Alireza Rezvani[1*], Maziar Izadbakhsh[1], Majid Gandomkar[1]

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Regular paper

Dynamic modeling of grid-connected photovoltaic system using artificial neural network and genetic algorithm

Journal of Electrical Systems

Photovoltaic (PV) systems have one of the highest potentials and operating ways for generating electrical power by converting solar irradiation directly into the electrical energy. The aim of this study is to simulate and control of a grid-connected PV source using artificial neural network (ANN) and genetic algorithm (GA) controller. Also, for tracking the maximum power point (MPP), ANN and GA are used. Data are optimized by GA and then these optimized data are applied in the neural network training. The simulation results are presented by using Matlab/Simulink and show that the ANN-GA controller can meet the need of the load easily and have less fluctuations around the maximum power point (MPP), also it can increase convergence speed to achieve the MPP. Moreover, to control both line voltage and current, a grid side P-Q controller has been applied.

Keywords: Photovoltaic; neural network; genetic algorithm; controller.

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1. Introduction

PV systems have one of the highest potentials and operating ways for generating electrical power by converting solar irradiation directly into the electrical energy. Although, developing photovoltaic energy sources can reduce fossil fuel dependency, PV panels are low-energy conversion efficient [1], [2], [3].

The most prevalent techniques are perturbation and observation (P&O) algorithm [3], [4], incremental conductance (IC) [5], [6], fuzzy logic [7], [8] and ANN [9- 12]. P&O and IC can track the MPP all the time, regardless of the atmospheric conditions, type of PV panel, by processing real values of PV voltage and current. Due to the aforementioned inquiries, the profits of P&O and IC methods are low cost execution and elementary method. One of the drawbacks of these techniques is vast variation of output power around the MPP even under steady state; therefore, it is caused to the loss of available energy more than the other method [13]. Nevertheless, rapid changing of weather condition affects the output power and these methods cannot track easily the MPP.

Using fuzzy logic can solve the two mentioned problems dramatically. In fact, fuzzy logic controller can reduce oscillations of output power around the MPP and losses. Furthermore, in this way, convergence speed is higher than the other two ways mentioned. A weakness of fuzzy logic in comparison with ANN refers to oscillations of output power around the MPP [14], [15].

Nowadays, artificial intelligence (AI) methods have numerous applications in determining the size of PV systems, MPPT control and optimal structure of PV systems. In most cases, multilayer perceptron (MLP) neural networks or radial basis function network (RBFN) are employed for modeling PV module and MPPT controller in PV systems [16], [17]. ANN based controllers have been applied to estimate voltages and currents corresponding to the MPP of PV module for irradiances and variable temperatures. A review on AI techniques applications in renewable energy production systems has been presented in these literatures [9], [18].

[*] Corresponding author: A.Rezvani , E-mail: alireza.rezvani.saveh@gmail.com

[1] Department of Electrical Engineering, Saveh Branch ,Islamic Azad University, Saveh ,Iran

In [19-21], GA is used for data optimization and then, the optimum values are utilized for training neural networks and the results show that, the GA technique has less fluctuation in comparison with the conventional methods. However, one of the major drawbacks in mentioned papers that they are not practically connected to the grid in order to ensure the analysis of PV system performance.

In this paper first, temperature and irradiance as inputs data are given to GA and optimal voltages (V_{mpp}) corresponding to the MPP are obtained then, these optimum values are used in the neural network training. Photovoltaic module is connected to the grid using a P-Q controller of grid side to exchange active and reactive power and observe system efficiency in different weather conditions.

The paper is organized as follows: In part 2 structure of PV module is described. Parts 3 and 4 discussed steps of implementing the GA and ANN, respectively. In part 5 P-Q controller is described and in part 6 the results are presented based on current study.

2. Photovoltaic Cell Model

A PV module is a collection of PV panels. A PV cell can be represented by an equivalent circuit, as illustrated in Fig.1. The characteristics of the PV cell can be represented by the following equations [5, 10, 12].

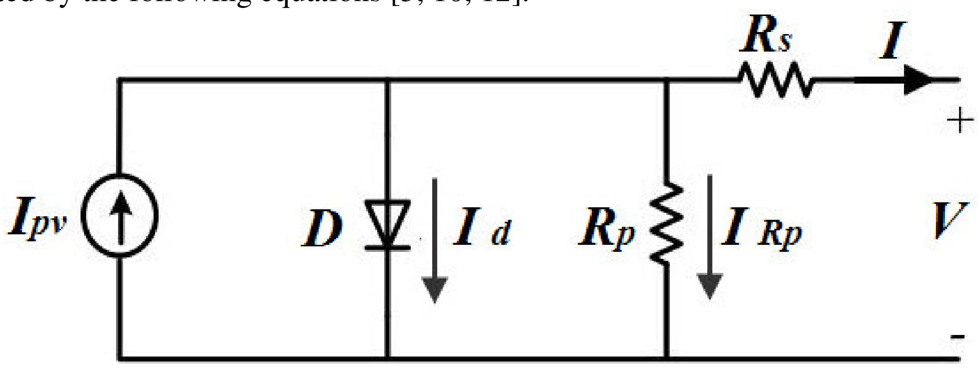


Fig. 1. Equivalent circuit of one photovoltaic array

$$I_{PV} = I_d + I_{RP} + I \tag{1}$$

$$I = I_{PV} - I_0 \left[\exp\left(\frac{V + R_S I}{V_{th} n} \right) - 1 \right] - \frac{V + R_s I}{R_P} \tag{2}$$

$$V_{th} = \frac{N_s kT}{q} \tag{3}$$

$$I_0 = I_{0,n} (\frac{T_n}{T})^3 \exp[\frac{q * E_g}{n * k} (\frac{1}{T_n} - \frac{1}{T})] \tag{4}$$

