6

Solar Power Generation Forecasting using Artificial Neural Network and Generalized Neural Network Approach

6.1 INTRODUCTION

In this chapter, Forecasting of SPV plant generation using neural network approaches like artificial neural network and the Generalized neural network is done. These forecasting methods can help to maintain the reliability of the system when PV system is integrated with electrical grid. In this study, two locations are considered as discussed in chapter 3. In the following sections, different case studies are considered for generation forecasting for rooftop and ground-based solar power plant and results are presented.

6.2 FORECASTING OF SOLAR POWER PLANT GENERATION

In this section, artificial neural network and generalized neural network approaches are used to forecast the power generation of solar photovoltaic plants under particular time horizons in various seasons. So, time horizon is considered as 15-minute average, daily average, and monthly average and seasons as summer, rainy and winter.

6.2.1 Forecasting Model Assessment for Rooftop Based Solar Power Plant Generation

In this section, rooftop based 58 kW grid-connected Crystalline-Silicon and 43 kW grid-connected Amorphous-Silicon PV system installed at Indian Institute of Technology Jodhpur, Rajasthan, located in Jodhpur is considered.

6.2.1.1 Forecasting Of 15 Minute Averaged PV Power Generation For a 58kW C-Si based Rooftop PV System

In this case study, we have taken 58 kW C-Si based rooftop photovoltaic system. Description of the plant is already discussed in chapter 3. In this case study, we have taken one day historical 15 – minute averaged solar power generation data from the mentioned SPV plant. Here the input parameters are solar irradiation, ambient temperature and wind velocity, which are required along with plant generation output data. All the input parameters were periodically averaged as per the required time horizon. Forecasting modeling began from data pre-processing that is data averaging, data subdivision in training, validation, and testing phase. In previous chapter, data normalization is already discussed and normalization scales the data to a range of 0.1 to 0.9. 60% data is used for training, 20% for validation and rest 20% for testing propose.

In section 4.2.2. is basic architecture and development of neural network model and its working are presented. On the basis of previous studies, we have chosen the feed forward multilayered neural network (FFMLNN) for this case study. In proposed forecasting model, the number of input variable = 4, Number of outputs = 1, Number of input layer neurons = 4, Number of Hidden layer neurons = 10, Number of Hidden layer = 1 trained with back propagation algorithm are considered as shown in Fig. 6.1.

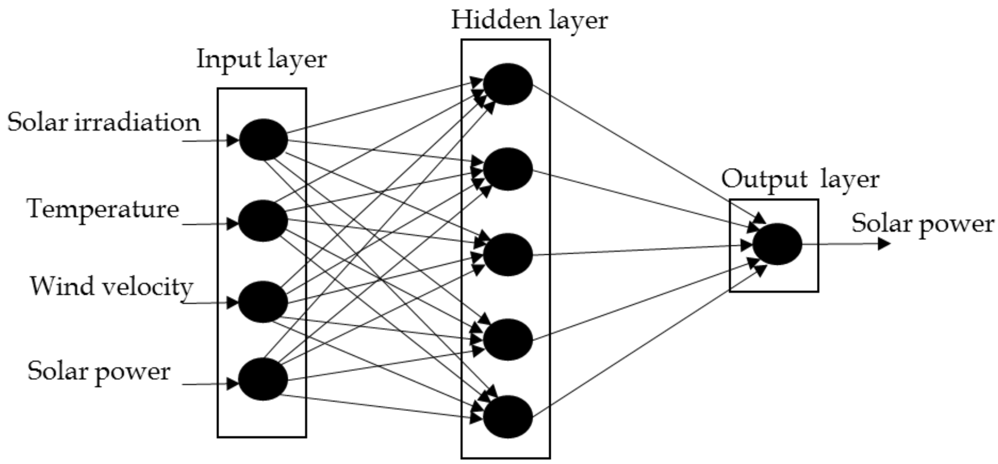
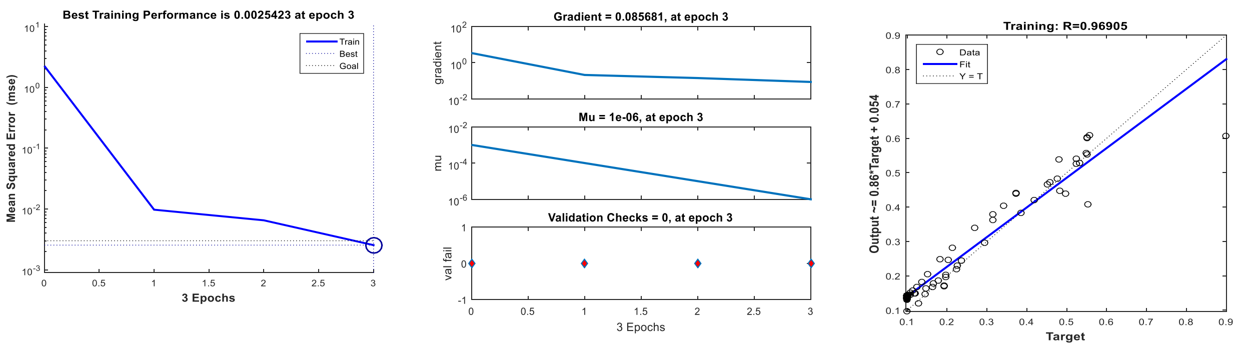


Figure 6.1: Feed-forward multi-layered neural network training structure

Here, if the solar power generation pattern is abnormal on a particular time horizon, this variation from the normal generation pattern will be seen in forecasting results. In order to improve the accuracy of the model, to obtain better modeling results, the feature of adaptive, artificial neural network (ANN) has been used for solar power generation forecasting. But the drawback of ANN model is the requirement of large training time which depends on the size of training file, type of ANN, error functions, learning algorithms, hidden nodes. So Generalized Neural Network is a possible solution this problem. In the previous chapter, the development and working of the generalized neural network is discussed in detail. In this section, GNN forecasting model is applied to the same number of input and output variables as in ANN forecasting model.

- **Results and Discussion**

Forecasting models using Artificial Neural Network and Generalized Neural Network were evaluated against the actual power generation of the plant and models are evaluated using minimum and maximum error and Root Mean Square Error (RMSE). The results of ANN model, training performance of model, values of training parameters and the coefficient of determination are shown in Figure 6.2. Figure 6.3 shows the comparison of actual solar power output, ANN and GNN model.



(a) (b) (c)

Figure 6.2: ANN performance (a) Training performance of ANN model (b) Variation in training parameters during training of ANN (c) Testing performance of ANN model

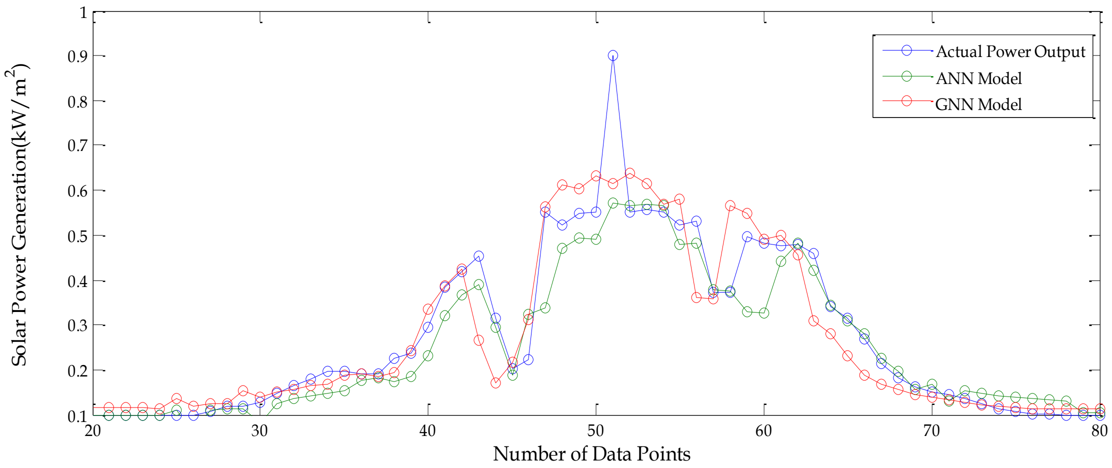


Figure 6.3: Comparison of ANN, GNN model with actual power output

The comparative results of actual solar power output, ANN model, and GNN model have been compared in Figure 6.3 and the maximum, minimum and root mean square error of ANN and GNN model for assessment of forecasting model is shown in Table 6.1. The root mean square error results describe that accuracy of forecasting increases in generalized neural network and can give better output compare to ANN model for solar power generation forecasting.

