting; fuzzy logic; sky-condition; SPV system.

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1. Introduction

Last few years have seen tremendous growth in the field of renewable power generation especially in the field of solar energy which employs PV system comprising a number of solar cells (Chauhan and Saini, 2004; Singh, 2003; Zhou *et al.*, 2010). Its advantage is that it generates no greenhouse gas emissions and simple scalability in terms of power needs while the disadvantage is that the output power diminishes due to dust, clouds and other obstructions in the atmosphere (Liu *et al.*, 2015; Jimenez-Perez and Mora-Lopez, 2016). Therefore, an intelligent modelling technique has been introduced to accurately estimate the power generation in SPV system based on sky-conditions.

Detailed literature analysis reveals that the intelligent model available in the literature have been defined for clear sky-condition, however, very few models are available in the literature that discussed about variation in sky condition. The objective of the present research is to do the comparative analysis of Fuzzy logic, ANN and ANFIS models in forecasting short-term PV power of SPV systems employing HIT PV modules for different sky conditions i.e. sunny sky, hazy sky, partially foggy/cloudy sky and fully foggy/cloudy sky conditions and for composite climate zone. The performance has been evaluated based on statistical indicators.

The work has been arranged as follows. The data and methodology are presented in Section 2. Section 3 discusses the performance characterization of SPV system. Section 4 is developed to statistical error tests. Results and discussions are presented in Section 5. Conclusion followed by references is presented in Section 6.

2. Data and Methodology

2.1 Meteorological data: In this work, the parameters namely solar irradiance and cell temperature have been achieved from the collaboration of Indian Meteorological Department and National Institute of Solar Energy for composite climate zone (Ajit, 2009; Bansal and Minke, 1988). Further, the normalization of the parameters in 0.1-0.9 range has been done to avoid convergence issues.

2.2 Intelligent modelling for estimating the power of SPV system: Intelligent modelling methods namely fuzzy logic, ANN and ANFIS have been employed to forecast the power in a solar photovoltaic system (Perveen *et al.*, 2019). The details of methodologies are discussed section-wise as follows:

2.2.1 Fuzzy logic: The first section discusses the fuzzy logic modelling where the membership functions are defined in 0.1-0.9 range and a set of rules are explained in the fuzzy logic toolbox of MATLAB. The model has been developed using Mamdani-Sugeno in fuzzy inference system to forecast the power of SPV system for input parameters namely solar cell temperature and solar insolation while the PV power is the output and presented in Fig. 1 (Chen *et al.*, 2013; Rizwan *et al.*, 2014; Perveen *et al.*, 2018).

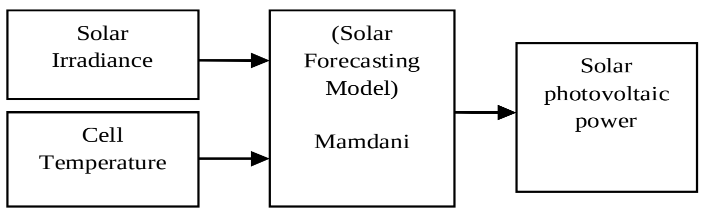

Figure 1. Fuzzy logic based model for estimating power in a solar photovoltaic system.

2.2.2 Artificial Neural Network (ANN): The second section presents an artificial intelligent modelling techniques i.e. Artificial Neural Network (ANN) employing a feed-forward neural network. Model-based on ANN are planned and designed in such manner that output is simulated from the input variables for power forecasting in the SPV system and are presented in Fig. 2 (Azadeh *et al.*, 2013; Azimi *et al.*, 2016; Al-Waeli *et al.*, 2019; Notton *et al.*, 2019).