Where, I is the output current, V is the output voltage, I_{pv} is the photocurrent of the PV cell (A), I_d is the diode current, I_{RP} is the shunt leakage current, I_0 is the diode reverse saturation current, n is the ideality factor (1.36) for a p-n junction. V_{th} is known as the thermal voltage. q is the electron charge ($1.60217646 \times 10^{-19}$ C), k is the Boltzmann constant ($1.3806503 \times 10^{-23}$ J/K), T (in Kelvin) is the temperature of the p-n junction. E_g is the band gap energy of the semiconductor ($E_g \approx 1.1$ eV for the polycrystalline Si at 25°C) and $I_{0,n}$ is the nominal saturation current. T is the cell temperature, T_n is cell temperature at reference conditions. Red sun 90W is taken as the reference module for simulation and the name-plate details are given in Table 1.

Table 1: Red sun 90w module

I_{MP} (Current at maximum power)	4.94 A
V_{MP}(Voltage at maximum power)	18.65V
P_{MAX} (Maximum power)	90W
V_{OC} (Open circuit voltage)	22.32
I_{SC} (Short circuit current)	5.24
N_P(Total number of parallel cells)	1
N_S (Total number of series cells)	36

3. Maximum Power Tracking (MPPT) – ANN and GA

3.1 The Steps of implementing GA and ANN

In order to pursue the optimum point of maximum power in any environmental condition, ANN and GA technic are used. Besides, GA is used for optimum values and then optimum values are used for ANN training [21], [22]. The procedure of GA is as follows. 1. determining the target function, 2. determining the initial population size, 3. appraising the population using the target function, and 4. conducting convergence test stop if convergence is provided.

The objective function of GA is used for its optimization using Matlab software by following: finding optimum $X=(X_1, X_2, X_3 ...,X_n)$ to put the F(X) in maximum value, where the number of design variables is intended as 1. And X is the design variable equal to array current and also $F_{(X)}$ is the array output power which should be maximized. To determine the objective function, power should be set based on the PV system current (I_x). GA parameters are presented in Table 2. The relationship between voltage and current of the array as demonstrated by the following equations.

$$F_{(X)} = V_X * I_X \tag{5}$$

$$V_X = n_s \left(v_0 - \frac{R_S}{n_p} I_X + (nk(T+273)/q)\,Ln*\left(\frac{I_{PV} - \frac{I_X}{n_P} + I_0}{I_0}\right) \right) \tag{6}$$

To determine the objective function, the power should be arranged based on the current of array (I_X):

$$F_{(X)} = n_s \left(v_0 - \frac{R_S}{n_p} I_X + (nk(T+273)/q)\,Ln*\left(\frac{I_{PV} - \frac{I_X}{n_p} + I_0}{I_0}\right) \right) * I_X \tag{7}$$

$$0 < \; I_X < I_{SC} \tag{8}$$

Table 2: Genetic algorithm parameters

Number of Design Variable	1
Population size	20
Crossover constant	70%
Mutation rate	12%
Maximum Generations	20

The current constraint should be considered too. With maximizing this function, the optimum values for V_{mpp} and MPP will result in any particular temperature and irradiance intensity.

4. MPPT improvement by combination of proposed neural network with GA

ANN is the most appropriate for the approximation (modeling) of nonlinear systems. Non-linear systems could be approximated by multi-level neural networks and these multi-level networks have better results in comparison with of the other algorithms [16], [18]. For this aim, in this paper, feed forward neural network for MPPT process control is used. The main section of this method is that, the data required for training process must be obtained for each PV module and each specific location [11]. Based on PV characteristic which depends on PV model and climate change, ANN should be trained periodically. Neural network inputs can be selected as PV array parameters like V_{oc} , I_{sc} and climate data, temperature or both of them .The output is usually selected one reference signal like duty cycle or DC link voltage or V_{mpp}. Temperature and solar irradiation can be considered as input variables and V_{mpp} and P_{mpp} are output variables as shown in Fig.2. The block diagram of the proposed MPPT scheme is shown in the Fig.3.