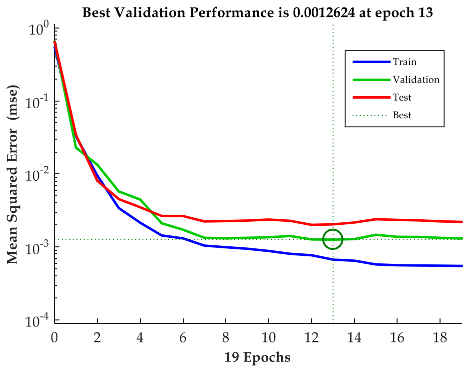
Table 6.1: Testing performance of ANN and GNN for solar power forecasting modeling

Sr. No.	Model Name	Max Error	Min Error	RMSE
1	ANN	0.05	-.115	0.131
2	GNN	0.21	-0.125	0.055

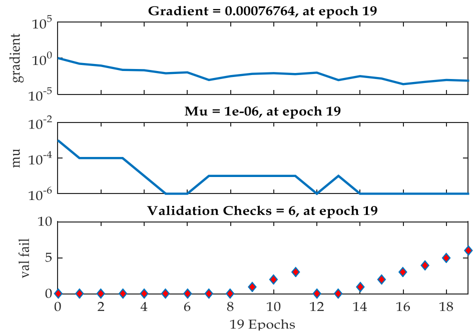
6.2.1.2 Analysis of Solar Power Variability Due to Seasonal Variation and its Forecasting For 43 kW A-Si Based Rooftop PV System

The main objective of this work is to analyze the effect of solar power variability on the accuracy of solar power generation forecasting due to seasonal variation. In this work, the variability of solar power generation in different seasons and its forecasting is carried out based on the data collected from a 43 kW amorphous silicon rooftop-based solar photovoltaic plant installed in IIT Jodhpur. Data collection and site description is already discussed in the third chapter. Main seasons of Indian which is Monsoon, Winter and Summer seasons are considered for the study. Here we are taken three continuous days (from 2nd to 4th) in Rainy (August), Winter (January) and Summer (June) season. In this work proposed ANN and GNN model is used to comparative study for forecasting solar power generation based on seasonal data.

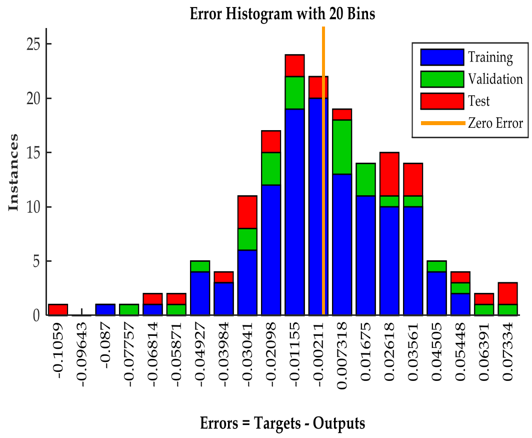
For Rainy season



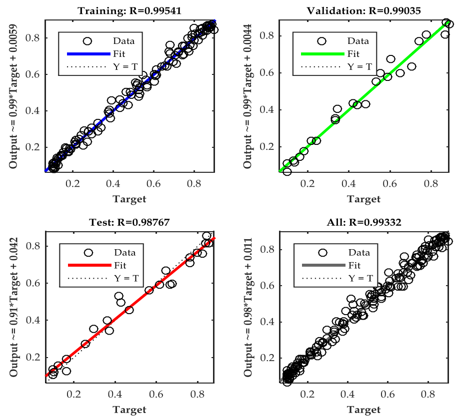
(a)



(b)



(c)



(d)

Figure 6.4: (a) Training performance of ANN model (b) Variation in training parameters during training of ANN(c) Error Histogram for testing, training and validation phase (d) Testing performance of ANN model

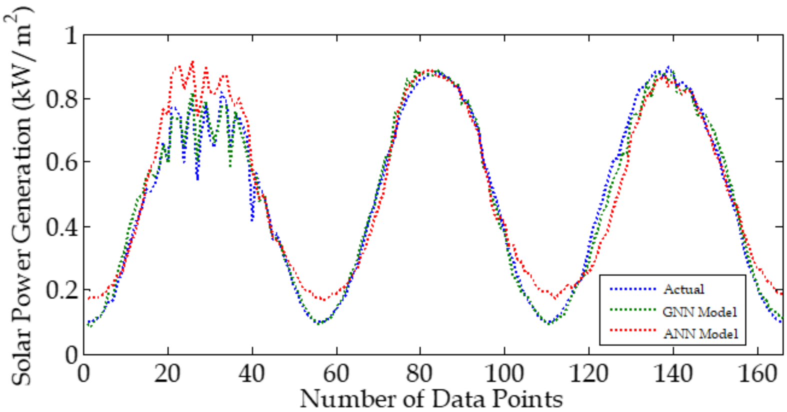
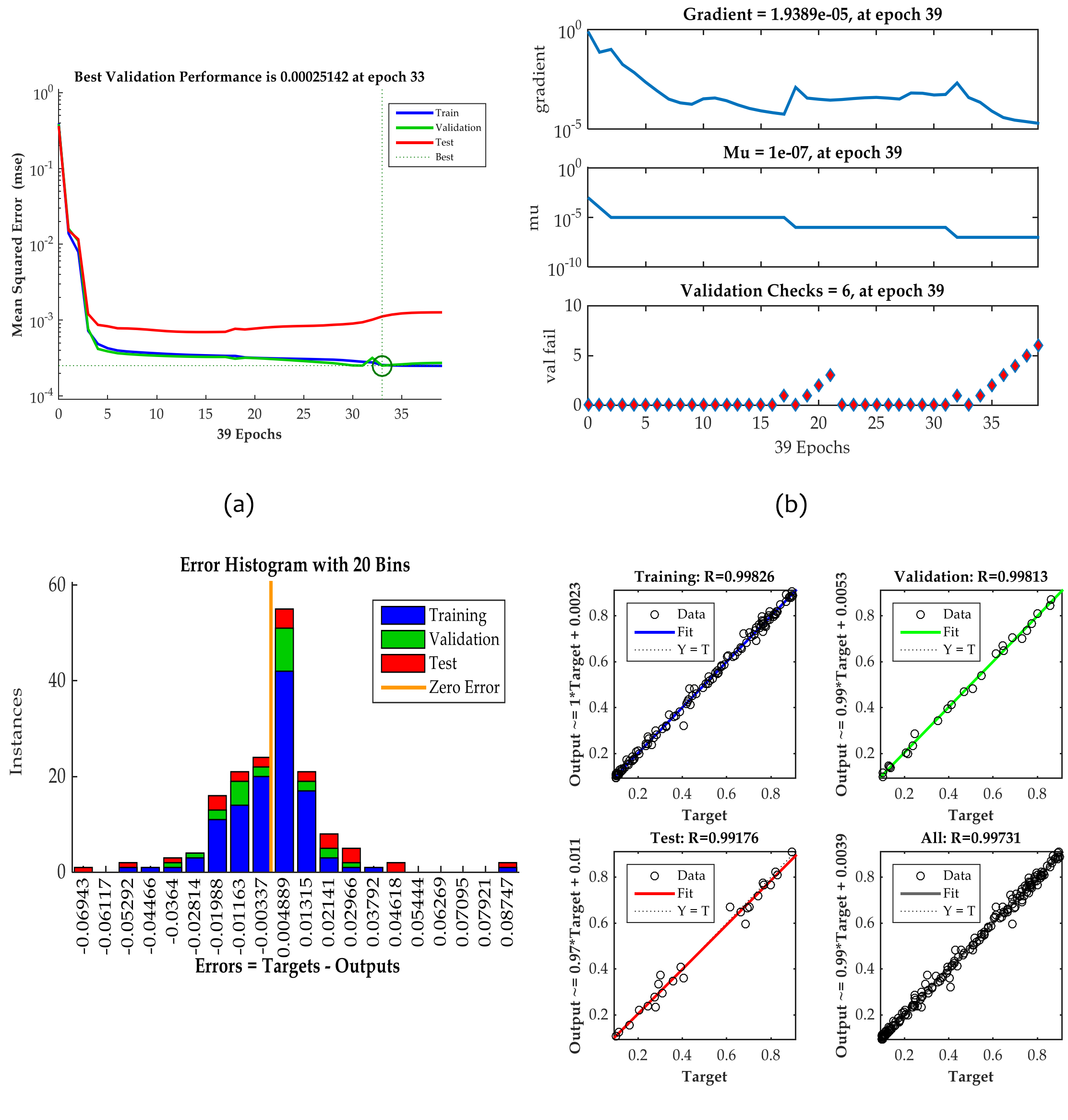