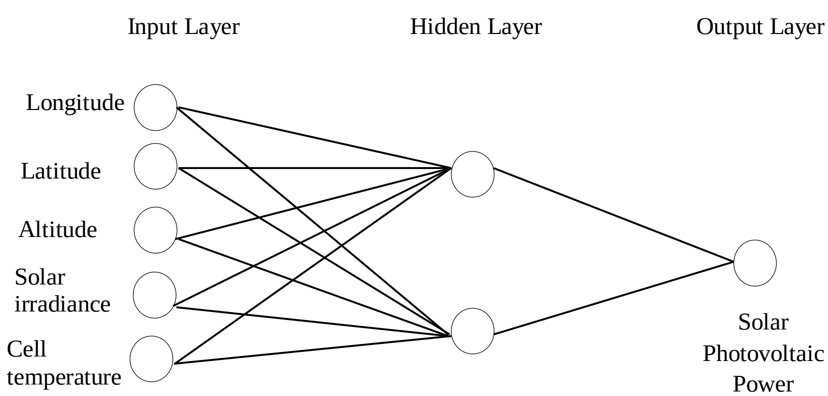

Figure 2. ANN architecture for estimating power in the SPV system.

2.2.3 Adaptive Neural Fuzzy Inference System (ANFIS): The third section presents the combination of ANN and fuzzy logic modelling. ANFIS applies the graphical analysis of Fuzzy-Sugeno system lying within the framework of adaptive networks and relates back-propagation and least squares method using MATLAB software for training and testing the data. The main advantage of using ANFIS methodology is that the convergence rate is much faster (Abu-rub *et al.*, 2013; Jang and Sun, 1995).

3. Performance Characterization of SPV System

In the present work, 210 W HIT solar PV module is chosen and operated at Maximum Power Point (MPP) conditions. Influenced by parameters namely solar irradiance and cell temperature and based on the standard test condition, the power generation can be defined by Eq. (1-2) as shown below (Riffonneau *et al.*, 2011):

$$O_{PV} = \left[O_{PV,STC} * \frac{G_T}{1000} * \left[1 - \gamma * \left(T_j - 25\right)\right]\right] * N_{PVs} * N_{PVp} \quad (1)$$

$$\text{and } T_j = T_m + \frac{G_T}{800} * \left(N_{OCT} - 20\right) \quad (2)$$

where $O_{PV,STC}$ is the photovoltaic system rated power output at standard test conditions, O_{PV} is the power output of photovoltaic array at MPP, G_T is solar irradiance in W/m^2 at standard test condition, N_{PVS} is the photovoltaic arrays in series in number, γ is a temperature parameter at maximum power point, N_{PVP} is photovoltaic arrays in parallel in number in ^{o}C, T_j is the junction temperature of solar panel in ^{o}C. Given the efficiency of the module is 16.7%, T_m is ambient operating temperature range between - 4^{o}F to 115^{o}F and N_{OCT} (Normal operating cell temperature) is 114.8^{o}F.

4. Statistical Error Tests

For evaluating the performance of the models, statistical error tests namely MAPE, NMAE and nRMSE respectively have been used for analysis (Dolara *et al.*, 2018).

4.1 Mean absolute percentage error (MAPE):

$$MAPE_{\%} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{E}{m_i}\right| * 100 \quad (3)$$

4.2 Normalized mean absolute error (NMAE):

$$NMAE_{\%} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{E}{\max(m_i)}\right| * 100 \quad (4)$$

4.3 Normalized root mean square error (nRMSE):

$$nRMSE_{\%} = \frac{\sqrt{\frac{1}{n}\sum_{i=1}^{n}|E|^2}}{\max(m_i)} * 100 \quad (5)$$

where n is the number of observed data, m_i and e_i are the i_{th} measured and estimated data respectively, and E = (m_i - e_i) is the absolute error. This definition of error is normalized over the maximum hourly measured data.

5. Results and Discussions

Intelligent models have been developed for SPV system which employs 210 W HIT solar PV module operated at Maximum Power Point Tracking (MPPT) conditions. The data at the input layer comprises cell temperature, solar irradiance and the output layer is the PV power. Fuzzy logic, artificial neural network and ANFIS methodologies have been employed in forecasting power of SPV systems for composite climate zone and are presented in Table 1.