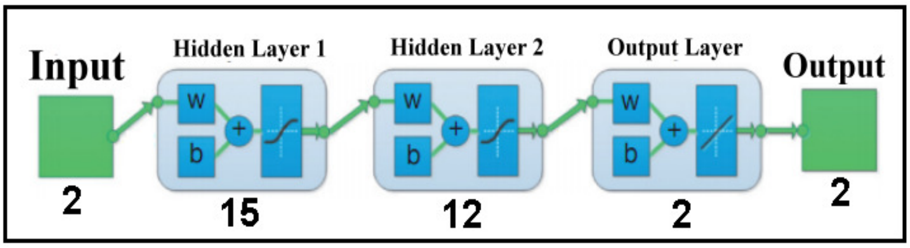


Fig. 2. Feed forward neural network for MPPT

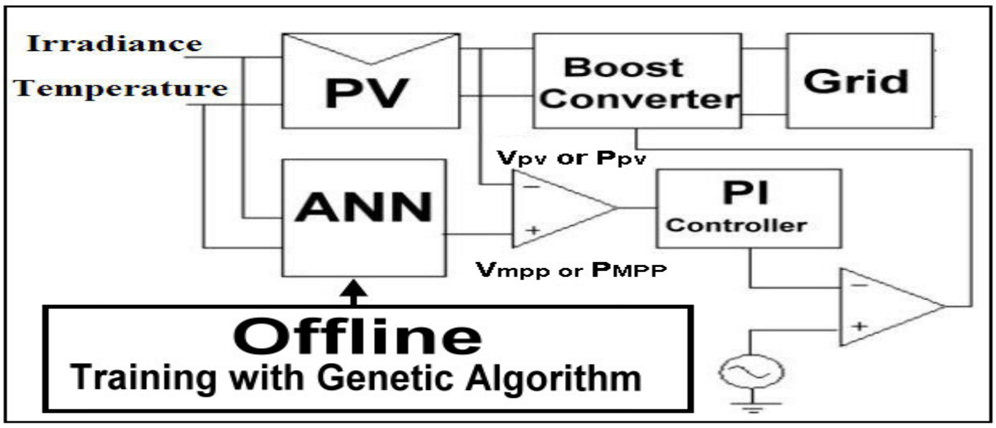


Fig. 3. Proposed MPPT Scheme

The output of PV system has varied during time and environmental conditions. Thus, periodic training of the ANN is needed. Training of the ANN is a set of 390 data as shown in Figure 4 (irradiance between 0.05 to 1 kilo watt per square meter (Kw/m^2) and temperatures between –5 °C to 55 °C) and also, a set of 390 V_{mpp} corresponding to MPP is obtained by GA as shown in Fig. 5.

For implementation of ANN, number of layers, number of neurons in each layer, transmission function in each layer and type of training network should be determined. Proposed ANN has three layers which first and second layers have 15 and 12 neurons, respectively and third layer has 2 neurons. The transfer functions of first and second layers are Tansig and for third layer is Purelin. The training function is Trainlm. The acceptable sum of squares for network is supposed to be 10^{-9} which training this neural network in 300 iterations, will converge to a desired target. After training operation, the output of ANN should be closed to optimum output of GA. Fig. 6 shows the output of the ANN with the amount of target. Fig. 7 illustrates the output of the neural network test which showing a negligible training error percentage of about %3.

