Journal of Energy, Environmental & Chemical Engineering
2017; 2(2): 32-40
http://www.sciencepublishinggroup.com/j/jeece
doi: 10.11648/j.jeece.20170202.13

Output Power Prediction of Photovoltaic Module Using Nonlinear Autoregressive Neural Network

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To cite this article:

Samuel Bimenyimana, Godwin Norense Osarumwense Asemota, Li Lingling. Output Power Prediction of Photovoltaic Module Using Nonlinear Autoregressive Neural Network. *Journal of Energy, Environmental & Chemical Engineering*. Vol. 2, No. 2, 2017, pp. 32-40. doi: 10.11648/j.jeece.20170202.13

Received: June 1, 2017; **Accepted**: June 15, 2017; **Published**: July 26, 2017

Abstract: Precise prediction of generated output power plays an essential aspect in many sectors of power system like in solar energy sources which is the current topic being discussed on. It is of great role in every system but the prediction of output power for solar energy system is a tough task due to the influence of numerous parameters and fluctuations. Photovoltaic module being main part of the solar power system has many factors which can influence its performance where temperature is paramount. In this paper, the output power of a certain photovoltaic module was estimated under change of temperature and prediction of its future output power was done referring to the estimated power by nonlinear neural network. Both monthly and annual predictions were done through training, validation and test processes. The best monthly performance was achieved equal to 0.9743 at epoch 3 with regression values for training, test and validation all equal to 0.74274, 0.7166, 0.83388 and 0.75604 respectively. While the best annual best performance was achieved equal to 0.10284 at epoch 6 with regression values for training, test, validation and all equal to 0.76576, 0.73665, 0.71678 and 0.75386 respectively. Finally, results showed that nonlinear autoregressive neural network was good and effective for prediction of the photovoltaic module output power.

Keywords: Photovoltaic Output Power, Prediction, Empirical Formula, Temperature, Nonlinear Autoregressive Neural Network

1. Introduction

The electricity demand is always increasing day to day due to both daily growth of population number and modernization desires. Due to this fact, renewable energies are being used all over the world because of their advantages especially solar energy. It is a form of energy where the sunlight can be converted into thermal or electrical energy. In this paper, It is the sunlight being converted into electrical energy to supply loads not into thermal energy [1]. The photovoltaic PV modules as part of the system convert that solar energy into electrical energy and can be used to supply either DC loads or AC loads [2, 3]. There are factors which can influence their performance such as weather conditions, tilt angle, azimuth angle, temperature, wind speed, shadow effects and electrical loads [4]. Due to above factors, many algorithms have been used by researchers [5-21] to predict or forecast PV module performance and neural network was mostly chosen, because of its precision, computational efficiency and simplicity. Engineering places need high premium on prediction, because it enables how to determine future systems behavior, especially for optimally advanced operations and planning in electrical engineering practice [9]. Neural Network systems have been applied in solar energy sector to forecast future system's values from day ahead, to month up to annual forecasting. Neural network uses human brain learning system principle to carry out the working conditions between input-output either for linear or nonlinear system all with minimal computing procedures. Also, neural networks are approximators [22, 23]. Numerical methods have been used to predict the weather and solar power, at the expense of very high computing power [24-29]. This paper is organized in five sections where first section is the introduction, second section is about the photovoltaic module’s output power and methodology, third section discusses neural network, fourth section discusses prediction simulation results and fifth section is the paper conclusion.

2. Photovoltaic Module

2.1. Equivalent Circuit of PV Cell

The following figure 1 describes a single diode equivalent circuit of a PV module and PV related equations 1-9 [30-36] are written after figure 1.

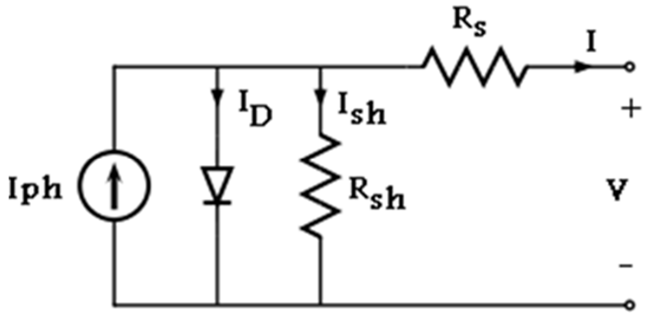

Figure 1. *Equivalent circuit of PV cell [31].*

Voc is the open circuit voltage: the voltage at which no current flows through external circuit, It is know as the maximum voltage which a solar cell can deliver and corresponds to the forward bias voltage at which the dark current current density compensates the photocurrent, Isc the short circuit current: the current that flows through external circuit when the electrodes of the solar cell are short circuited”[30], Pmax: the maximum power, FF: the fill factor, Imp and Vmp the maximum current and voltage at maximum power, η: stands for the effeciency. Pin is the input power, I(t): the incident radiation (W/m^2), Ac: PV collector area (m^2). Photovoltaic module or solar module is usually used to express combination of solar cells connected together to build up and supply the level of required power to a certain load where three parameters (V_{oc}, I_{sc}, W_p) can be given under some standard tests conditions (for example 1000 w/m^2 and 25°C) [32].