It has been observed from Table 1 that the average mean absolute percentage error by using fuzzy logic methodology is 0.10%; with ANN methodology the mean absolute percentage error reduced to 0.04%; and with ANFIS methodology the mean absolute percentage error further reduced to 0.01% which reveals that the obtained results are precise and accurate. This is due to the reason that it employs both fuzzy logic approach and artificial neural network. Further, the graphical representation between the measured and forecasted power employing different methodologies has been presented in Fig. 3.

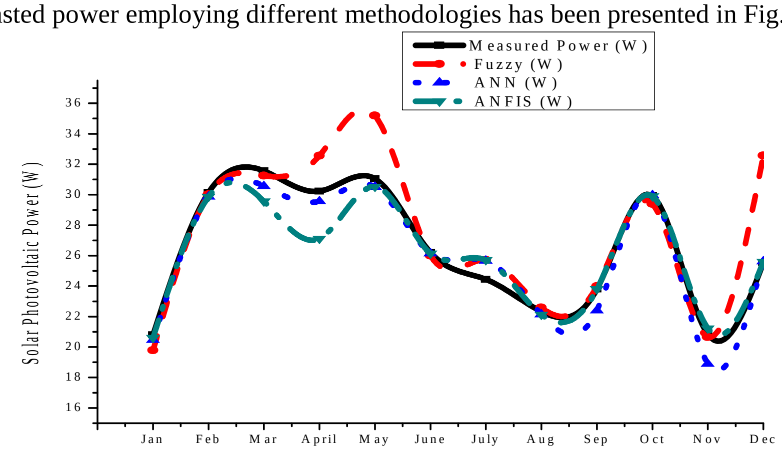

Figure 3. Graphical analysis of measured and forecasted PV power employing fuzzy logic, ANN and ANFIS methodologies.

Table 1. Intelligent methodologies for forecasting power in a solar PV system employing HIT solar PV modules under composite climate zone

Month	Solar Irradiance (W/m^2)	V_{oc} (V)	I_{sc} (A)	Cell Temp (^oC)	Measured Power (W)	Fuzzy				ANN				ANFIS			
						Forecasted Power (W)	MAPE (%)	NMAE (%)	nRMSE (%)	Forecasted Power (W)	MAPE (%)	NMAE (%)	nRMSE (%)	Forecasted Power (W)	MAPE (%)	NMAE (%)	nRMSE (%)
Jan	361.15	81.47	0.42	28.14	20.80	19.79	0.18	0.09	0.11	20.46	0.01	0.01	0.02	20.61	0.00	0.00	0.00
Feb	461.52	82.03	0.61	35.69	30.15	30.02	0.07	0.05	0.07	29.87	0.00	0.00	0.01	29.87	0.00	0.00	0.00
Mar	548.24	83.64	0.62	40.12	31.56	31.25	0.01	0.03	0.03	30.56	0.01	0.02	0.00	29.56	0.00	0.00	0.00
April	575.12	79.62	0.60	42.53	30.23	32.56	0.15	0.06	0.04	29.56	0.00	0.02	0.00	27.12	0.00	0.00	0.00
May	559.67	77.35	0.59	46.22	31.05	35.19	0.12	0.05	0.06	30.52	0.00	0.00	0.00	30.53	0.00	0.00	0.00
June	537.17	76.92	0.55	45.24	26.20	26.00	0.07	0.06	0.07	26.14	0.00	0.00	0.00	26.14	0.01	0.00	0.01
July	537.81	76.66	0.05	48.28	24.45	25.72	0.05	0.04	0.05	25.67	0.02	0.02	0.03	25.71	0.00	0.00	0.00
Aug	428.80	76.90	0.47	53.27	22.33	22.59	0.06	0.04	0.05	22.14	0.03	0.01	0.04	22.13	0.00	0.00	0.00
Sep	437.51	77.78	0.50	51.62	23.80	23.99	0.13	0.07	0.09	22.40	0.27	0.12	0.19	23.80	0.07	0.03	0.04
Oct	466.57	78.74	0.63	53.21	29.92	29.40	0.07	0.06	0.07	29.97	0.01	0.00	0.01	29.90	0.00	0.00	0.00
Nov	369.82	78.48	0.44	45.08	20.85	20.65	0.13	0.05	0.06	18.90	0.03	0.01	0.02	21.23	0.00	0.00	0.00
Dec	370.84	80.66	0.47	43.36	25.53	32.57	0.12	0.01	0.09	25.62	0.10	0.08	0.43	25.61	0.00	0.00	0.01
Avg.	471.19	79.19	0.50	44.40	26.41	27.48	0.10	0.05	0.07	25.98	0.04	0.03	0.06	26.02	0.01	0.00	0.01

