

Shuvho, Md. Bengir Ahmed; Chowdhury, Mohammad Asaduzzaman; Ahmed, Shameem; Kashem, Mohammod Abul

Article

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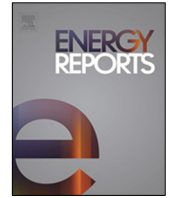
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Research paper

Prediction of solar irradiation and performance evaluation of grid connected solar 80KWp PV plant in Bangladesh



Md. Bengir Ahmed Shuvho^a, Mohammad Asaduzzaman Chowdhury^{a,*},
Shameem Ahmed^a, Mohammad Abul Kashem^b

^a Department of Mechanical Engineering, Dhaka University of Engineering & Technology (DUET), DUET, Gazipur 1707, Bangladesh

^b Department of Computer Science and Engineering, Dhaka University of Engineering & Technology (DUET), DUET, Gazipur 1707, Bangladesh

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ABSTRACT

Energy security is the triggering factor for a developing country. Thus, for ensuring energy security renewable energy such as PV plant could be a best alternative. This study deals with the performance analysis of 80 KWp grid-connected solar power plant in Dhaka. This study presents a solar irradiation predict model based on fuzzy logic and artificial neural networks which aims to achieve a good accuracy at different weather conditions. The accuracy of predicted solar irradiation will affect the power output forecast of grid-connected photovoltaic systems which is important for power system operation and planning. Used data are taken from NASA. The performance of ANN is better than fuzzy logic model by comparing RMSE, R^2 and percentage of accuracy. These fuzzy logic and ANN models can be used to forecast solar irradiation of Dhaka city in different environment condition and to provide enough information about the feasibility of solar power projects.

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1. Introduction

Life without a sustainable supply of energy is almost unimaginable. The importance of energy is even more supplementary in the context of developing countries, which have traditionally experienced prolonged periods of energy crises.

Socio-economic development of any country depends on per capita consumption of energy. On the other hand increased consumption of energy has direct effect on environment which in turn affects the economic development. Energy is available in different forms in the universe. These various forms of energy are related and can be transformed from one form to another. Hence, energy cannot be destroyed, it can only be converted to other forms only. Presently, fossil fuels are used to generate electrical energy in most of the countries of the world. But this form of energy is expensive, exhaustive, non-renewable and day by day decreasing. As a part of fuel diversification drive, Bangladesh can look forward to replacing fossil fuel and non-renewable energy with renewables in order to match its local energy demand. Hence, various other forms of renewable energy gained popularity, solar energy is one of those renewable energy that are available in abundant in the universe. Electricity generated from

solar power is relatively cost effective compared to imported oil-based electricity, which makes it a go to option in the near future. Solar energy is believed to be the most efficient and sustainable source of energy with absolutely no contribution to environmental degradation.

Many characteristics make solar energy technology unique and different from other kinds of renewable energy. Due to no emissions being released, it is considered an environmentally friendly. Because the sun comes up every day it is considered a secure source of energy. Solar energy harvesting systems can easily scale to varied sizes and there exists many ideas for implementation: such as panels, roof tiles, and paints. Flexibility in mounting and the small amount of maintenance required for solar panels make them attractive. In addition, solar energy systems can be easily implemented in remote areas without the need for long power lines. The fact that solar panels can directly deliver electrical energy is advantageous, as the need for an electric generator is removed. Vast amounts of solar energy are available on the surface of the earth with all locations receiving at least some sun. Even though solar panels are still a little expensive, cost has been dropping exponentially and continues to drop.

Testing and modeling the PV module/system in the outdoor environment with specifying the influences of all significant factors, are very important to check the system performance and to facilitate efficient troubleshooting for photovoltaic module/system through considering hourly, daily and monthly or annual basis (King, 2003).

* Corresponding author.

E-mail addresses: bengir.duet@gmail.com (M.B.A. Shuvho), asadzmn2014@yahoo.com (M.A. Chowdhury), shameem21bd@gmail.com (S. Ahmed), drkashem1@yahoo.com (M.A. Kashem).

Table 1
STC performance of the solar panel.

PV module (STC)		Inverter	
Parameters	Specification	Parameters	Specification
Type of module	Mono-crystalline	Model	BOSCH 250
P_{max}	250 W	Input (DC)	
I_{am}	8.25 A	Nominal Power, W	12 250
V_{am}	30.31 V	Voltage range, V	1000
I_{sc}	8.82 A	Nominal current, A	22/11
V_{oc}	37.9	Maximum current, A	33/12.5b
Temperature coefficient of P_{max}	0.44%/°C	Output (AC)	
Nominal operating cell temperature (NOCT)	48.4 °C	Voltage range, V	160–280
Module area, m ²	(1620.16 * 966.24)	Nominal current, A	19.2
No. of modules		Nominal frequency, Hz	50
Efficiency	13%	Efficiency, %	98/97.7
Weight/module, kg	21	Weight, kg	64



Fig. 1. Experimental investigation of solar panel.



Fig. 2. Sun simulator testing lab.

Photovoltaic output power depends on many factors; such as sun position, weather conditions, module temperature, thermal characteristics, module material composition and mounting structure (Ayomp, 2010).