$$\mathrm{I} = \mathrm{Iph} - \mathrm{Io}(\exp \mathrm{q}\,\frac{(\mathrm{V+IRs})}{\mathrm{N.k.T}} - 1) - \frac{\mathrm{V+IRs}}{\mathrm{Rsh}} \tag{1}$$

$$\mathrm{Io} = \mathrm{IoR} * (\frac{\mathrm{Tc}}{\mathrm{Tref}})^3 * \exp(\frac{\mathrm{q*Eg}(\frac{1}{\mathrm{Tref}} - \frac{1}{\mathrm{Tc}})}{\mathrm{K.N}}) \tag{2}$$

$$\mathrm{Tc} = ((\mathrm{NOCT} - 20) * \frac{\mathrm{G}}{0.8}) + (\mathrm{Ta}) \tag{3}$$

$$\mathrm{Voc} = \frac{\mathrm{NKT}}{\mathrm{q}} \ln\left(\frac{\mathrm{Iph}}{\mathrm{Io}} + 1\right) \tag{4}$$

$$\eta = \frac{\mathrm{Pmax}}{\mathrm{Pin}} = \frac{\mathrm{Imp*Vmp}}{\mathrm{I(t)*Ac}} \tag{5}$$

But the change in operating conditions will also change these characteristics [35, 36]

From above typical curve, it is very clear that characteristic parameters such as voltage, current and power depend on the operating conditions, then the ensuing power formula can be written as:

$$\mathrm{Pmax} = \mathrm{Vmp} \times \mathrm{Imp} = \mathrm{FF} \times \mathrm{Voc} \times \mathrm{Is}c \tag{6}$$

With fill factor (FF), short circuit current (Isc), open circuit voltage (Voc) provided by the manufacturer under standard conditions [37]. As a result of several complex operating conditions and different factors such as conversion efficiency (η), sunlight intensity (I), operating temperature (T) and daylight angle, Many equations have been developed to estimate output power of a photovoltaic module, where empirical formula have been used in [38-41] to estimate the maximum DC power of a PV module under fixed orientation.

$$Ps = \eta \times \mathrm{S} \times \mathrm{I}[1 - 0.005(\mathrm{T} + 25)] \tag{7}$$

The efficiency η of a PV module can be expressed as:

$$\eta = \frac{\mathrm{Pmax}}{\mathrm{S{\times}I}} \tag{8}$$

If I stands for sunlight incident radiation (W/m^2), S: area of the collector (m^2) and P_{max} is the PV module maximum power. By combining these two equations, also referring to [42-43] about photovoltaic module, we can reformulate equation 7 and obtain a new simple formula to estimate the DC output power when temperature is varying while other factors are fixed.

$$\mathrm{Ps} = \mathrm{Pmax}[1 - 0.005(\mathrm{T} + 25)] \tag{9}$$

2.2. Methodology

Meteorological temperature data from 1/1/2014 up to 31/12/ 2014 were used as time series data to estimate output power time series of the photovoltaic module through simplified empirical formula as written in equation 7. The following parameter values were found on the nameplate of that PV module in the laboratory: P_{max} =50 W, I_{sc} = 2.99 A, V_{oc} = 21.5 V, V_{mp} = 18 V, I_{mp} = 2.7 A, Area: 0.3402 m^2. The temperature data used here are from one city in Africa, Rwanda where Kigali was chosen because of its moderate weather favorable for solar energy production. The temperature data samples were recorded three times in a day (6:00am, 12:00 and 18:00pm) [44]. For example: 1/1/2014, the temperature was 21.0°C at 6: am, 22.8°C at 12:00 am and 23.0°C at 18:00 pm, applying temperature data in equation 9:

$$P_{s1} = 50[1\text{-}0.005(21+25) = 38.5 \text{ W},$$

$$P_{s2} = 50[1\text{-}0.005(22.8+25) = 38.05\text{W},$$

$$P_{s3} = 50[1\text{-}0.005(23+25) = 38 \text{ W}.$$

Therefore applying this formula to all temperature data and parameters of that photovoltaic module, we can obtain time series data of estimated DC power to be used in the nonlinear autoregressive neural network prediction for future behavior of that module.