From Figure 3, it has been revealed that the forecasted power employing ANFIS methodology closely follows the measured power as compared to others methods such as fuzzy logic and artificial neural network. Further, the power generation in SPV system is greatly influenced by external environmental factors namely sky-conditions, ambient temperature and solar insolation. Therefore, sunny, hazy, partially foggy/cloudy and fully foggy/cloudy sky conditions are considered and performance has been evaluated based on statistical error tests and are presented in Table 2.

Table 2. Short-term PV power forecasting employing HIT solar PV module under composite climate zone

Sky – conditions	Time (hr)	Cell Temp. (^oC)	Solar Irradiance (W/m^2)	Measured Power (W)	Fuzzy		ANN		ANFIS	
					Forecasted Power (W)	MAPE (%)	Forecasted Power (W)	MAPE (%)	Forecasted Power (W)	MAPE (%)
Sunny sky	7:00	34.11	140.93	7.00	7.02	0.0900	7.02	0.0027	7.03	0.0036
	8:00	40.55	273.76	13.83	15.00	0.0840	13.84	0.0015	12.85	0.0001
	9:00	48.14	486.12	28.00	30.34	0.0830	28.02	0.0009	28.01	0.0004
	10:00	52.23	625.25	39.83	41.66	0.0460	39.82	0.0002	39.83	0.0002
	11:00	57.79	783.13	52.33	54.17	0.0350	52.31	0.0005	52.34	0.0002
	12:00	62.86	875.34	59.33	60.50	0.0200	59.35	0.0003	59.06	0.0040
	13:00	64.69	888.95	62.00	61.17	0.0900	61.88	0.0018	61.99	0.0005
	14:00	63.91	744.96	43.17	42.00	0.0270	43.16	0.0000	43.46	0.0052
	15:00	61.55	726.73	48.33	46.32	0.0420	48.32	0.0001	48.33	0.0007
	16:00	58.04	549.15	34.33	31.51	0.0820	34.34	0.0004	34.35	0.0006
	17:00	52.72	361.6	20.83	19.32	0.0720	20.79	0.0024	20.82	0.0004
	Avg.	**54.24**	**586.90**	**37.18**	**37.18**	**0.0610**	**37.17**	**0.0014**	**37.10**	**0.0010**
Hazy sky	10:00	40.83	123.1	8.00	7.12	0.0100	8.39	0.0492	8.03	0.0031
	11:00	44.49	146.12	8.50	9.70	0.0020	9.45	0.1408	8.49	0.0011