Real time power generation should be investigated precisely for grid performance, because a high penetration of PV production could create instability in the grid (McCollum et al., 2018). The uncertainty of the photovoltaic performance models is still too high; the early existing PV performance models mainly deal with the ideal PV module characteristics rather than the dynamic situation under the surrounding conditions (McCollum et al., 2018; Bahauddin and Salahuddin, 2012; Ahmed et al., 2013; Shariar et al., 2011; Dincer and Rosen, 1998; Pillai and Banerjee, 2009; Sharma, 2011; Sharma and Chandel, 2013; Karafil et al., 2015; Bai and Wang, 2006; Halabi et al., 2018).

In this study, performance of the 80 kWp PV system solar power plants were investigated. We predicted solar irradiation using fuzzy logic, ANN and performance of grid connected 80 kWp was investigated. Fig. 1 shows the location of grid connected power plant. Performance of the grid connected solar panel, Fuzzy logic and ANN analysis were investigated by the study of irradiation.

2. Performance of the solar panels

Table 1 shows the performance of a PV solar panel under standard test condition (STC). The performance (97.7%) of the inverter found under standard test condition (STC). During actual operation the efficiency is found 40%–45%.

3. Performance of the solar panels after sun simulator test

A solar simulator or sun simulator is a device which has similar intensity and spectral composition to the nature of sunlight. It is widely used as a controllable indoor test facility offering laboratory conditions for solar cells. A solar simulator usually consists of three major components: (i) light source(s) and associated power supply; (ii) any optics and filters used to modify the output beam to meet the requirements; (iii) necessary controls to operate the simulator. Xenon lamps or other artificial light sources are usually chosen as the light source of a standard solar simulator. However, there are differences between artificial light source(s) and nature sun light, both in intensity and spectral composition, which only with the help of optics and filters can be modified to meet the nature sun light. Furthermore, as the outdoor condition is time dependent, it is necessary to define a standard test condition for the solar simulator. The testing lab of sun simulator is shown in Fig. 2. The sun simulator test was performed at 25 °C and this temperature is the standard test condition for solar panel. Performance measured from the sun simulator is represented in Table 2.

4. Fuzzy logic and ANN analysis for irradiation

4.1. Fuzzy logic

The relationship between the input parameters (temperature, wind speed, and humidity) and the output parameter (tilt angle

Table 2
Test data of sun simulator.

Serial no	I_{sc}	V_{oc}	P_m	I_{pm}	V_{pm}	Eff. (%)	F.F	R_s (Ω)	PWR (kW)
M60 EV30117	8.165	37.661	194.39	6.463	30.077	13.129	0.632	1.379	194.390
M60 EV30118	7.983	37.677	189.68	6.208	30.556	12.811	0.631	1.42	189.680
M60 EV30119	8.626	37.614	189.62	6.170	30.735	12.808	0.618	1.437	189.620
M60 EV30120	7.914	37.613	189.28	6.158	30.740	12.785	0.635	1.453	192.390
M60 EV30121	8.171	37.630	194.37	6.461	30.084	13.128	0.632	1.371	194.370
Mean	8.172	37.639	191.45	6.292	30.438	12.9322	.629	1.412	192.09

Table 3
Fuzzy linguistic variables and parameters.

Parameter	Linguistic variable	Range
Temperature ($^{\circ}\text{C}$)	Low (L), medium (M), high (H)	18.6–27.7 ($^{\circ}\text{C}$)
Wind speed	Very low (L), low (L), medium (M), high (H)	2.07–3.11 (m/s)
Humidity	Very low (L), low (L), medium (M), high (H)	55–80 (%)
Tilt angle	very very low (VVL), very low (VL), Low (L), medium (M), high (H), very high (VH), very very high (VVH)	2.14–47 (degree)
Irradiation	very very low (VVL), very low (VL), Low (L), medium (M), high (H), very high (VH), very very high (VVH)	3.95–5.16 ($\text{kWh}/\text{m}^2/\text{day}$)

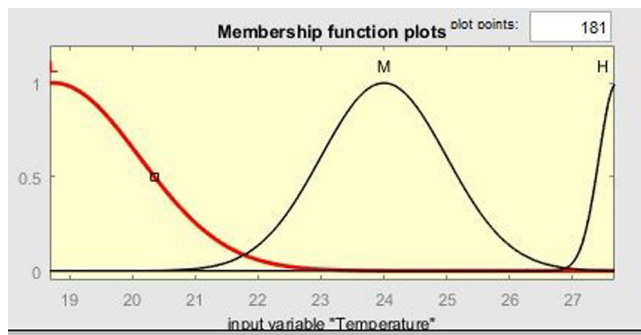


Fig. 3. Input variable Gaussian membership functions for temperature.

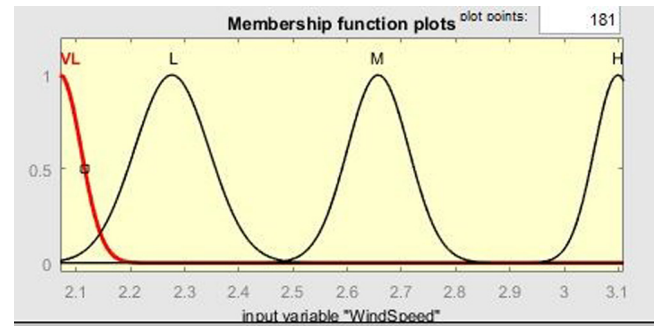


Fig. 4. Input variable Gaussian membership functions for wind speed.