Figure 6.5: Comparison of ANN, GNN model with actual power output

For summer season



(a) (b)

(c) (d)

Figure 6.6: (a) Training performance of ANN model (b) Variation in training parameters during training of ANN(c) Error Histogram for testing, training and validation phase (d) Testing performance of ANN model

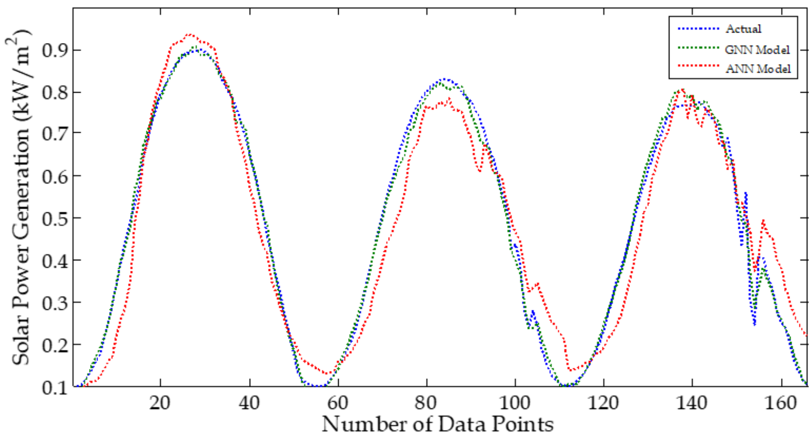


Figure 6.7: Comparison of ANN, GNN model with actual power output

Winter seasons

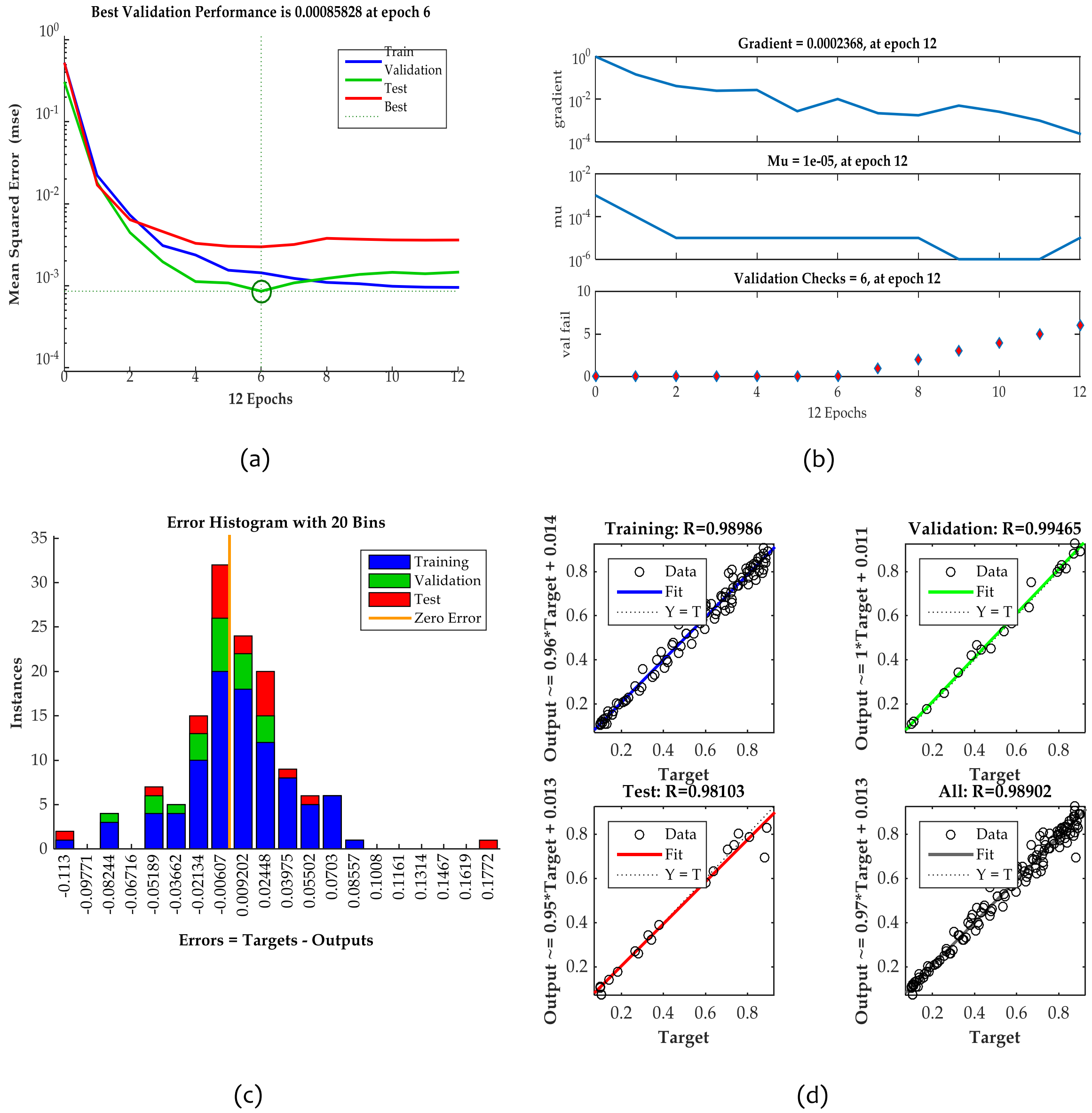


Figure 6.8: (a) Training performance of ANN model (b) Variation in training parameters during training of ANN(c) Error Histogram for testing, training and validation phase (d) Testing performance of ANN model

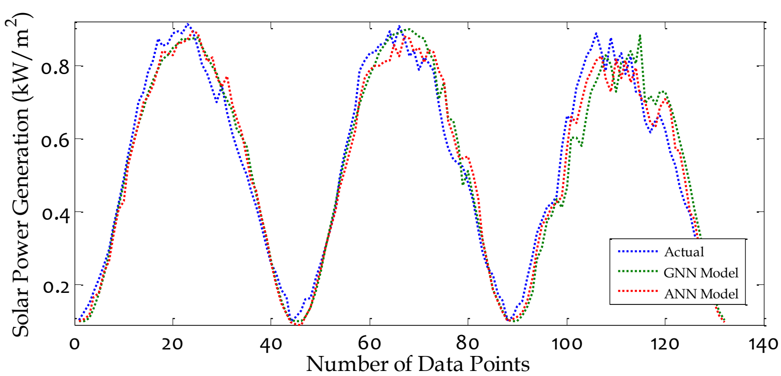


Figure 6.9: Comparison of ANN, GNN model with actual power output

- **Results and Discussion**

This section explains the results and discussion, including the comparative analysis of the accuracy of forecasting model using error metric indices like root mean square error, mean square error, max. error, min error and the coefficient of determination ($\boldsymbol{R^2}$) in between ANN and GNN forecasting model. These comparative results are shown in Table 6.2 and Figures 6.4-6.9. It can be seen that generalized neural network gives less error with more accuracy compared to artificial neural network. In winter season the error is high (compared to other seasons) due to high variation in input parameters.