	12:00	43.56	307.56	19.67	24.20	0.2300	20.25	0.0123	19.66	0.0004
	13:00	52.55	519.54	45.00	45.46	0.0100	44.82	0.0031	44.98	0.0003
	14:00	42.4	467.65	39.00	37.40	0.0410	39.25	0.0060	39.01	0.0001
	15:00	49.36	313.06	24.50	21.50	0.0170	24.54	0.0012	24.51	0.0004
	16:00	41.05	185.35	11.00	10.09	0.0830	11.68	0.0828	11.00	0.0001
	Avg.	**44.89**	**294.63**	**22.24**	**22.21**	**0.0561**	**22.63**	**0.0422**	**22.24**	**0.0008**
Partially foggy/ cloudy sky	8:00	45.79	134.08	9.67	10.26	0.0610	9.72	0.0045	9.66	0.0008
	9:00	47.49	179.69	27.33	12.99	0.5250	27.32	0.0038	12.36	0.0670
	10:00	52.07	355.98	32.50	30.14	0.0730	33.33	0.0125	27.53	0.0031
	11:00	55.57	463.45	44.00	40.78	0.0730	44.01	0.0010	32.56	0.0108
	12:00	58.38	547.32	39.50	44.39	0.1240	39.24	0.0013	43.92	0.0005
	13:00	59.96	519.74	39.83	31.40	0.2120	39.95	0.0130	39.49	0.0026
	14:00	55.52	492.69	50.17	40.93	0.1840	50.28	0.0024	39.78	0.0009
	15:00	61.3	647.1	37.33	51.69	0.3850	37.60	0.0178	50.22	0.0010
	16:00	59.64	562.02	21.17	35.16	0.6610	21.20	0.0114	37.59	0.0139
	17:00	50.88	299.99	15.33	18.22	0.1880	15.39	0.0034	20.88	0.0096
	18:00	50.73	235.3	7.33	12.65	0.7250	7.53	0.0473	15.30	0.0076
	19:00	47.99	156.43	7.33	7.23	0.0130	7.75	0.0858	8.81	0.2480
	Avg.	**53.78**	**382.82**	**27.62**	**27.99**	**0.2687**	**27.78**	**0.0305**	**28.18**	**0.0170**
Fully foggy/ cloudy sky	9:00	19.08	170.77	12.50	10.75	0.1400	12.60	0.0066	12.48	0.0011
	10:00	19.02	74.87	8.33	10.62	0.2750	8.35	0.0030	8.40	0.0099
	11:00	23.29	96.49	11.17	8.72	0.2190	12.78	0.1733	10.98	0.0442
	12:00	18.5	41.2	7.83	8.10	0.0340	7.82	0.0018	7.81	0.0036
	13:00	18.57	140.77	10.67	10.46	0.0200	10.66	0.0002	10.63	0.0056
	14:00	18.59	87.31	9.83	11.14	0.1330	10.11	0.0243	10.01	0.0735
	15:00	17.86	164.25	12.00	10.83	0.0970	12.01	0.0016	12.00	0.0004
	Avg.	**19.27**	**110.81**	**10.33**	**10.09**	**0.1311**	**10.62**	**0.0301**	**10.33**	**0.0198**