Table 1. *Estimating power.*

Date	STC °C	P_{max} [W]	t_o °C	P_s [W]
1/1/2014 6:00	25	50	22.4	38.15
1/1/2014 12:00	25	50	24.6	37.60
1/1/2014 18:00	25	50	24.4	37.65
31/12/2014 6:00	25	50	21.0	38.50
31/12/2014 12:00	25	50	22.8	38.05
31/12/2014 18:00	25	50	23.0	38.00

From Table 1, there will be 1095 estimated power time series data from 1/1/ 2014 until 31/12/2014 which are for prediction using nonlinear neural network.

3. Artificial Neural Network

Artificial Neural Networks (ANNs) among soft computing system models which operate as human brain structure operation. Biologically, it is well known that neurons are the basic parts of the human body. Neural networks receive inputs from many sources, combine and process them in special ways to generally execute nonlinear operation on the result. According to ANN structure and operation, it is a system that receives inputs, process data and provide an output [45-51]. It consists of three layers which are input layer, hidden layer and output layer and its function can be written as follow:

$$Y_j = f(\sum_i W_{ij} X_{ij}) \tag{10}$$

Y_j is the output node j, f: transfer function, W_{ij}: value of connection weight between node j and node i in the lower layer, X_{ij}: the input signal from the node i in the lower layer to node j. Nonlinear autoregressive ANN can be used to solve many problems either in engineering or in other domain.

Nonlinear Autoregressive Neural Network

Due to daily temperature change with time, the estimated power time series was characterized by variations which make them complex to linear model. Therefore a nonlinear autoregressive neural network was applied to that time series for prediction. Describing a discrete, nonlinear model can be briefly written as [50]:

$$y(t) = (y(t-1) \ldots . y(t-d) \tag{11}$$

This equation describes how to predict the values of a data series y at time t (month, year, etc.) using d the past values of that series [49]. To prove it, neural network time series tool in MATLAB has been used for prediction of power through one month and year. January 2014 was chosen randomly. The prediction was conducted in three steps which are training, validation and testing. During training step, the network was adjusted according to network error. Validation step continuously measures model performance, for its sub-goals and consequent network generalizations, until there is no further room for its improvement. The testing step has no effect on the training and it provides independent measure of the network performance during and after training, this is so because, both the network input and output targets of the regression plots were the same (perfect training). But, there is hardly any perfect training achievable, unless a re-training exercise was embarked upon. The Levenberg-Marquardt algorithm has been used during training and data were randomly divided as: 70% for training, 15% for validation and 15% for testing [51].

4. Prediction

4.1. One Month Prediction

The process was first to estimate output power referring to January 2014 temperatures (3 temperature samples every day (6:00am, 12:00am, 18:00pm) and built time series of 93 samples used as a training set in January 2014. Table 2 shows the training step during January 2014, the results showed the best prediction was achieved at epoch 3 with best validation performance of 0.09743 as it is clearly shown in figures 2-6.

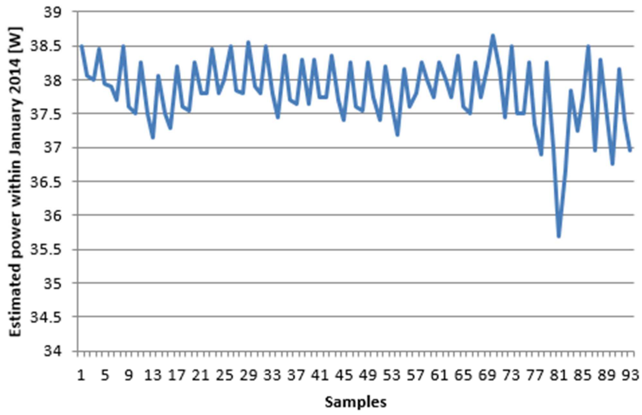

Figure 2. *Monthly fluctuation of estimated power in January 2017.*

Temperature characteristic curve shows a marked dip in output power for sample 80 at close to 35.7°C). This temperature is critical to sample PV output power.