Table 6.2: Comparative analysis of ANN and GNN model for solar power generation forecasting

Seasons / Values	Rainy (2-4th August)		Summer (2-4th June)		Winter (2-4thJanuary)	
	ANN	**GNN**	**ANN**	**GNN**	**ANN**	**GNN**
RMSE	0.3435	.0705	0.1231	0.0747	0.3534	0.0494
MSE	0.1512	.0050	0.0417	0.0056	0.1478	0.0025
Max. Error	0.0722	0.1574	0.1602	0.1529	0.1528	0.1543
Min. Error	-0.0974	-0.2276	-0.0791	-0.1640	-0.1285	-0.1587
R	0.99859	.99945	0.99843	.99998	0.99654	.99839

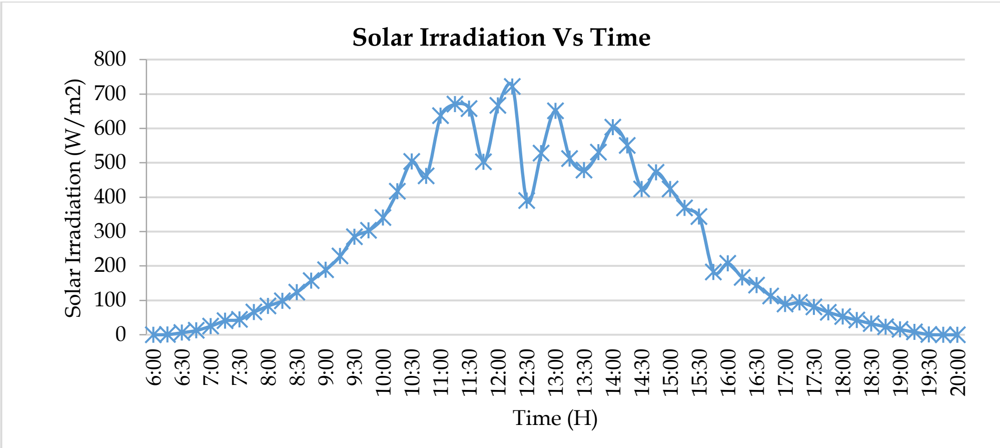
6.2.1.3 Ground-based measurement for solar power variability forecasting modeling using Generalized Neural Network

In this work, ground-based measurements are used for the forecasting of 43 kW A-Si SPV plant generation with the help of historical data of solar irradiation, ambient temperature, module temperature, wind velocity and solar power generation for one day which is 15 Minute averaged data of plant generation for 2nd August.

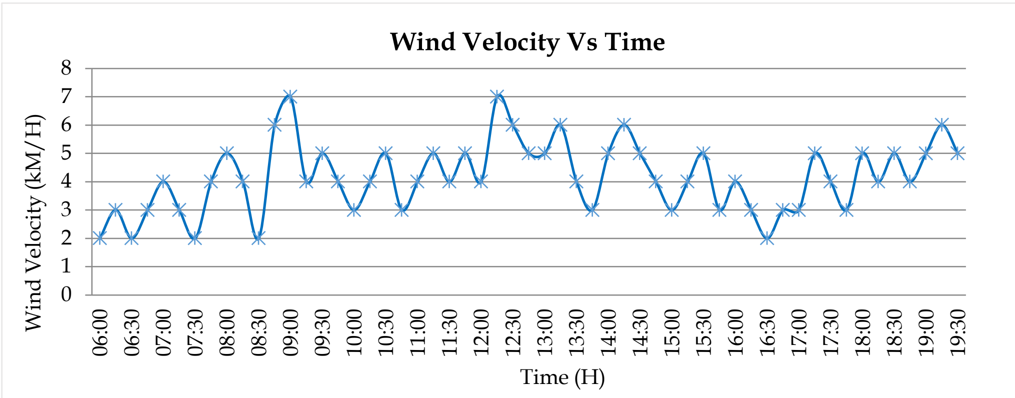
The purpose of the study, forecast as per the schedule in the Indian Power sector a time slot of 15 minutes is considered for each forecasting. The proposed forecasting model using the artificial neural network and generalized neural network model is applied to the input parameter for solar power generation forecasting. The input parameters for forecasting modeling are:

- Solar radiation (SR)
- Ambient temperature (AT)
- Module temperature (MT)
- Wind velocity (WV)

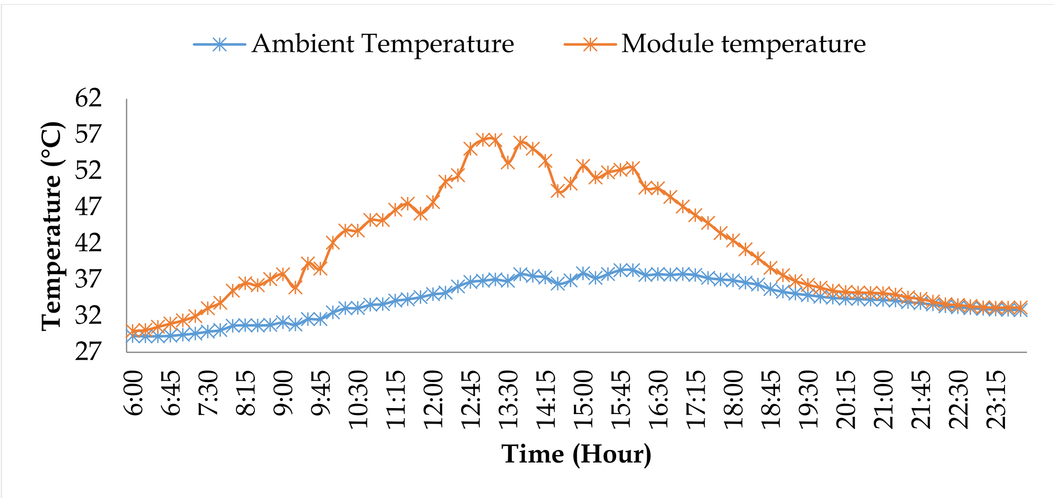
So Figure. 6.10 (a)-(c) shows the variation of solar irradiation, wind velocity, ambient and module temperature input variable with respect to time.



(a)



(b)



(c)

Figure 6.10: Daily variation of (a) solar irradiation (b) wind velocity and (c) ambient and module temperature with respect to time.

In Figure 6.11 it can be seen that the mean square error reduces within 9 epochs in training of ANN model. After the training is completed the comparative forecasted results from ANN model is shown in Figure 6.12. Error deviation with solar radiation is indicated in the Figure

6.13. In this figure, it is shown that error deviation during the morning time, especially in the lower range of solar radiation (0-400 W/m²) requires special attention. This error deviation is increasing with a specific range of solar radiation in between 400-1000 W/m². So on the basis of this study, we can say that higher ambient temperature, module temperature, and wind velocity is also playing an important role in solar power variability which can be observed in the result of solar power generation forecasting and error deviation result.