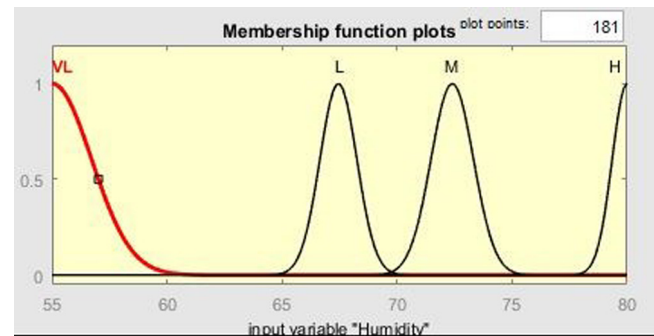


Fig. 5. Input variable Gaussian membership functions for humidity.

and irradiation) was considered in constructing rules. The fuzzy linguistic characteristics and fuzzy expression for the input and output parameters are shown in Table 3. Each input parameter has three membership functions: low (L), medium (M), and high (H) as shown in Figs. 3, 4, and 5. The two output parameters have 7 membership functions: very very low (VVL), very low (VL), low (L), medium (M), high (H), very high (VH), and very very high (VVH) as shown in Fig. 6. The membership functions were selected based on the knowledge of authors (Mohammadi et al., 2015). The MATLAB software was utilized for the linguistic variables with associated membership functions. Meteorological data were retrieved from NASA power data access viewer (Power Data Access Viewer, 0000)

4.2. Fuzzy logic rules

In this study, the fuzzy rule base containing a set of IF-THEN statements for 12 rules with three inputs, namely temperature, wind speed, humidity and with two multi-response output, tilt angle and irradiation are considered. Twelve rules were identified on the available data shown in Table 4, the constructed rules are presented in Table 5 and fuzzy rules interface is shown in Fig. 7.

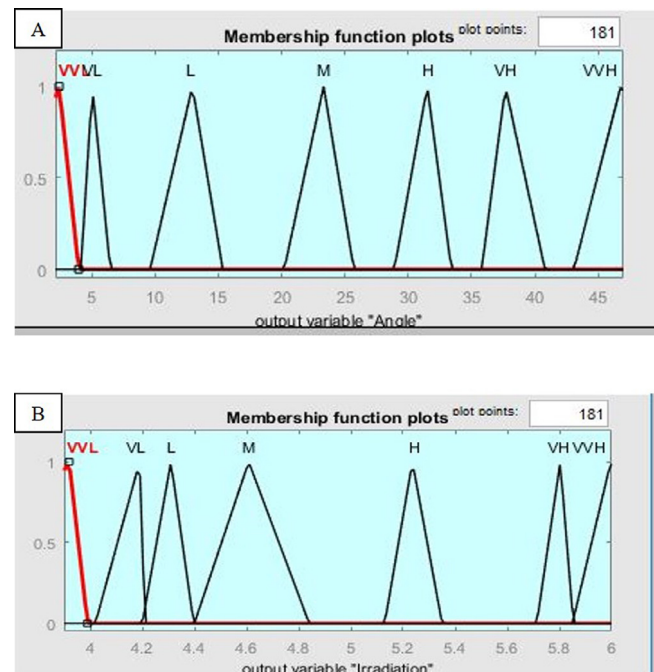


Fig. 6. Output triangular membership function for A Tilt angle and B Irradiation.

Table 4
Meteorological data for fuzzy logic.

Months	Inputs			Outputs	
	Temperature (°C)	Wind speed (m/s)	Humidity (%)	Tilt angle (Degree)	Irradiation (kWh/m ² /day)
January	18.61	2.59	69	45.09	4.29
February	21.81	2.85	58	37.44	5.18
March	25.69	3.00	55	26.23	5.96
April	26.61	3.11	65	14.40	5.83
May	27.11	3.05	73	5.02	5.28
June	27.67	2.88	79	4.06	4.49
July	27.42	2.59	80	2.14	4.09
August	27.44	2.34	80	9.39	4.20
September	26.67	2.21	79	20.40	3.95
October	24.95	2.07	74	32.30	4.43
November	21.81	2.30	68	41.99	4.37
December	19.22	2.40	71	46.94	4.07

Table 5
Rules used for fuzzy logic model.

Rule number	If statements for input parameters			Then statements for output response	
	Temperature	Wind speed	Humidity	Tilt angle	Irradiation
1	L	M	L	VVH	L
2	L	H	VL	H	H
3	M	H	VL	M	VVH
4	M	H	L	L	VH
5	H	H	M	VL	H
6	H	H	H	VL	M
7	H	M	H	VVL	VL
8	H	L	H	L	L
9	H	L	H	M	VVL
10	M	VL	M	H	M
11	L	L	L	VH	M
12	L	L	M	VVH	VL

The fuzzy output is generated for the fuzzy logic rules by following the maximum minimum compositional process (Chowdhury et al., 2019).