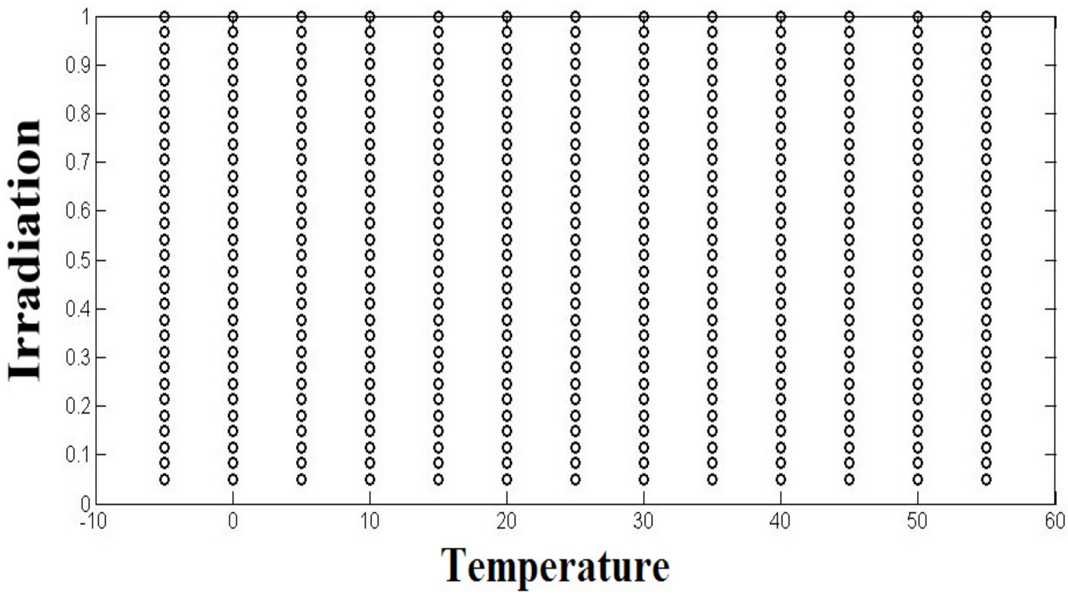


Fig. 4. Inputs data of irradiation and temperature

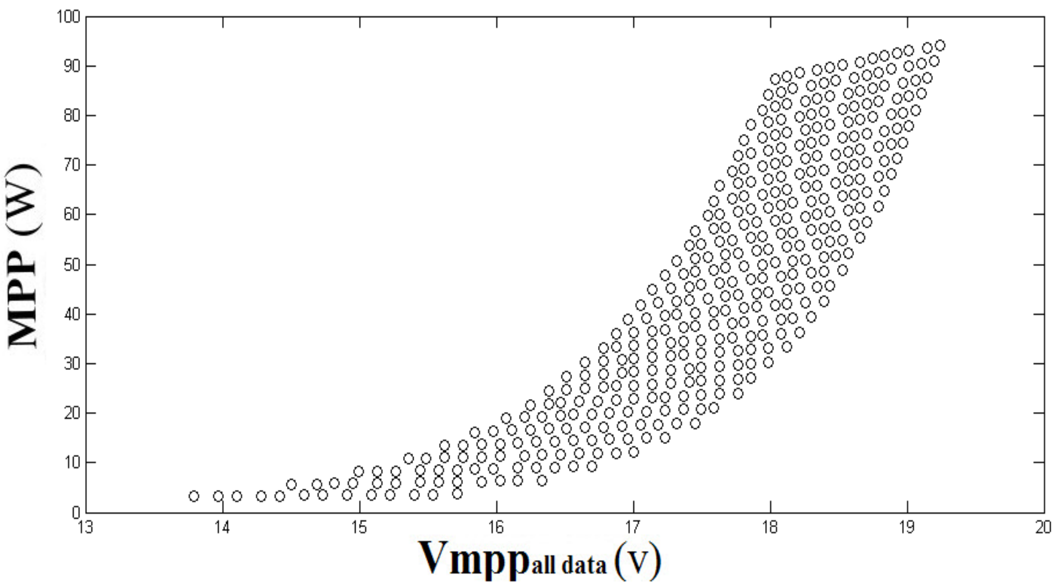
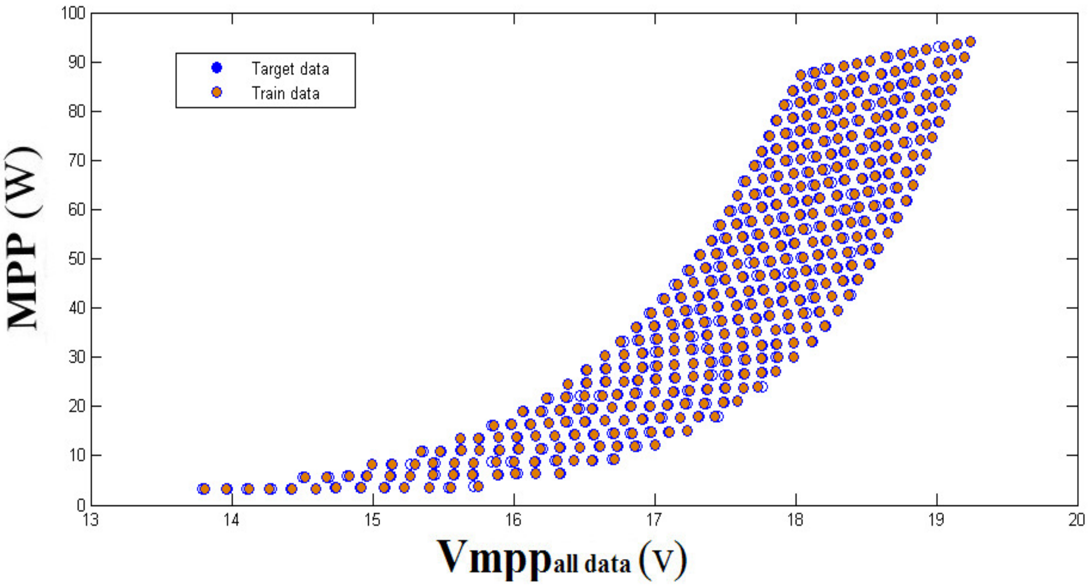
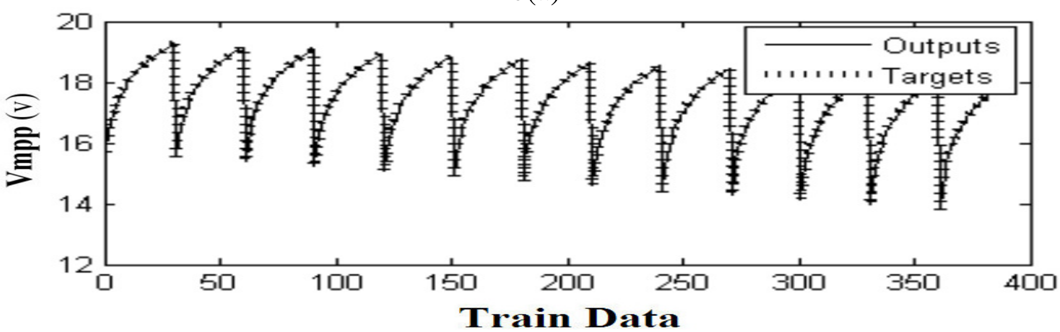


Fig. 5. The output of V_{mpp} - M_{pp} optimized by (GA)