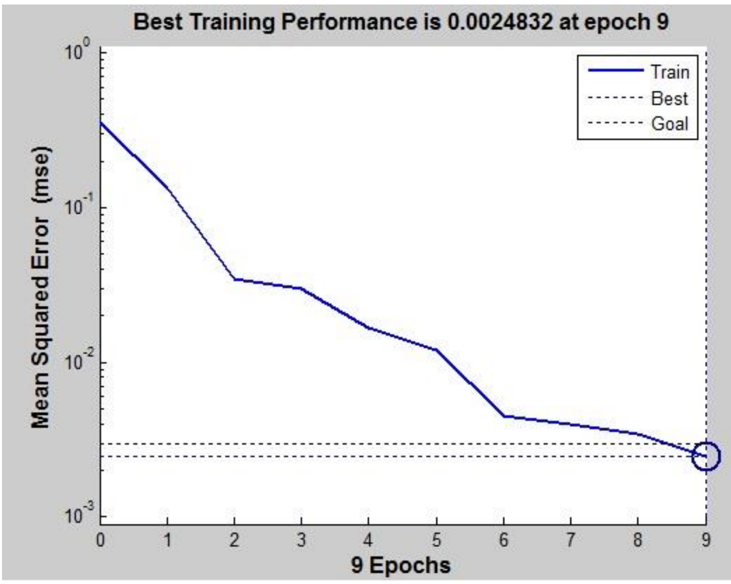


Figure 6.11: Mean square error in ANN model

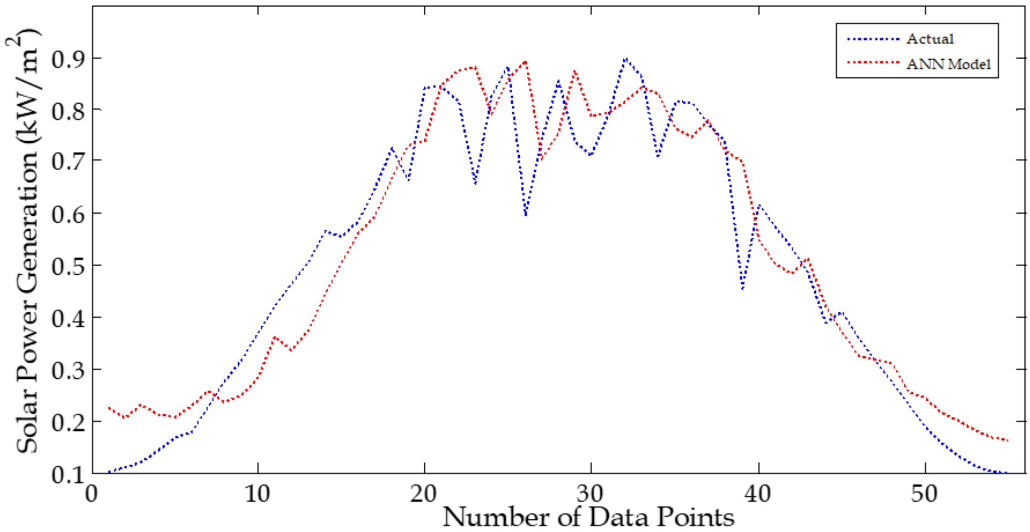


Figure 6.12: Solar power generation forecasting using ANN model

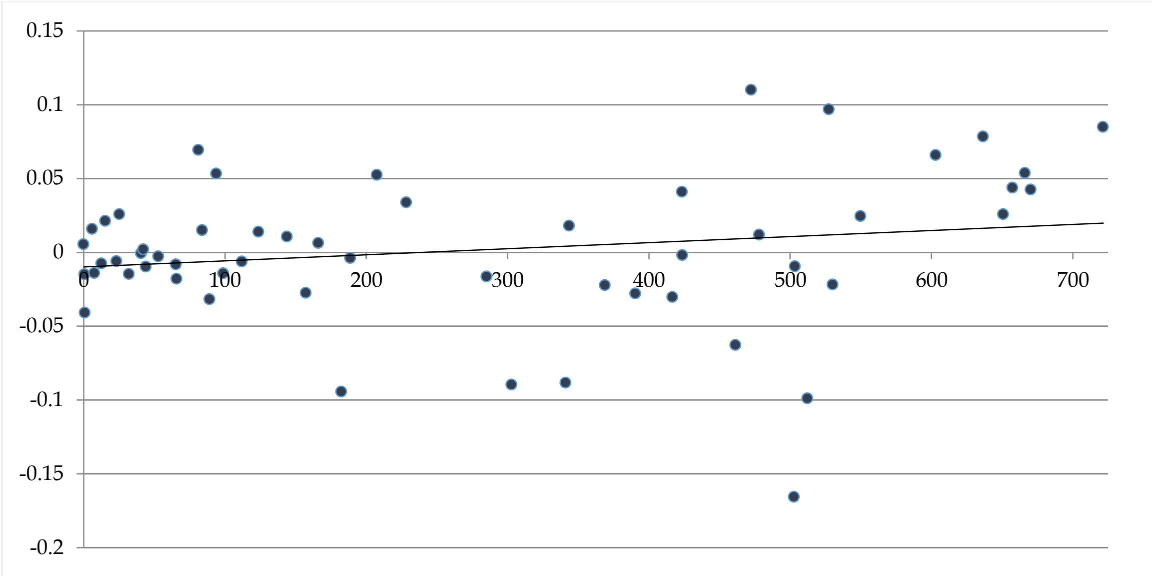


Figure 6.13: Error with respect the actual solar irradiation

The comparative test results in the figure show that actual data with ANN and GNN model output. We can see error variation in Figure 6.13 with respect to solar irradiation. This problem is highly nonlinear and complex in nature. In this problem, Generalized Neural Network is comparatively performing better than ANN model as shown in Figure 6.14. It takes lesser computation time compare to ANN model.

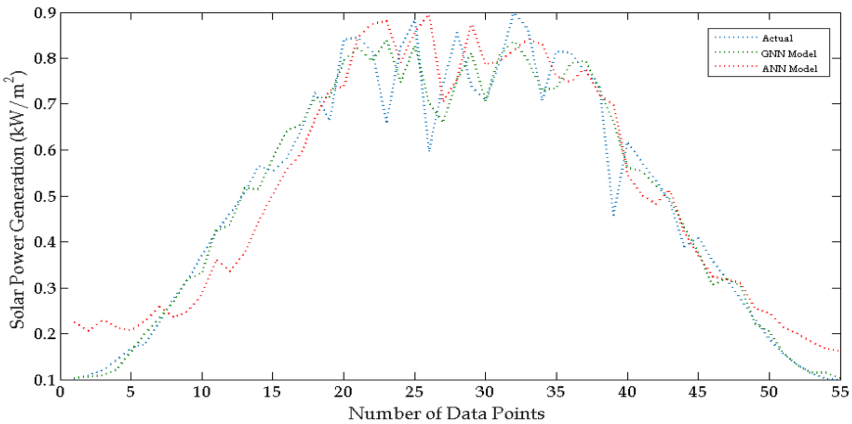


Figure. 6.14: Comparison of Actual Data, ANN and GNN model

The obtained results from each of the models were organized and assessed in terms of the magnitude of the error metric between the forecasted output and the actual solar power generation. This was achieved by measuring root of the average of the squares of errors (RMSE) which is shown in Table 6.3. According to the resultant errors is less in the case of GNN model as compared to ANN model. Figure 6.15 also shows that the error deviation in GNN is less compared to ANN.