Table 2. *Data Training for January 2014.*

N	Train	Test	Validate	Iteration	MSE train	MSE test
2	70%	15%	15%	24	0.104853	0.175262
4	70%	15%	15%	9	0.192011	0.170776
6	70%	15%	15%	19	0.0768394	0.0751154
8	70%	15%	15%	9	0.115351	0.0715724
10	70%	15%	15%	25	0.0599643	0.0599643

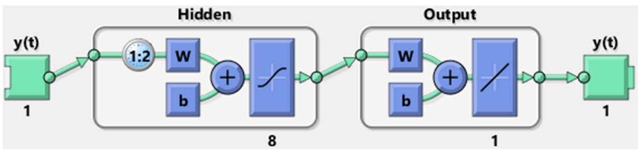

Figure 3. *NAR structure with 8 hidden neurons and 2 delays.*

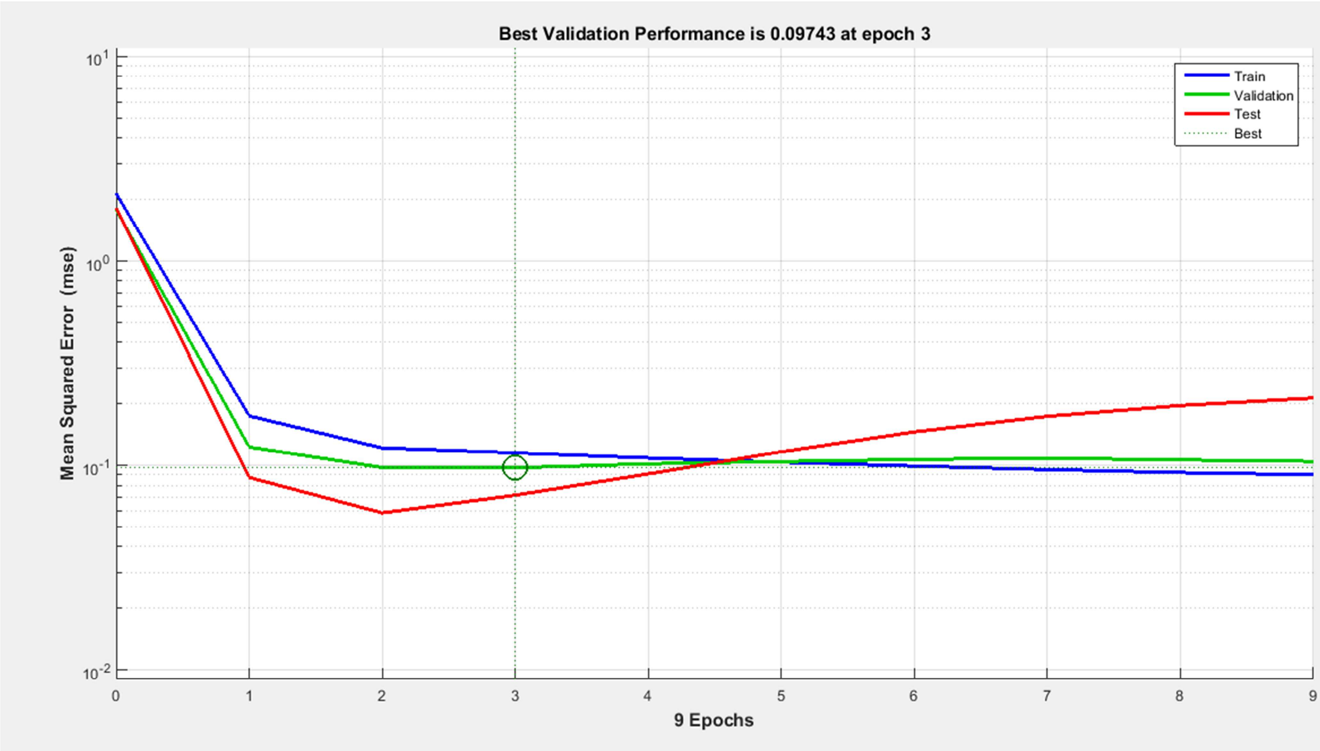

Figure 4. *Performance plot of best neural network prediction during January.*

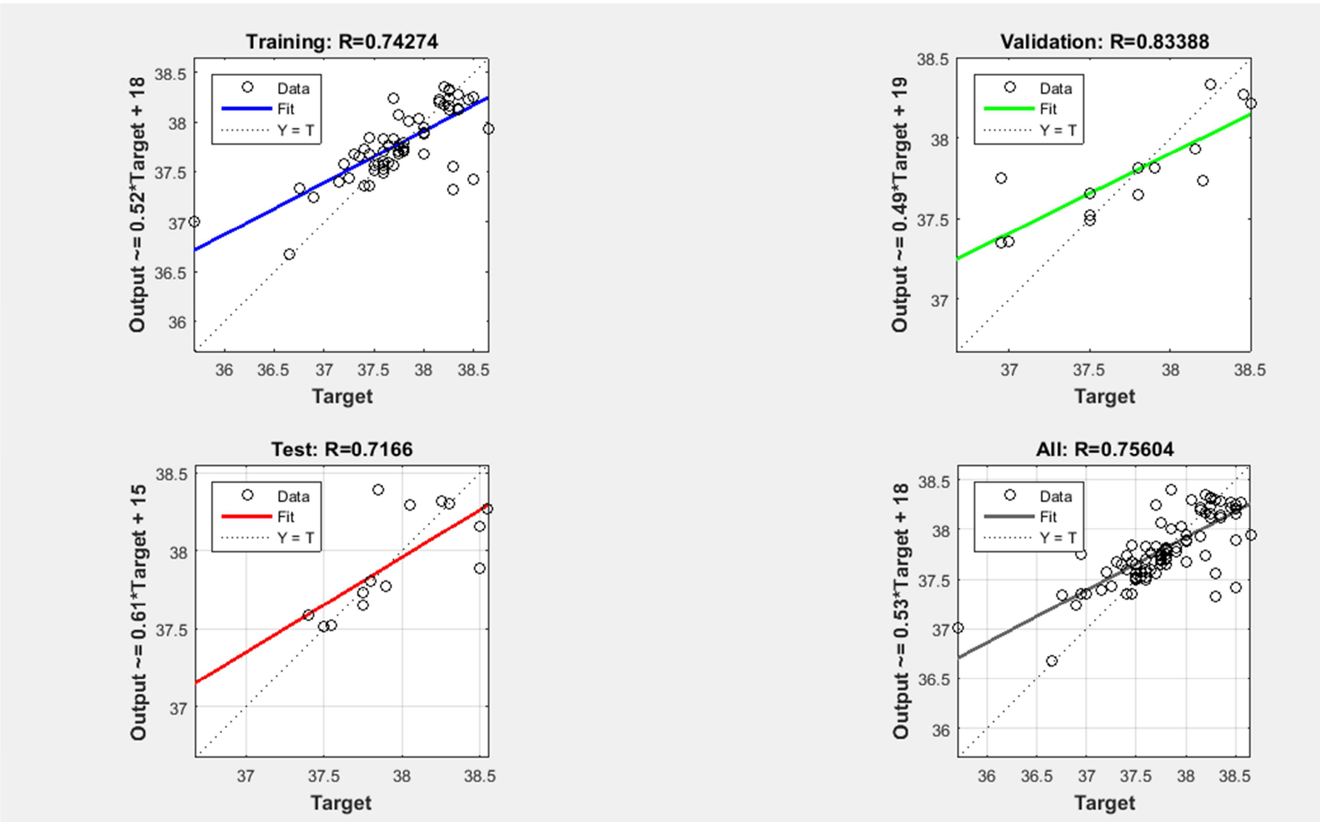