4.3. Defuzzification

The fuzzy output from the fuzzy interface system requires a defuzzification process. Numeric data are found from the fuzzy set data by the defuzzification process. Researchers utilize several methods of defuzzification, including center of sum (COS), mean of max, largest area, weight average, and centroid. In this study, a defuzzification process, called the centroid of area (COA) technique (Zalnezhad and Sarhan, 2014), is used to obtain the numeric value from the fuzzy interface system. Given its extensive utilization and acceptance, the COA defuzzification technique was used to obtain more correct results (Topcu and Saridemir, 2008).

The defuzzified value defined by X^* is obtained using the COA method.

$$X^* = \frac{\sum_{i=1}^n x_i \cdot \mu(x_i)}{\sum_{i=1}^n \mu(x_i)} \quad (1)$$

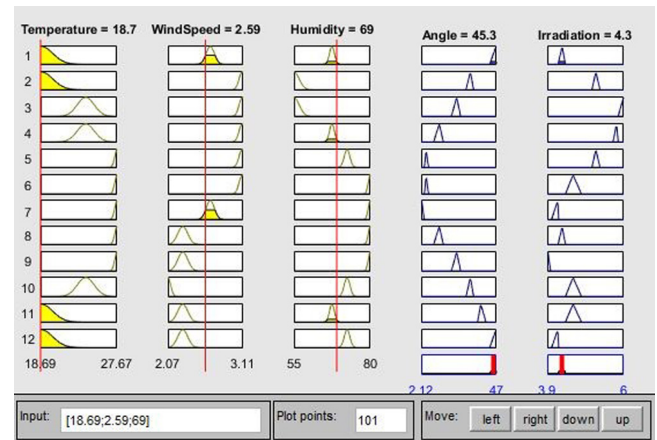
where x_i represents the samples, $\mu(x_i)$ is the membership function, and n denotes the number of elements.

Surface plot for predicted tilt angle is shown in Fig. 8 and surface plot for predicted solar irradiation is shown in Fig. 9.

In this study, root mean square error (RMSE) and fraction of variance (R^2) were used for predicting the fuzzy logic model performance with the measured values. The rate of error (e_i) and the accuracy of the fuzzy logic model (A) were determined by the following formula.

$$RMSE = \sqrt{\frac{\sum_{i=1}^N (F_i - M_i)^2}{N}} \quad (2)$$

$$R^2 = 1 - \frac{\sum_{i=1}^N (F_i - M_i)^2}{\sum_{i=1}^N (F_i)^2} \quad (3)$$

**Fig. 7.** Fuzzy rules interface.

$$e_i = \frac{(|M - F|)}{M} \times 100\% \quad (4)$$

$$A = \frac{1}{N} \sum_i \left(1 - \frac{(|M - F|)}{M}\right) \times 100\% \quad (5)$$

where F is the predicted fuzzy value and M is the measured experimental value, and N is the number of experiment (see Tables 6–8).

5. Artificial neural network

ANN is a connectionist system based on the neural structure of the human brain (biological neural networks), which processes data among a number of neurons. The basic unit of ANN is neurons, which are connected to one another with a weight factor