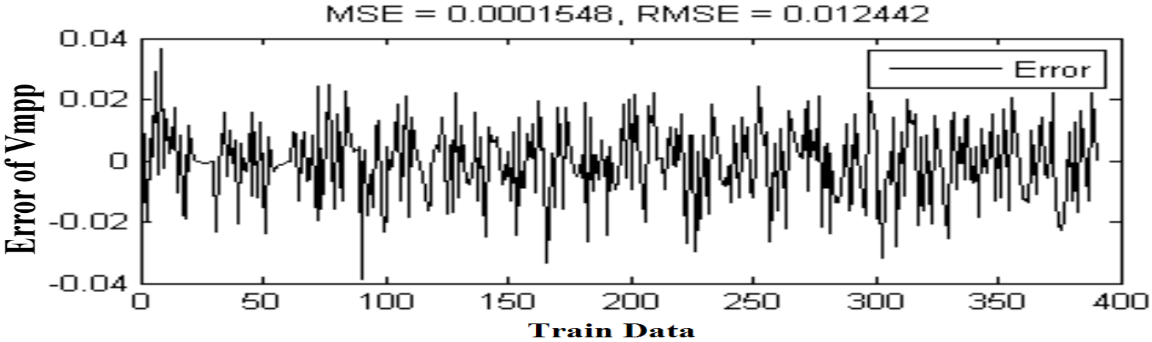
Target data
Train data
MPP (W)
Vmpp all data (V)

6(a)



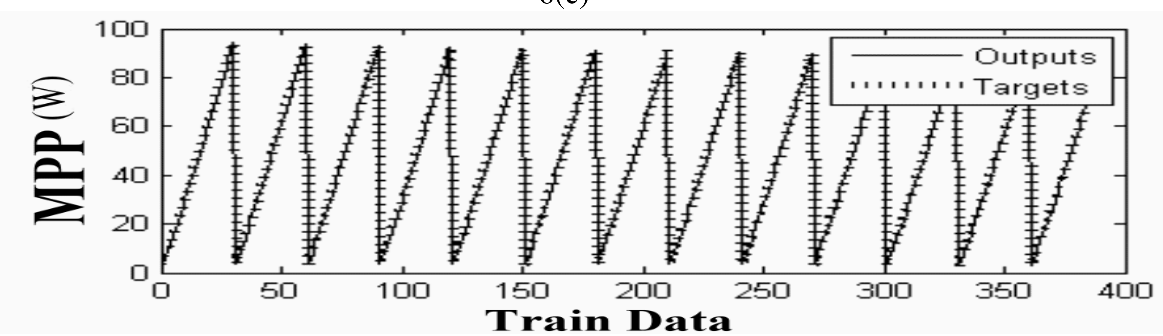
Outputs
Targets
Vmpp (v)
Train Data

6(b)



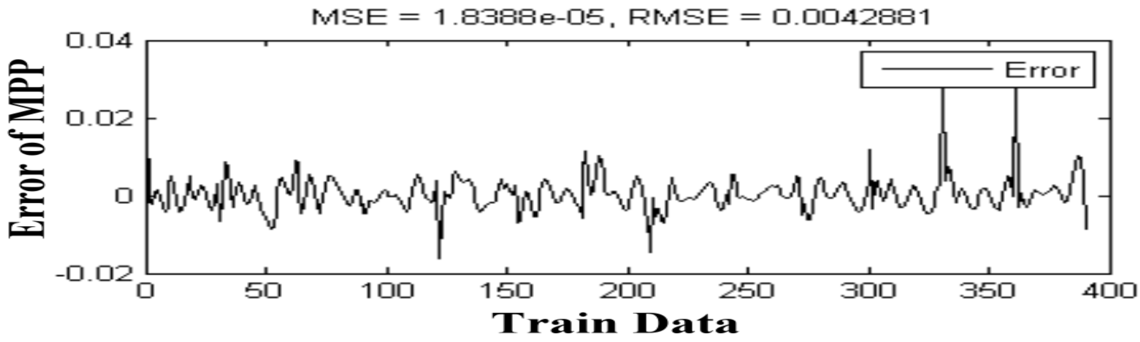
MSE = 0.0001548, RMSE = 0.012442
Error
Error of Vmpp
Train Data

6(c)