Figure 5. *Regression for Training, validation, testing and all three regressions combined (January 2014).*

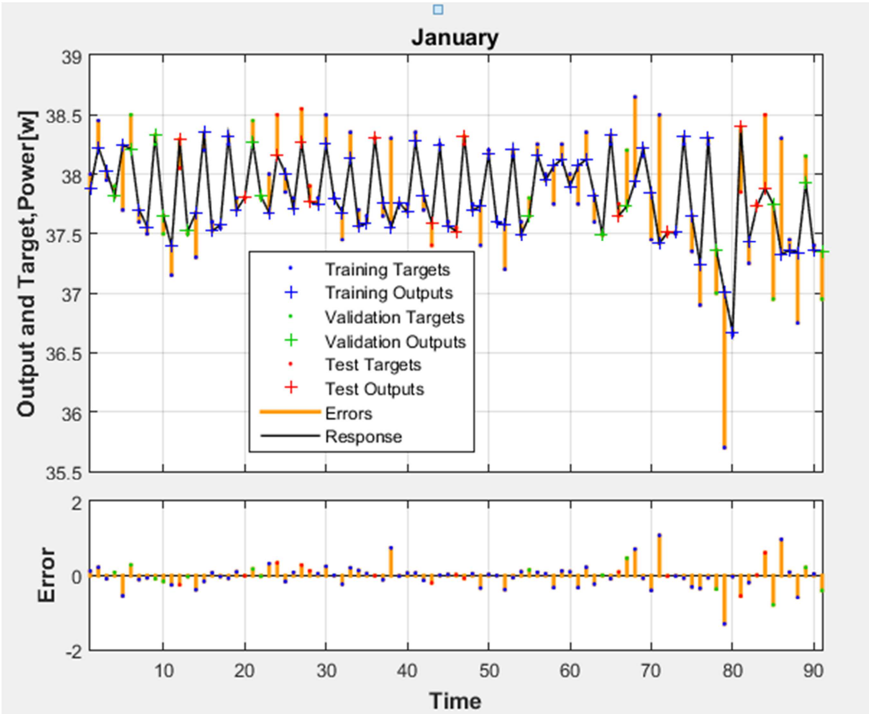

__Figure 6.__ Simulation results for January 2014 prediction.

Due to moderate temperature data, estimated power kept varying in a small variation range which made the prediction simple and fast during January 2014

4.2. One Year Prediction

The time series of output power data was made by estimating the power and figure 7 shows the time series data variations through the year 2014 while Table 3 and Table 4 show the training steps during prediction.