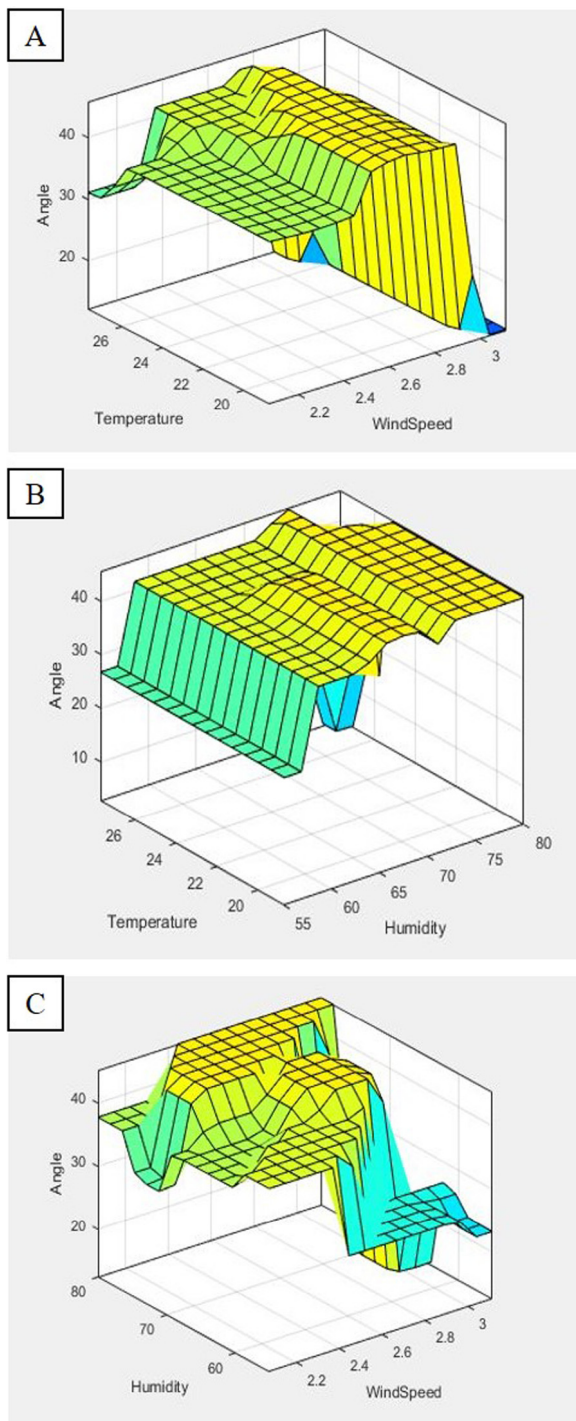


Fig. 8. Surface plot of predicted tilt angle (degree) values by fuzzy logic in relation to parameters change: **A** temperature and wind speed, **B** temperature and humidity and **C** Humidity and wind speed.

that determines the strength of the connections. ANN can be trained for a specific function by adjusting the value of these weight factors of the neurons.

One of the most widely used neural networks is the multi-layered perception (MLP) neural network. This neural network has been used by a number of researchers (MacDonald et al., 1999; Shuvho et al., 2019). A backpropagation algorithm is used to train this multilayered feed forward network. Backpropagation identifies the network error with respect to the network weight

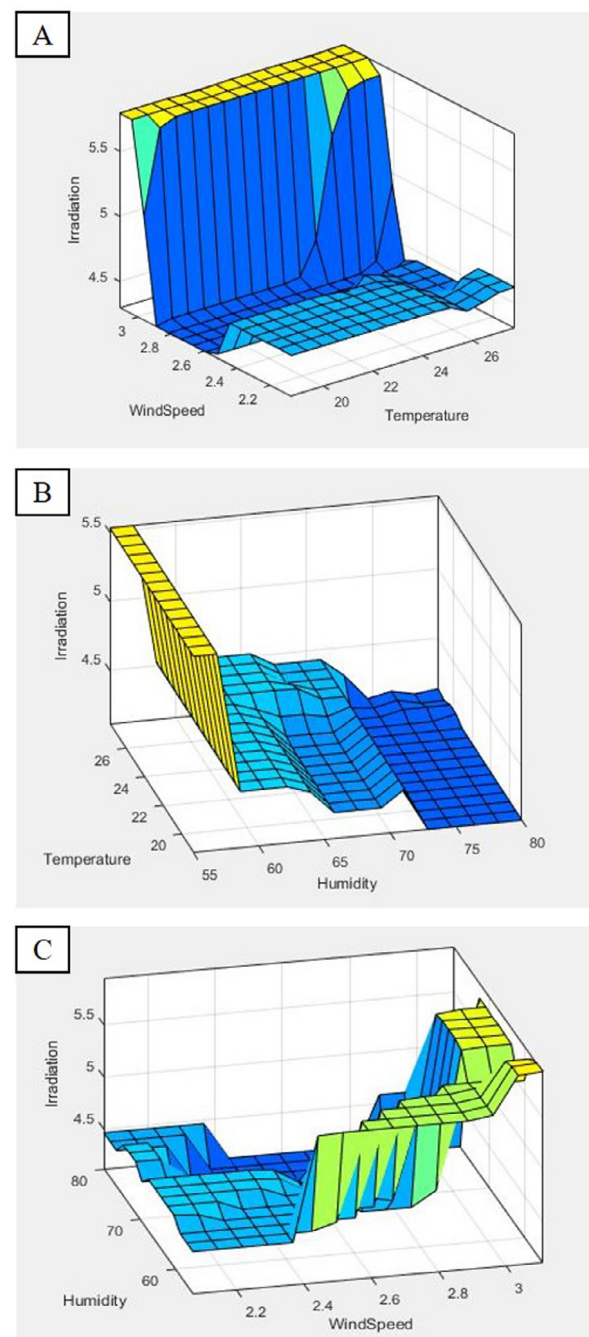


Fig. 9. Surface plot of predicted irradiation (degree) values by fuzzy logic in relation to parameters change: **A** temperature and wind speed, **B** temperature and humidity and **C** Humidity and wind speed.

and biases of the process. Fig. 10 shows a schematic of the MLP network. The MLP model maps a set of input data onto a set of appropriate output data. The MLP has multiple layers, such as input, hidden, and output layers of nodes, in a directed graph, with each layer connected to the next layer. MLP utilizes backpropagation, a supervised learning method, to train the network.

In this study, an MLP neural network was utilized to predict the solar irradiation for Dhaka region in relation to the input parameters, such as air temperature, relative humidity, atmospheric pressure, wind speed, earth temperature.

Numerous studies on ANN model has been made in recent years. These studies have given a prediction on monthly solar

Table 6
Fuzzy logic model error and accuracy for tilt angles.

Months	Tilt angle (°)	Predicted (fuzzy) tilt angle	Error (%)	Accuracy (%)
January	45.09	45.3	0.465735	99.53426
February	37.44	26.7	28.6859	71.3141
March	26.23	23	12.31414	87.68586
April	14.40	12.4	13.88889	86.11111
May	5.02	5.26	4.780876	95.21912
June	4.06	4.69	15.51724	84.48276
July	2.14	2.75	28.50467	71.49533
August	9.39	11.65	24.06816	75.93184
September	20.40	18.5	9.313725	90.68627
October	32.30	31.2	3.405573	96.59443
November	41.99	38.3	8.787807	91.21219
December	46.94	45.3	3.493822	96.50618

Table 7
Fuzzy logic model error and accuracy for irradiation.