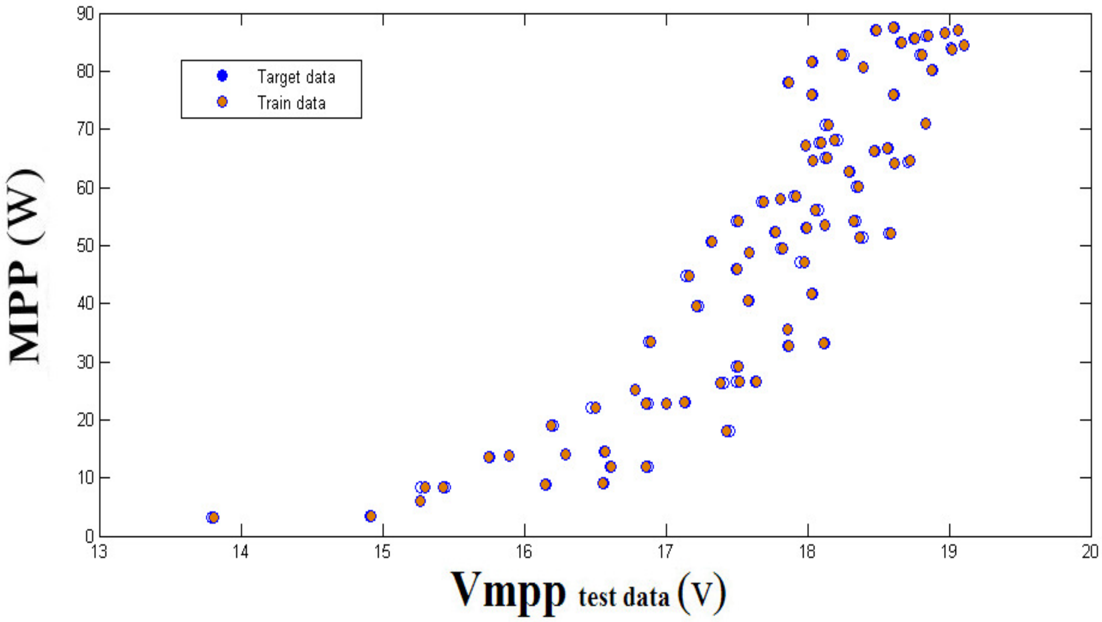
Outputs
Targets
MPP (W)
Train Data

6(d)

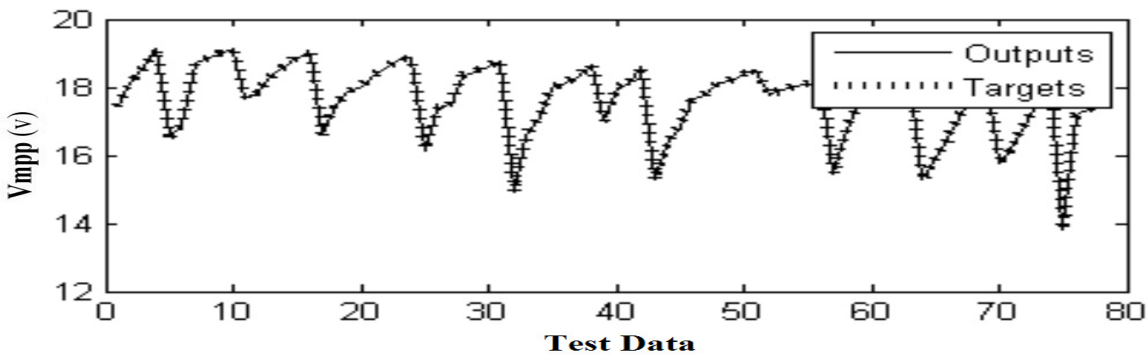


6(e)

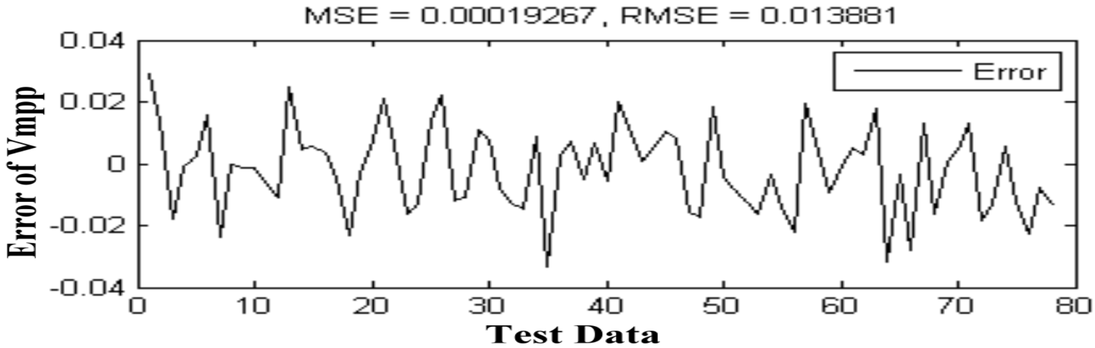
Fig. 6. shown the output of the neural network by fallowing: (a) The output of the neural network with the amount of training target data; (b) The output of the neural network (V_{mpp}) with the amount of training target data; (c) Percent of the total error of the (V_{mpp}) training data; (d) The output of the neural network (M_{pp})with the amount of training target data;(e) Percent of the total error of the(M_{PP}) training data.



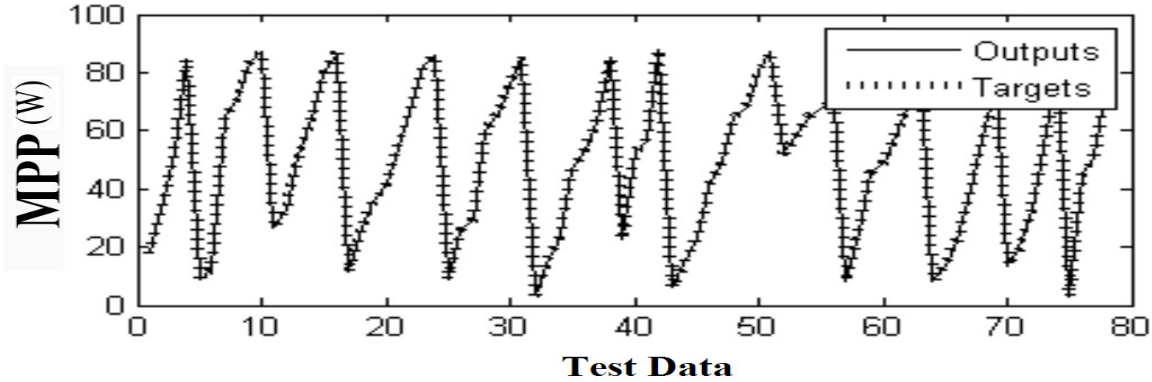
7(a)