Table. 6.3 Testing performance of ANN and GNN model for solar power forecasting

Sr. No.	Model Name	RMSE Error	Computational Time (Seconds)
1	ANN	0.1019	35
3	GNN	0.0903	15

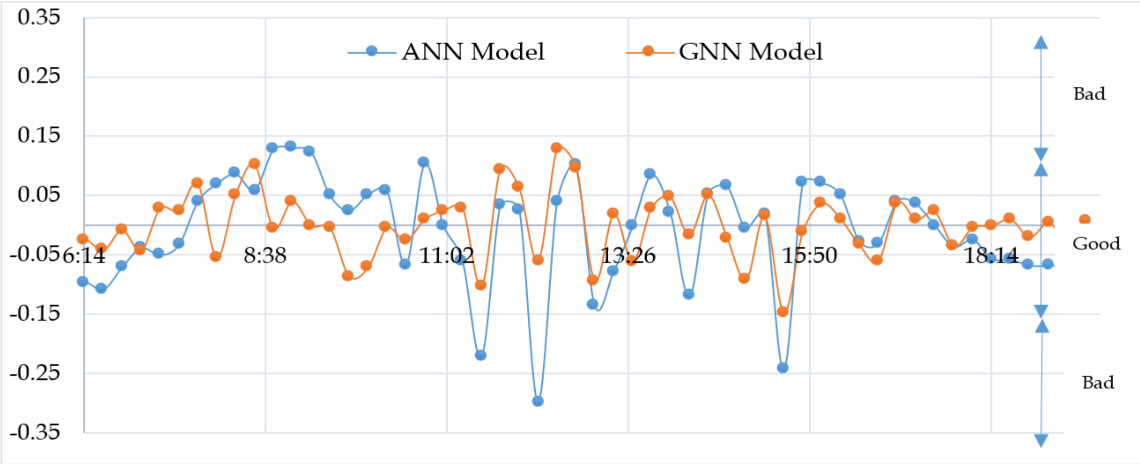
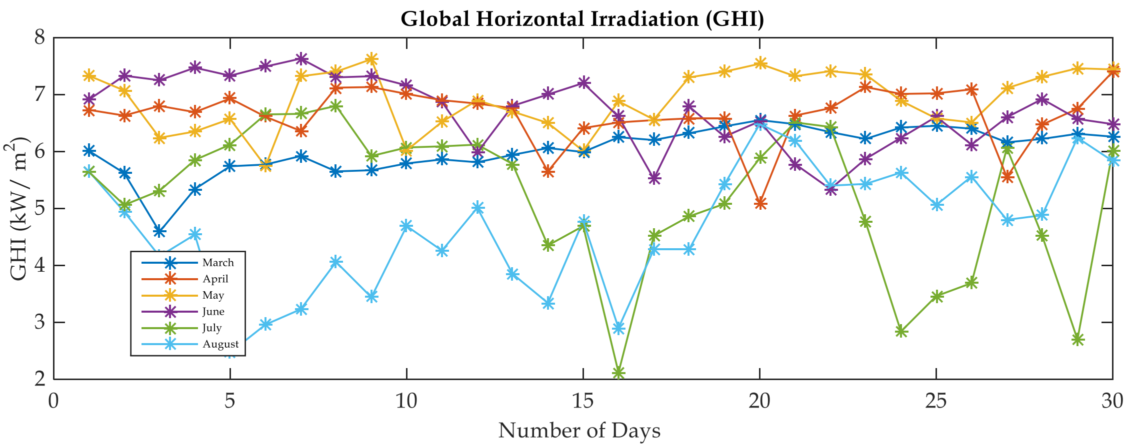


Figure 6.15 Error Analysis of ANN and GNN Model

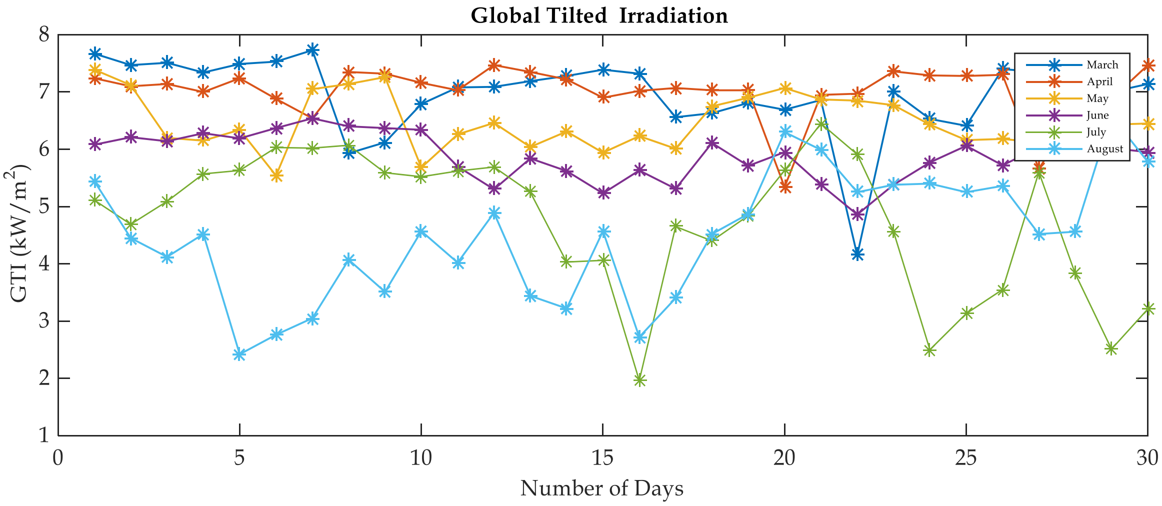
6.2.2 Ground Based 5 MW Solar Power Plant Generation Forecasting

In this section, we have investigated 5 MW ground-based Gujarat Power Corporation Limited (GPCL) Charanka, Gujarat solar photovoltaic power plant. These case studies considered daily averaged power generation data. Six-month historical data is collected for this study and these measured data were all recorded at one-hour intervals. Site description, data collection, and data description are discussed in chapter third section 3.3.1 to 3.3.3.

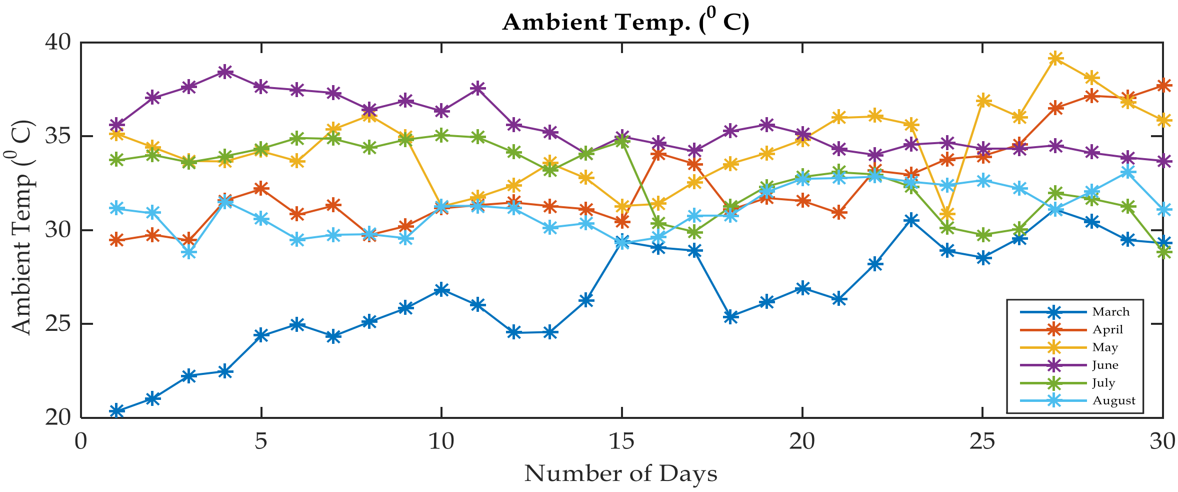
Data acquisition system monitored six parameters. The collected historical data during (March-August 2015) is global horizontal irradiation (GHI), global tilted irradiation (GTI), ambient temperature, module temperature, sun availability and solar PV plant generation is considered for the forecasting model shown in Figure 6.16 (a)-(f).