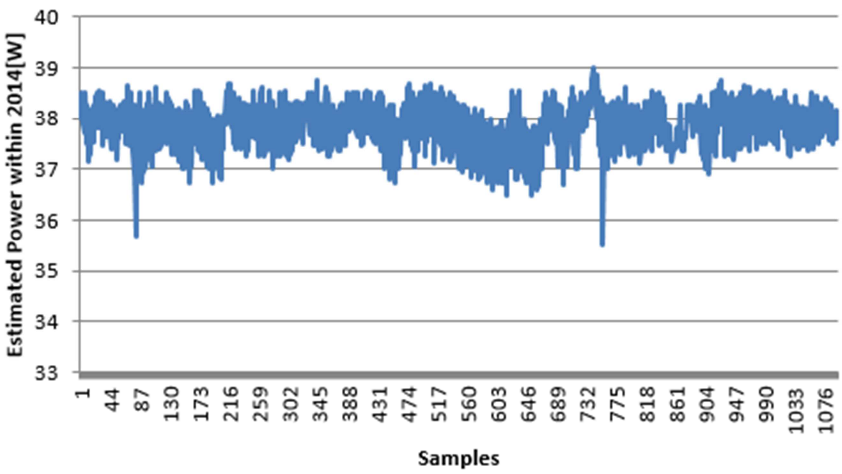

__Figure 7.__ Fluctuation of estimated power through a year 2017.

__Table 3.__ Keeping the number of delay d as 2 and changing the number of neurons.

N	Train	Test	Validate	MSE train	MSE test
2	70%	15%	15%	0.172392	0.142304
4	70%	15%	15%	0.161473	0.16484
6	70%	15%	15%	0.155790	0.188914
8	70%	15%	15%	0.178144	0.155430
10	70%	15%	15%	0.15857	0.212121

__Table 4.__ Keeping the number of neurons as 10, changing the number of delay d.

N	Train	Test	Validate	MSE train	MSE test
4	70%	15%	15%	0.106791	0.00997593
6	70%	15%	15%	0.902409	0.113457
	70%	15%	15%	0.106248	0.120606
10	70%	15%	15%	0.00857669	0.134288