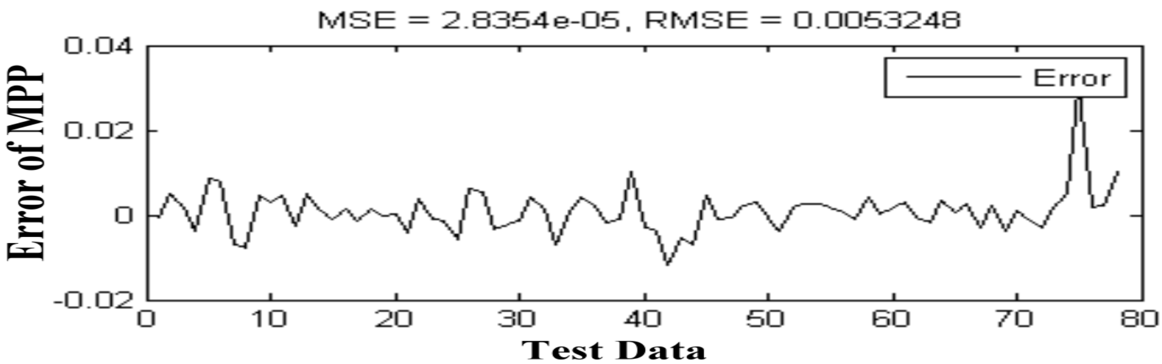
7(b)



7(c)



7(d)



7(e)

Fig. 7. shown the output of the neural network test by following: (a) The output of the neural network test with the amount of test target data; (b) The output of the neural network test (V_{mpp})with the amount of test target data; (c) Percentage error in test data (V_{mpp}); (d)The output of the neural network test (M_{pp}) with the amount of test target data; (e) Percentage error in (M_{pp})test data

5. Control strategy (P-Q)

Inverter control model is illustrated in Fig.8 The goal of controlling the grid side, is keeping the dc link voltage in a constant value regardless of production power magnitude. Internal control-loop which control the grid current and external control loop which control the voltage [23]. Also, internal control-loop which is responsible for power quality such as low total harmonic distortion (THD) and improvement of power quality and external control-loop is responsible for balancing the power. For reactive power control, reference voltage will be set same as dc link voltage. In grid-connected mode, photovoltaic module must supply local needs to decrease power from the main grid. One the main aspects of P-Q control loop is grid connection and stand-alone function. The advantages of this operation mode are higher power reliability and higher power quality.

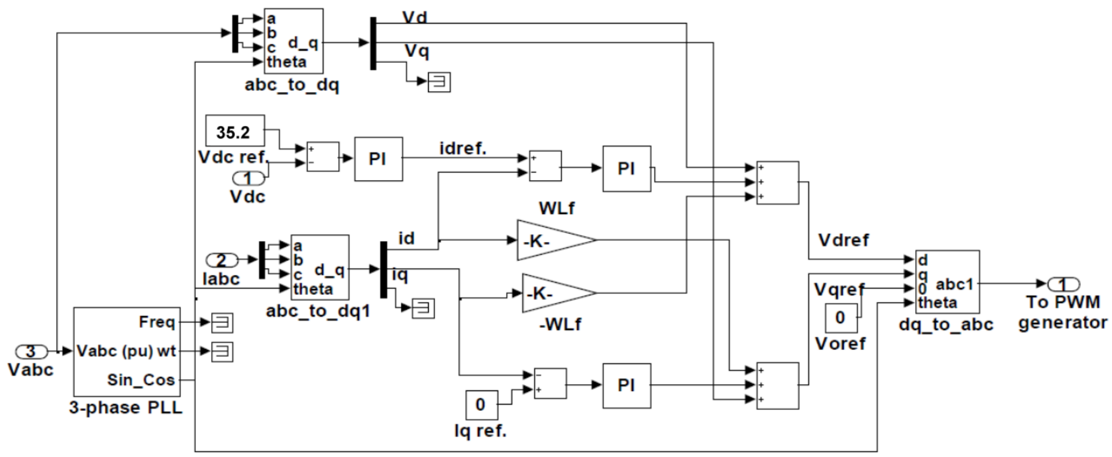


Fig. 8. The inverter control model

6. Simulation results

In this section, simulation results under different terms of operation with Matlab /Simulink is presented. System block diagram is shown in Fig.9.