Months	Irradiation (kWh/m ² /day)	Predicted (fuzzy) irradiation	Error (%)	Accuracy (%)
January	4.29	4.3	0.2331	99.7669
February	5.18	5.53	6.756757	93.24324
March	5.96	5.93	0.503356	99.49664
April	5.83	5.79	0.686106	99.31389
May	5.28	5.24	0.757576	99.24242
June	4.49	4.62	2.895323	97.10468
July	4.09	4.13	0.977995	99.022
August	4.20	4.17	0.714286	99.28571
September	3.95	4.17	5.56962	94.43038
October	4.43	4.62	4.288939	95.71106
November	4.37	4.62	5.720824	94.27918
December	4.07	4.12	1.228501	98.7715

Table 8
Performance of the fuzzy logic model.

Output	RMSE	R ²	A (%)
Tilt angle	3.6157	0.981489	87.23
Irradiation	0.15695	0.998937	97.47

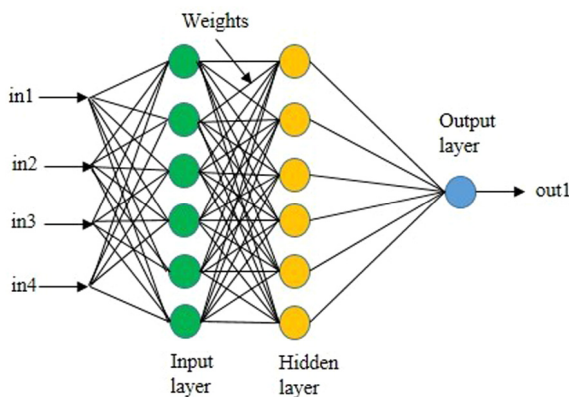


Fig. 10. Typical structure of an MLP network.

irradiation. As ANN is of nonlinear behavior and no need for primary assumption to develop data relationships, it becomes a necessary tool for estimating solar irradiation. ANN models are developed to model various solar radiation variables in different locations. Yadav and Chandel (2014) gave a review on artificial neural network models to identify best suitable method for solar radiation prediction. Yadav et al. (2014) designed a neural network model to determine most relevant input parameters for prediction of solar radiation. Kisi (2013) tried fuzzy genetic approach to estimate solar radiation and gave a compare with ANN

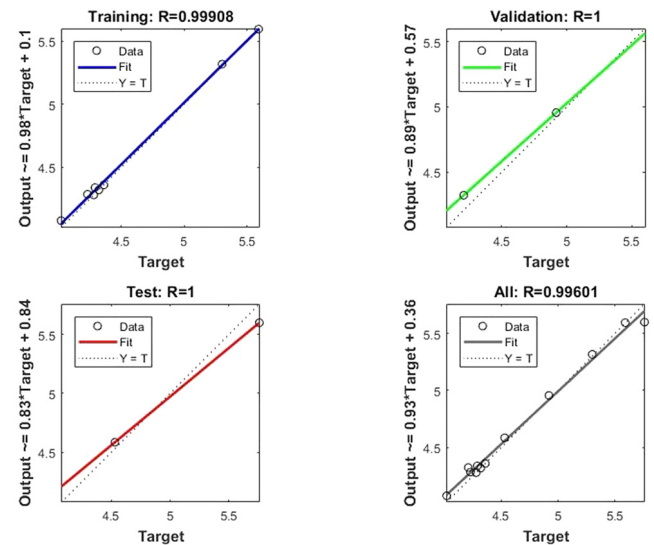


Fig. 11. Performance regression plot for predictive model.

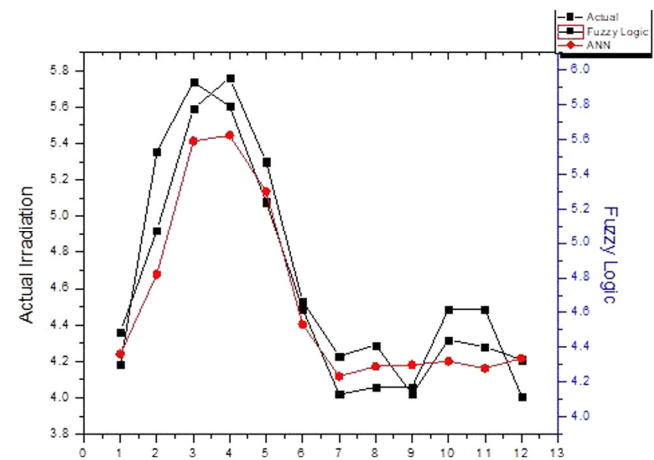


Fig. 12. Comparison graph of ANN and Fuzzy logic with actual irradiation.

approach. Egeonu et al. (2015) developed a temperature based ANN model trained with the Levenberg Marquardt algorithm to provide a forecast on solar radiation in Nigeria. Uenkal (2015) applied artificial neural network approach for giving a model and prediction of mean perceptible water and solar radiation in specific location in Turkey based on meteorological data.