Following inferences can be drawn from Table 2 shown as:

Sunny/Clear sky: 1st June 2015 is considered as a sunny day based on the annual analysis of solar radiation data and availability of sunshine hours. Further, the graphical representation between measured and forecasted power for sunny sky condition have been shown in Figure 4 from which it has been concluded that the forecasted power employing ANFIS methodology represented by cyan colored dash-dot line on hour basis closely follows the measured power represented by the black solid line, whereas some deviation can be seen in terms of fuzzy logic approach represented by red colored dashed line and ANN approach represented by blue colored dot line. The maximum power output is observed to be 62 W during the day with average MAPE of 0.0610% using the fuzzy logic methodology; and the error reduced to 0.0014% by employing ANN methodology; and with ANFIS methodology the mean absolute percentage error has further reduced and is observed to be 0.0010% respectively.

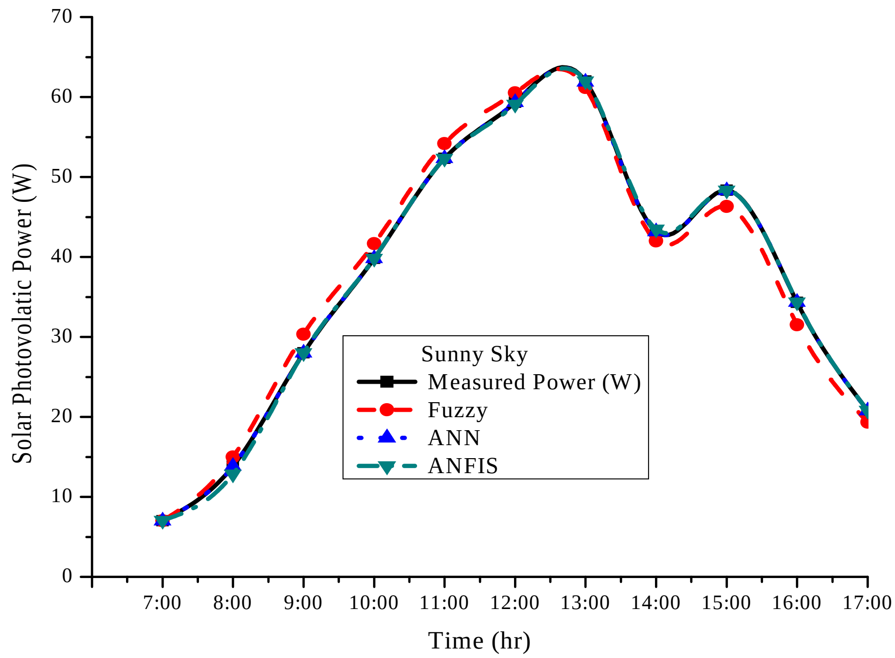

Figure 4. Graphical analysis of measured power and forecasted power employing fuzzy logic, ANN and ANFIS methodologies for sunny sky condition.

Hazy sky: 26th December 2015 is considered as a hazy day based on the annual analysis of solar radiation data and availability of sunshine hours. Further, the graphical representation between measured and forecasted power for hazy sky condition have been shown in Figure 5 from which it has been concluded that the forecasted power employing ANFIS methodology represented by cyan dash-dot line on hour basis closely follows the measured power represented by the black solid line, whereas some deviation can be seen in terms of fuzzy logic approach represented by red dashed line and ANN represented by a blue dot line. The maximum power output is observed to be 50 W during the day with averaged mean absolute percentage error by employing fuzzy logic methodology is 0.0561%; by employing ANN methodology the mean absolute percentage error is 0.0422%; and by employing ANFIS methodology the error is 0.0008% respectively.

Partially foggy/cloudy sky: 3rd August 2015 is considered as partially foggy/cloudy day based on the annual analysis of solar radiation data and availability of sunshine hours. Further, the graphical representation between measured and forecasted power for partially foggy/cloudy sky condition have been shown in Figure 6 from which it has been concluded that the forecasted power employing ANFIS methodology represented by cyan dash-dot line on hour basis closely follows the measured power represented by the black solid line, whereas some deviation can be seen in terms of fuzzy logic approach represented by red dashed line and ANN represented by blue dot line. The maximum power output is observed to be 44 W during the day with averaged mean percentage error by employing fuzzy logic methodology is 0.2687%; by employing ANN methodology the mean absolute percentage error is 0.0305%; and by employing ANFIS methodology the error is 0.0170%.

Fully foggy/cloudy sky: 3rd January 2015 is considered as a fully foggy/cloudy day based on the annual analysis of solar radiation data and availability of sunshine hours. Further, the graphical representation between measured and forecasted power for fully foggy/cloudy sky condition have been shown in Figure 7 from which it has been concluded that the forecasted power employing ANFIS methodology represented by cyan dash-dot line on hour basis closely follows the measured power represented by the black solid line, whereas some deviation can be seen in terms of fuzzy logic approach represented by red dashed line and ANN represented by a blue dot line. The maximum power output is observed to be 12 W during the day with averaged mean absolute percentage error by employing fuzzy logic methodology is 0.1311%; by using ANN methodology the error is 0.0301%; and by employing ANFIS methodology the mean absolute percentage error is 0.0198% respectively.