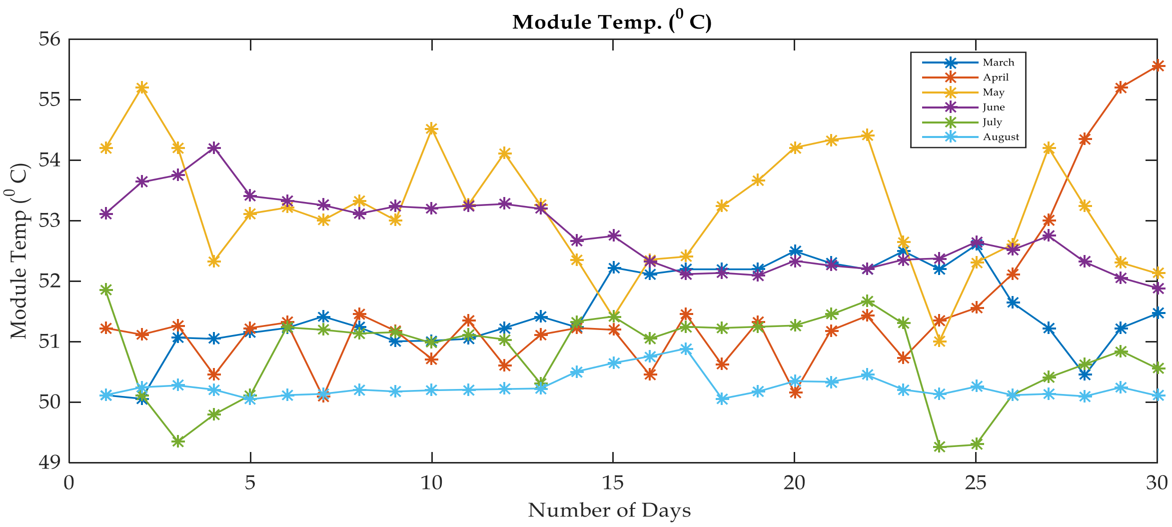
(a)


Global Tilted Irradiation
GTI (kW/m^2)
Number of Days
March
April
May
June
July
August

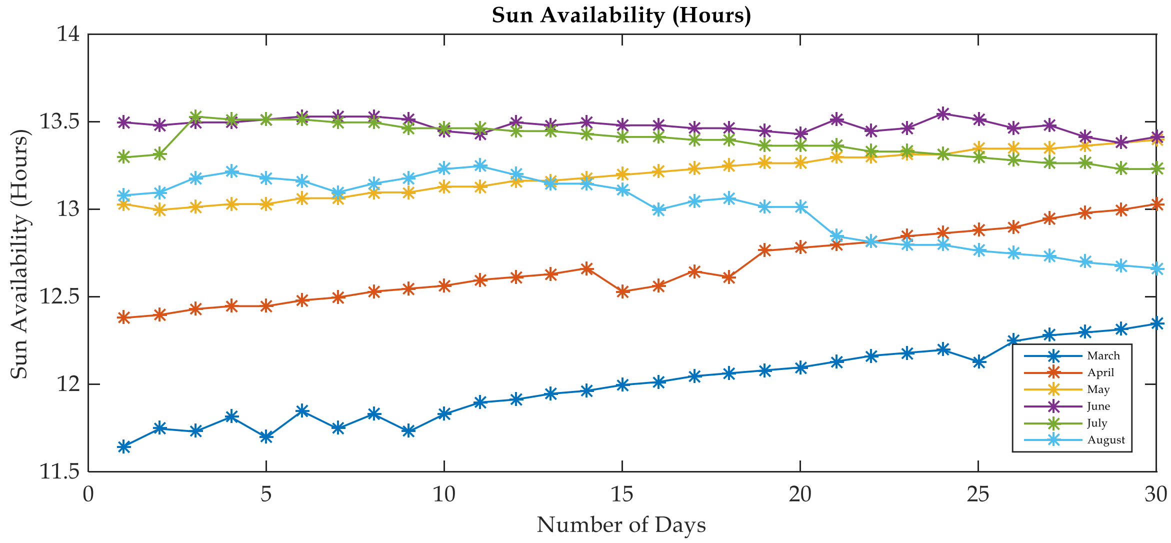
(b)


Ambient Temp. (^{0} C)
Ambient Temp (^{0} C)
Number of Days
March
April
May
June
July
August

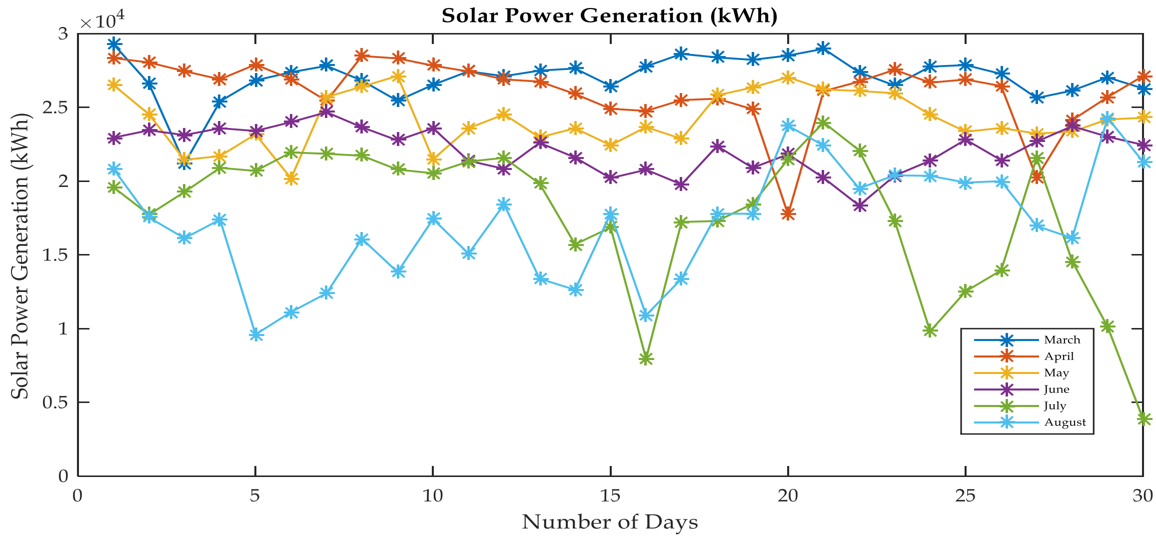
(c)


Module Temp. (^{0} C)
Module Temp (^{0} C)
Number of Days
March
April
May
June
July
August

(d)



(e)

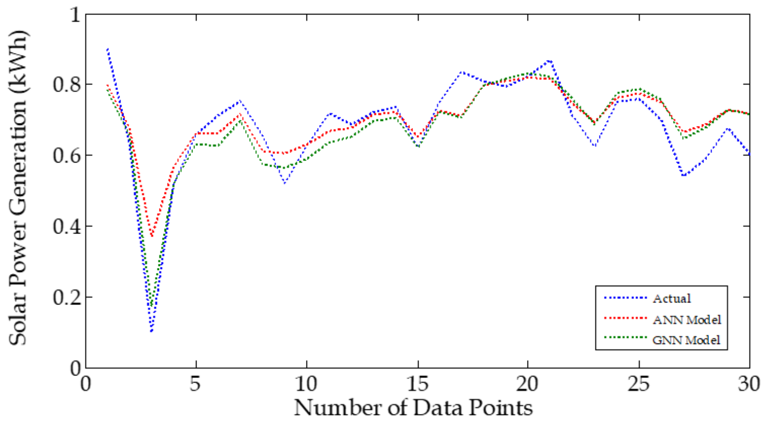


(f)