In this present paper, a feed forward back propagation neural network with one hidden layer to estimate the monthly solar radiation for Dhaka city in Bangladesh as shown in Table 9. Table 10 shows error and accuracy of the ANN model, and Table 11 represents performance of the ANN model. Here the input layer consists of five units and hidden layer with 15 neurons and output layer with 1 neuron to estimate solar irradiation, 70% of the total data was used for training, 15% for testing and 15% for validating the developed model as shown in Fig. 11. Fig. 12 represents the comparison among actual solar irradiation, predicted irradiation by fuzzy logic and ANN models. Stability analysis for the ANN model will be carried out in future study by the Lyapunov synthesis algorithm (Yu and Li, 2001; Jiang and Wang, 2001) and Korkobi et al. (2008) have proposed a stable back propagation algorithm to provide stable adaptive updating process.

Table 9
Meteorological Data for ANN.

Month	Air temperature °C	Relative humidity %	Atmospheric pressure kPa	Wind speed m/s	Earth temperature °C	Daily solar radiation - horizontal kWh/m ² /d
January	19.7	53.8%	100.9	1.9	21.5	4.36
February	23.0	49.2%	100.7	2.1	25.6	4.92
March	26.4	52.4%	100.4	2.2	29.3	5.59
April	27.1	69.5%	100.2	2.5	29.1	5.76
May	27.6	78.0%	99.9	2.5	29.2	5.30
June	27.9	84.5%	99.5	2.4	28.7	4.53
July	27.7	86.3%	99.6	2.2	28.1	4.23
August	27.6	85.7%	99.7	1.9	28.1	4.29
September	27.0	84.7%	100.0	1.7	27.5	4.02
October	25.5	80.1%	100.4	1.5	26.0	4.32
November	22.5	72.8%	100.8	1.6	22.9	4.28
December	20.2	61.0%	101.0	1.7	21.1	4.21

Table 10
ANN model error and accuracy for irradiation.

Months	Actual Irradiation (kWh/m ² /day)	Predicted (ANN) Irradiation (kWh/m ² /day)	Error (%)	Accuracy (%)
January	4.36	4.3616	0.036697	99.9633
February	4.92	4.8206	2.020325	97.97967
March	5.59	5.5901	0.001789	99.99821
April	5.76	5.6227	2.383681	97.61632
May	5.30	5.3005	0.009434	99.99057
June	4.53	4.5319	0.041943	99.95806
July	4.23	4.234	0.094563	99.90544
August	4.29	4.29	0	100
September	4.02	4.2992	6.945274	93.05473
October	4.32	4.3201	0.002315	99.99769
November	4.28	4.28	0	100
December	4.21	4.3373	3.023753	96.97625

Table 11
Performance of the ANN model.

Output	RMSE	R ²	A (%)
Irradiation	0.318129	0.999535	98.78669

6. Performance analysis of 80 kWp PV solar plant

System parameters such as array yield, performance ratio, specific yield were calculated by the following the reference [Kumar and Sudhakar \(2015\)](#). The performance results of the 80 kWp PV system power plant discussed in this section. In the mathematical model section, different performance indicators were discussed. [Figs. 13 and 14](#) show the monthly generation and specific yield of 80 kWp plant in two years and it can be observed that maximum generation was found in April due to maximum irradiation and minimum in December, 2016 due to winter session and less irradiation. In 2016, average energy generation and specific yield were found 6140.76 kWh and 77.76 respectively. In 2017, average generation and specific yield were found 4354.51 kWh and 54.43. These results show that in 2016 the plant utilized 77.76% capacity of the plant and in 2017, the plant utilized 54.43% capacity of the plant. In Bangladesh, April to August is a hot session and the average temperature is found 27–28 °C as shown in [Table 9](#). Thus power generation is found at maximum level.

Comparing the year 2016 and 2017 it can be observed that in 2016 energy generation is higher than 2017 because of 1 year depreciation. The specified module efficiency of 13% mentioned in the PV solar panel manual has been used in the calculation of nominal plant output to determine the performance ratio.

[Fig. 15](#) shows the monthly performance ratio of the 80 kWp plant. It can be observed that in June and August, 2016 performance ratios are highest and plant was utilized 79% nominal capacity in June and 77% nominal capacity in August 2016. Again

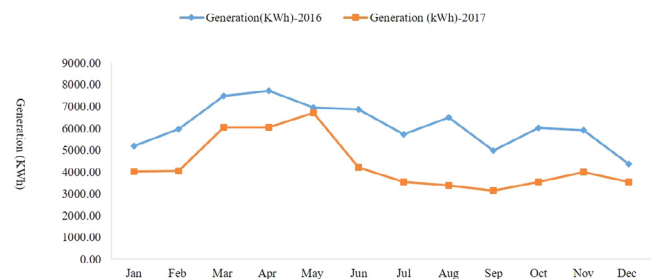


Fig. 13. Monthly generation of 80 kWp solar plant.