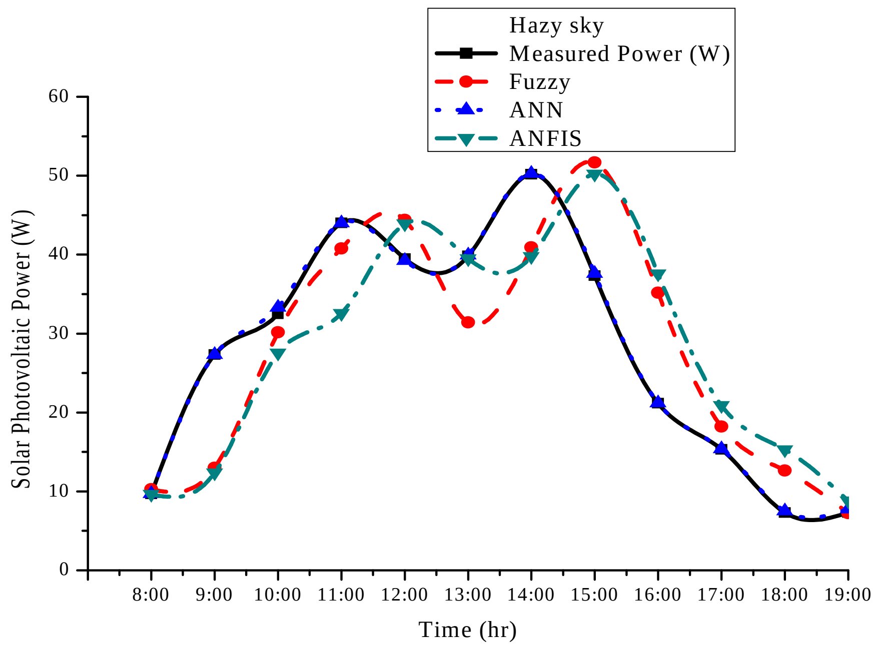

Figure 5. Graphical analysis of measured power and forecasted power employing fuzzy logic, ANN and ANFIS methodologies for hazy sky condition.

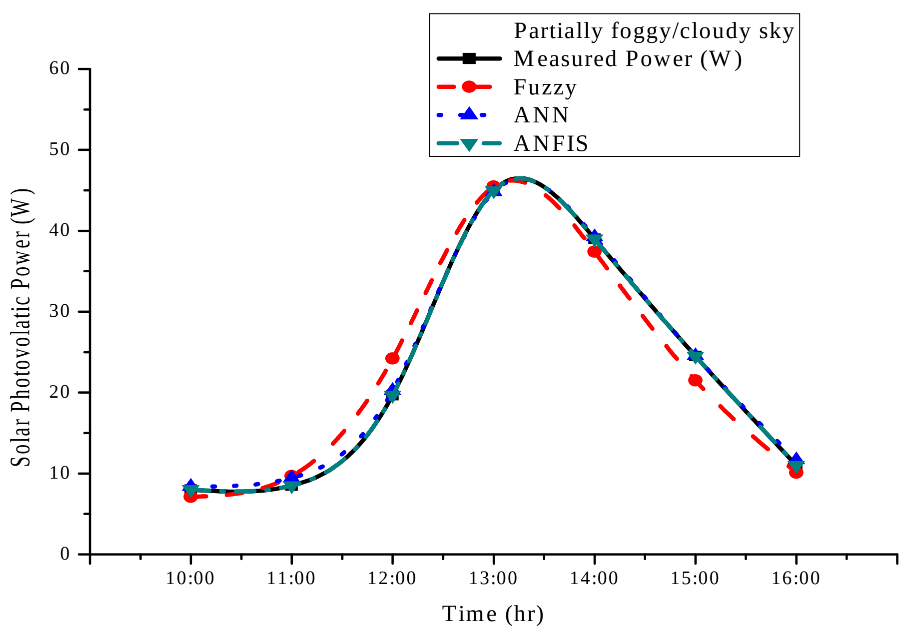

Figure 6. Graphical analysis of measured power and forecasted power employing fuzzy logic, ANN and ANFIS methodologies for partially foggy/cloudy sky condition.

From Table 2, it has been observed that out of the four models, especially the hazy sky model perform well with mean absolute mean percentage error of 0.0008% in forecasting the power of SPV system followed by sunny sky model with mean absolute percentage error of 0.0010%, partially foggy/cloudy sky model with mean absolute percentage error of 0.0170%, and fully foggy/cloudy sky model with mean absolute percentage error of 0.0198% respectively by using ANFIS methodology.