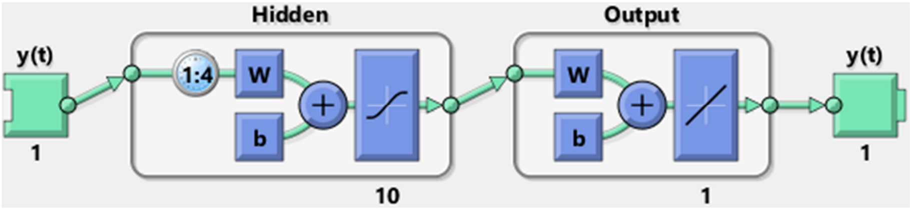

Figure 8. *NAR structure with 10 hidden neurons and 4 delays.*

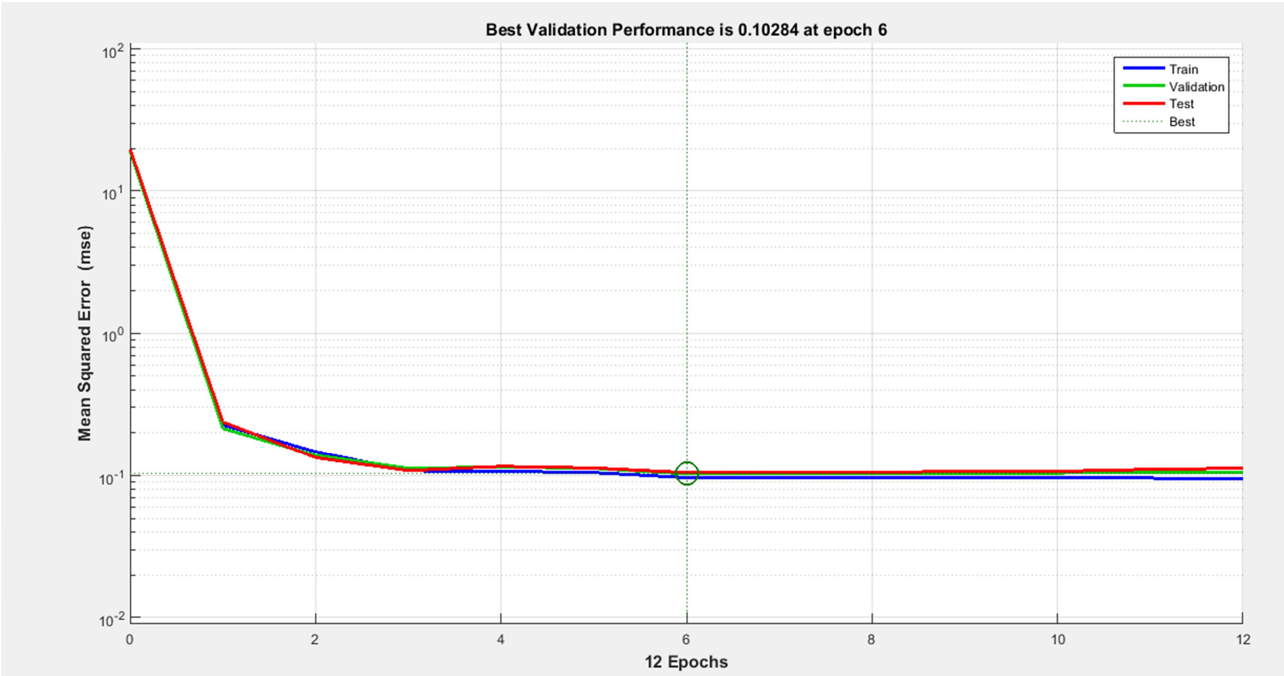

Figure 9. *Performance plot of best neural network prediction within 2014.*

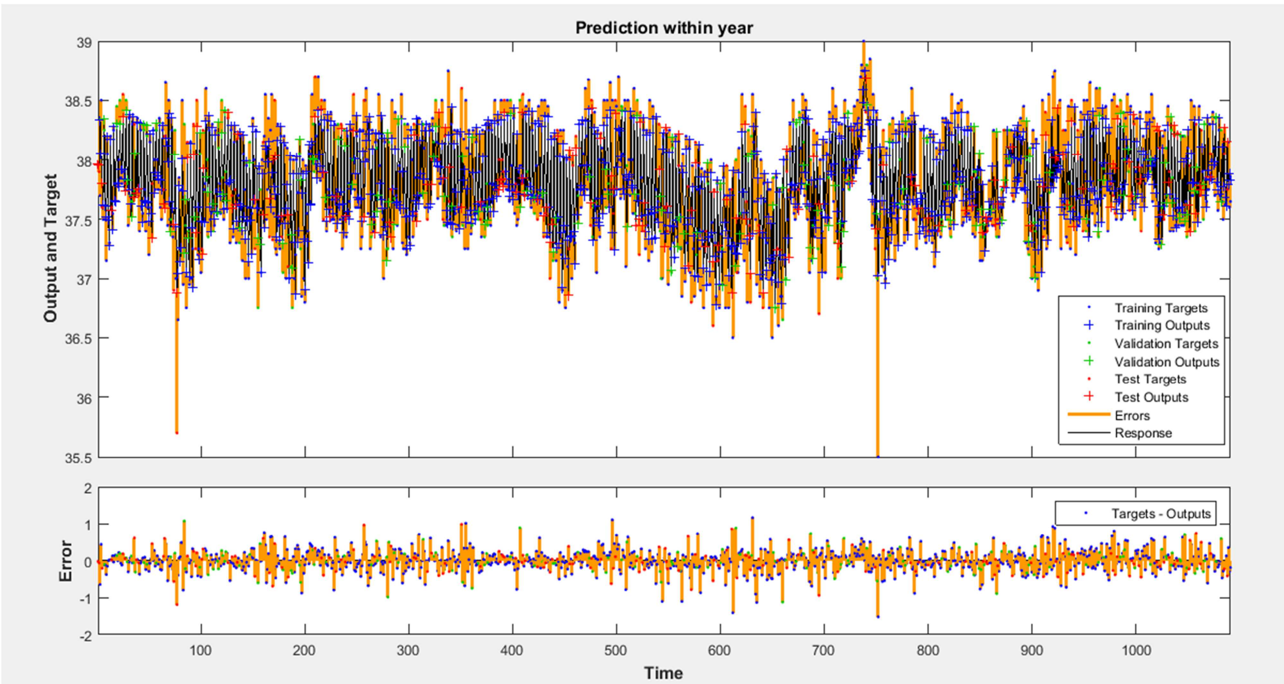

Figure 10. *Simulation results for 2014 prediction.*

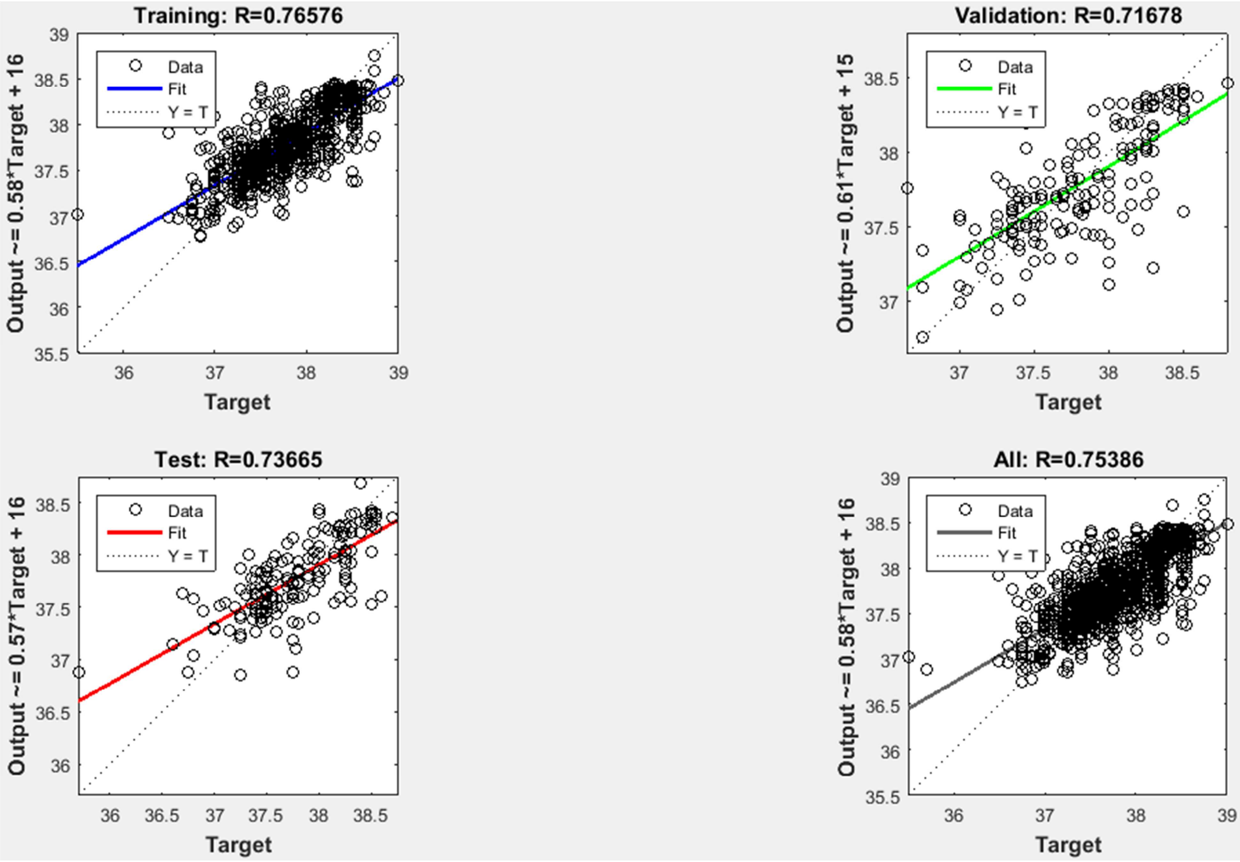

Figure 11. *Regression Training, validation, Testing and All combined (2014 prediction).*

Figures 1 - 11 clearly show that the best validation performance result achieved is 0.10284 at epoch 6.

5. Conclusion

Accurate Power prediction for solar energy systems plays an extremely important role in the future system's planning and operation. Therefore, the goal of this paper was to predict the monthly and annual output power of a photovoltaic module accurately using nonlinear autoregressive neural network. At the beginning, using neural network with hidden layer and modifying the number of neurons in the layer, numerous models were created and tested. Then according to regression values, the best model with best performance was selected both monthly and annually. Nonlinear autoregressive neural network was good and effective for prediction of photovoltaic module output power.

Acknowledgements

This work was funded by the National Natural Science Foundation of China (program No. 51475136), Natural Science Foundation of Hebei Province, China (Program No. E2014202230), Universities in Hebei Province, China Science and Technology Research Youth Fund (Program No. QN20151002), University Innovation Team Leader Program in Hebei Province (LJRC003).

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