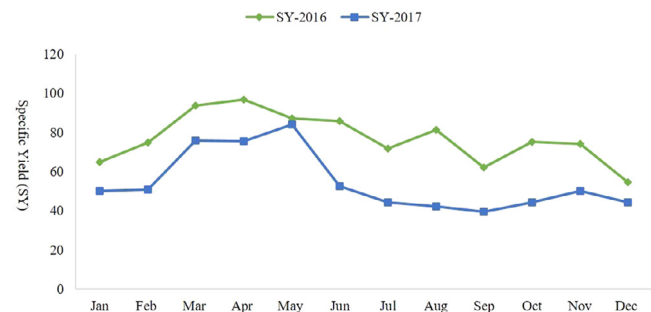


Fig. 14. Monthly specific yield of 80 kWp plant.

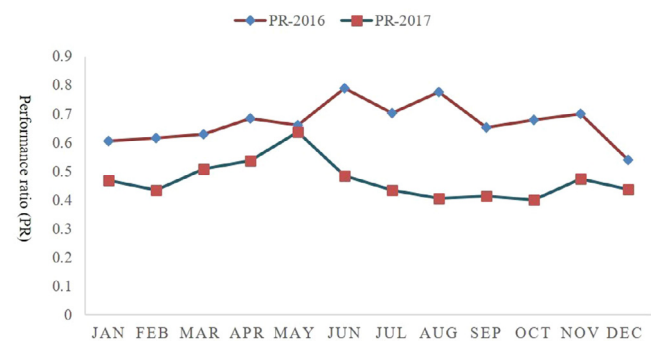


Fig. 15. Monthly performance ratio (PR) of the 80 kWp plant.

it can be observed that in 2017 performance ratio is less than 2016. In 2016 average performance ratio was found 0.67 and in 2017 average performance ratio was found 0.47. These results show that average 67% irradiation was utilized in 2016 and 47% irradiation was utilized in 2017.

Table 12

Performance summary of some selected grid connected PV systems.

Reference	Location	PV-Type	System size (kWp)	Final yield (kWh/kWp/day)	PV module efficiency (%)	Inverter efficiency	Performance ratio
Ayompe et al. (2011)	Dublin, Ireland	Mc-Si	–	2.4	14.9	89.20	81.5
Pietruszko and Gradzki (2003)	Poland	a-si	–	–	6.0	93.00	80.00
Kymakis et al. (2009)	Crete, Greece	P-Si	–	1.96–5.07	15.0	–	67.36
Chokmaviroj et al. (2006)	Thailand	–	–	2.91–3.98	12.0	92.16	70.00
Mondol et al. (2006)	Dublin, Ireland	–	3.056	1.69	7.60	75.00	0.6–0.62
Cucumo et al. (2006)	Italy	P-Si	–	3.40	7.95	98.0	–
Drif et al. (2007)	Spain	Isofoton I-106	2.5	1.60	5.71	87.03	49
Okello et al. (2015)	South Africa	P-Si	3.2	4.90	13.72	88.10	64.30
Sidrach-de Cardona and Lopez (1999)	Spain	–	2.0	3.80	8.50	88.00	64.00
Wittkopf et al. (2012)	Singapore	P-Si	–	3.12	11.80	–	81.00
Al Ali and Emziane (2013)	Abu Dhabi	a-Si/P-Si	142.5	–	–	94.80	–
Vasisht et al. (2016)	India	P-Si	20	4.1	13.71	–	85.00
Pundir et al. (2016)	India	P-Si	1816	–	8.76	–	63.58
Kamalapur and Udaykumar (2011)	India	–	50	–	–	–	55–89
Kumar and Nagarajan (2016)	India	Mc-Si	80	4.45	15.53	–	83.2
Padmavathi and Daniel (2013)	India		3 MWp	3.75	–	–	0.70
Shukla et al. (2016)	India	c-Si/a-Si	110	2.67–3.36	–	93.5–97.5	71.6–79.5
Sundaram and Babu (2015)	India		5 MWp	4.81	6.08	88.2	–
Kumar and Sudhakar (2015)	India	P-Si	10 MWp	1.96–5.07	13.2	97.0	86.12
Present study	Dhaka	c-Si	80	2.53	13	97.7	66

7. Conclusion

Photovoltaic energy is considered as one of the most promising renewable energy technologies. The performance of the PV system was compared with that of other heuristic models as well as grid connected PV systems installed across the globe as shown in Table 12. The salient findings from the study are summarized below.

- The accuracy of fuzzy logic model was obtained 97.47% and the accuracy of ANN model was obtained 98.78% with the actual irradiation.
- This study found that performance of ANN model is better than the fuzzy logic model for solar irradiation prediction.
- This predictive model of fuzzy logic and ANN will be helpful for researchers and engineers for design and planning of solar plants.
- 80 kWp power plant has been operating with good amount of performance ratio 66 PR.
- To derive maximum efficiency, design of the subject Photovoltaic system needs to be reviewed.

Future research investigations can be conducted on mapping of solar potential over Bangladesh along with the fuzzy logic and ANN model.

8. Future recommendation

Stability analysis of the fuzzy logic and ANN models will be carried out in future for verifying the convergence stability criteria of these results. Fuzzy logic and ANN models can be used to analyze hybrid renewable energy for future energy crisis mitigation. In addition to that these methods can be utilized to design management system of global warming and climate change challenges.

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