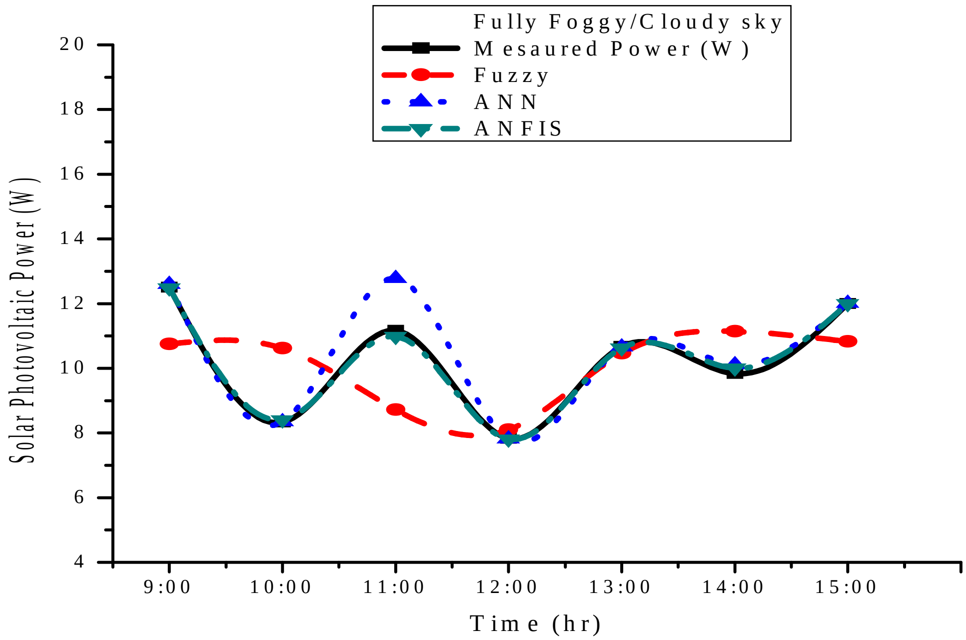

Figure 7. Graphical analysis of measured power and forecasted power employing fuzzy logic, ANN and ANFIS methodologies for fully foggy/cloudy sky condition.

6. Conclusion

In the present work, intelligent modelling techniques have been employed for estimating the power of a SPV system for composite climate zone. Simulations have been carried out using fuzzy logic, ANN and ANFIS methodologies for varying sky-conditions i.e. sunny sky, hazy sky, partially foggy/cloudy sky and fully foggy/cloudy sky conditions. Three criteria namely mean absolute percentage error, normalized mean absolute error and normalized root mean square error verifies the forecasting errors of the model. Obtained results reveal the accuracy of the ANFIS model which is far accurate and better than the artificial neural network and fuzzy logic models. ANFIS model has certain advantages such as the ease of design, robustness and adaptability with the non-linearity associated with the data. The ANFIS methodology integrates the features of both fuzzy logic and ANN which increases the system accuracy and makes the system response much faster. The result reveals the model implementation for a broad series of applications. The prediction of solar energy makes it suitable for installation of a monitoring station for a remote place and furthermore, can be extended for sizing of standalone PV system as a part of the future work.

Nomenclature

e_i	i_{th} estimated data (dimensionless)
MAPE	mean absolute percentage error (%)
m_i	i_{th} measured data (dimensionless)
nMAE	normalized mean absolute error (%)
nRMSE	normalized root mean square error (%)
N_{PVP}	photovoltaic arrays in parallel (number)
N_{PVS}	photovoltaic arrays in series (number)
O_{PV}	power output of photovoltaic array at MPP (W)
$O_{PV,STC}$	rated power output of photovoltaic array (W)
T_m	measured ambient temperature (^oC)
T_j	temperature of solar panel (^oC)
T_o	maximum ambient temperature (^oC)
γ	temperature parameter at MPP

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