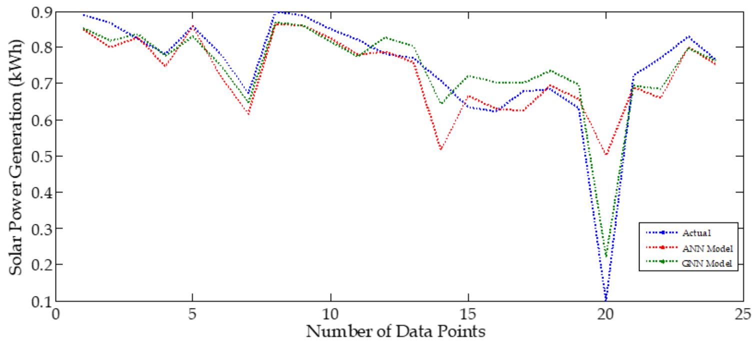
Figure 6.16: (a) Daily averaged GHI (b) averaged GTI (c) Ambient temperature (d) Module Temperature (e) Sun Availability and (f) solar power plant generation

6.2.2.1 Forecasting of 5 MW Solar Photovoltaic power Plant Generation using Generalized Neural Network

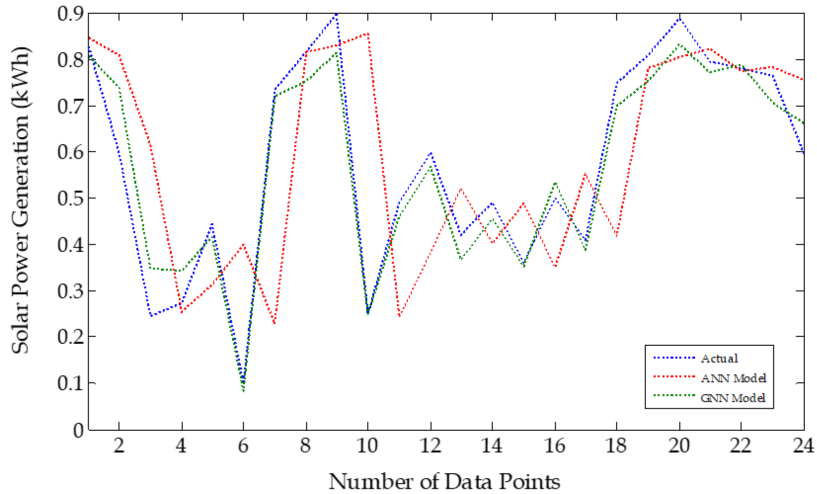
In the section, Artificial Neural Network and Generalized Neural Network based forecasting models are applied on six-month daily average data of 5 MW PV power plant. The comparison between actual power generation, ANN model output, and GNN model output are shown in Figure 6.17 (a-f).


Solar Power Generation (kWh)
Number of Data Points
Actual
ANN Model
GNN Model

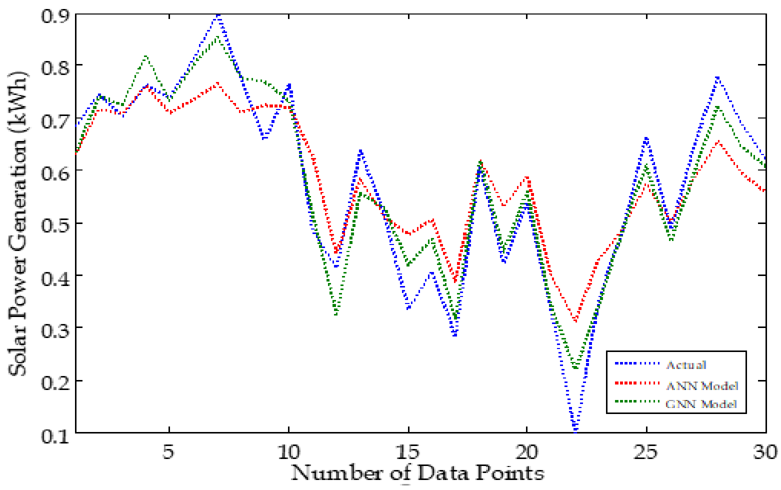
(a)


Solar Power Generation (kWh)
Number of Data Points
Actual
ANN Model
GNN Model

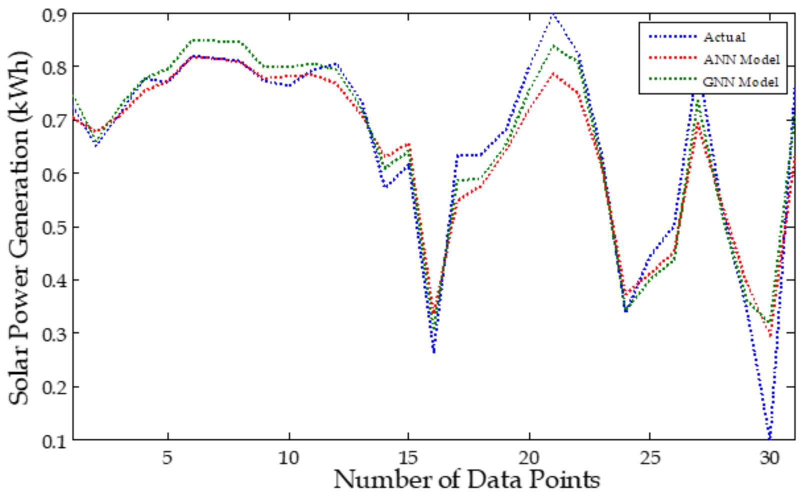
(b)


Solar Power Generation (kWh)
Number of Data Points
Actual
ANN Model
GNN Model

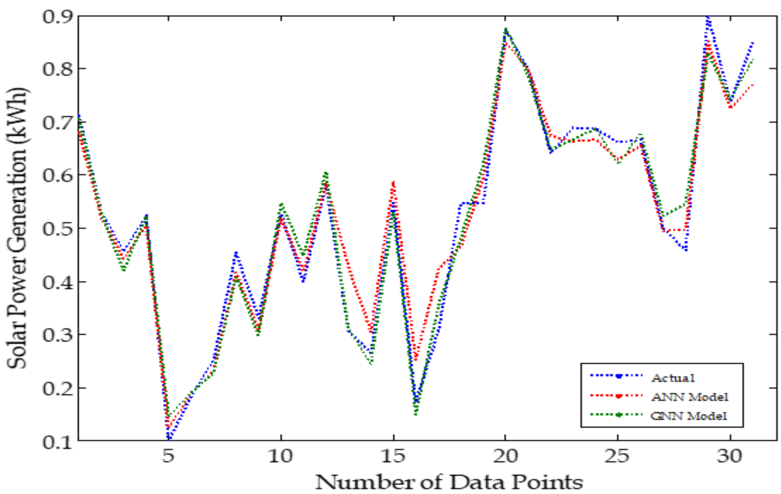
(c)



(d)



(e)



(f)

Figure 6.17: Actual and forecasted solar power generation for the month of (a) March (b) April (c) May (d) June (e)July and (f) August

Results

The results indicate that proposed ANN and GNN based forecasting models are capable to forecast for the time horizon of daily average data. These models can overcome the effect of trend and seasonality on the forecasting.

Testing and model validation results are shown in Table. 6.4. According to error analysis for the actual power generation versus model output, we found that root mean square error (RMSE) is less for GNN model as compared to ANN model. The value of R^2 shown indicates that GNN based forecasting model fares better compared to ANN model.

Table 6.4 Performance of proposed models

Values Months	RMSE		R^2	
	ANN	GNN	ANN	GNN
March	0.4084	0.0610	0.9456	0.9939
April	0.2306	0.0489	0.9769	0.9945
May	0.0772	0.0615	0.9870	0.9925
June	0.1973	0.0505	0.9732	0.9907
July	0.4143	0.0518	0.9843	0.9915
August	0.1146	0.0361	0.9612	0.9989

6.3 SUMMARY

Neural network based forecasting models like artificial neural network and generalized neural network were applied on the same generation data. Generalized neural network forecasting model output results are compared to the artificial neural network model output. A comparative study found that generalized neural network based forecasting model provides better forecasting results compared to the artificial neural network for the case studies considered in this work.

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