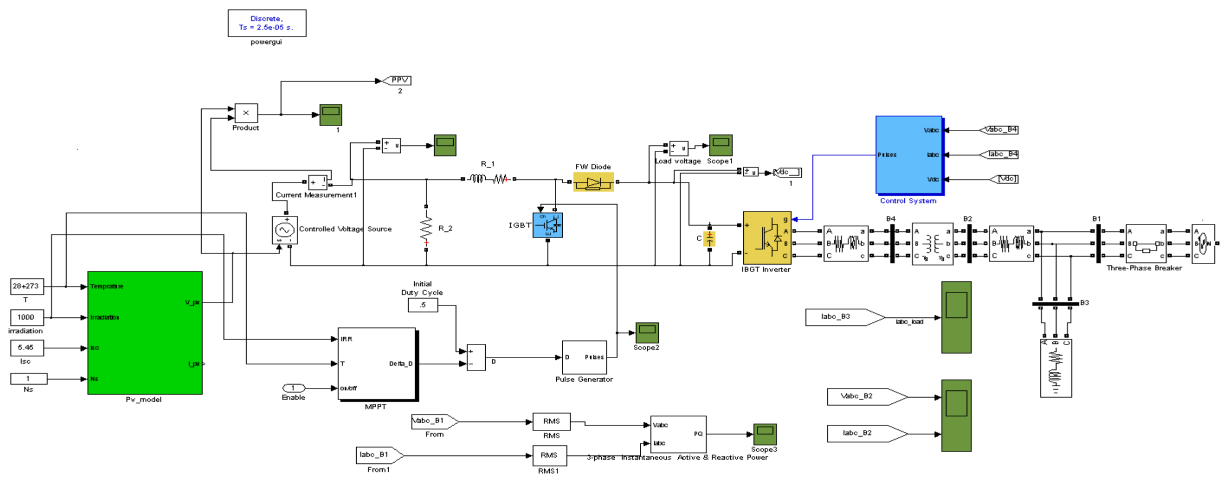


Fig. 9. Case study system

Photovoltaic parameters: output power= 90 W, Carrier frequency in V_{MPPT} PWM generator: 4000 Hz and in grid-side controller: 6000 Hz, boost converter parameters: L=0.07H, C=0.087, PI coefficients in grid-side controller: K_{pVdc}= 0.2, k_{iVdc}= 5, K_{pId}= 9, K_{iId}= 500, K_{pIq}= 9, K_{iIq}= 500, Vgrid= 220

6.1. Case study 1:

The 90w photovoltaic system is connected to grid using P-Q controller and the load is 90W and only absorbs active power as illustrated in Fig. 9. Also, the grid voltage is 220V. Simulation is carry out under “standard laboratory conditions” where irradiation intensity is 1000 [Kw/m^2], temperature is 25 °C. Controller’s response for grid voltage waveform, grid current waveform and photovoltaic module are depicted in Figs.10 to16, respectively.

According to Figs. 13 and 14 photovoltaic source can meet the need of load easily and grid voltage and current waveform reach to constant value by 1 per-unit that means the photovoltaic system can implement in stand-alone mode to supply the load. PV's output voltage and current wave form are shown in Figs. 15 and 16.

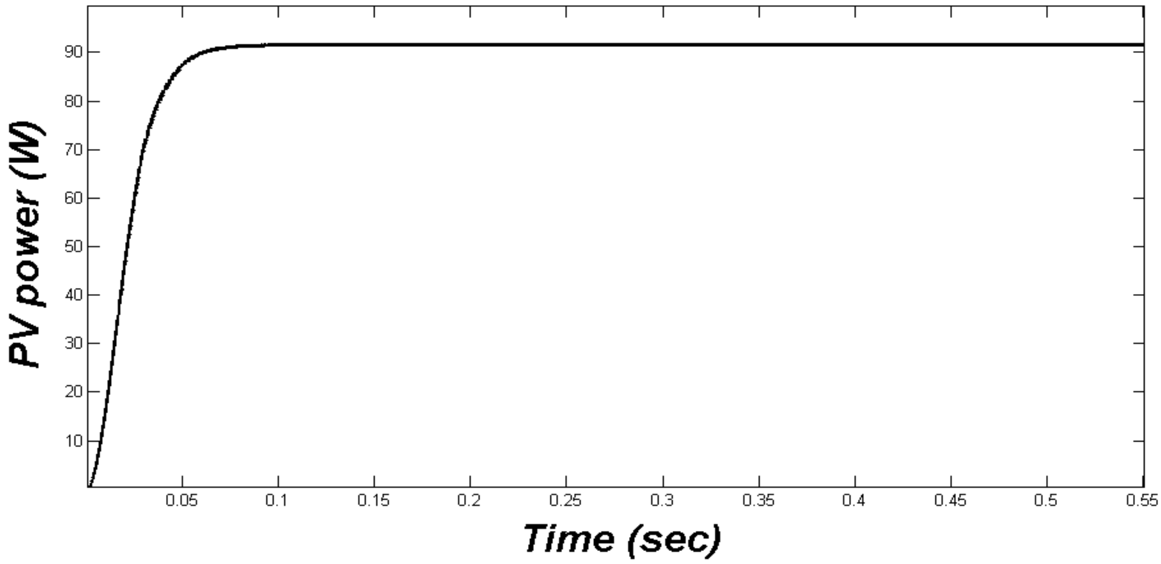


Fig. 10. Output Power of PV

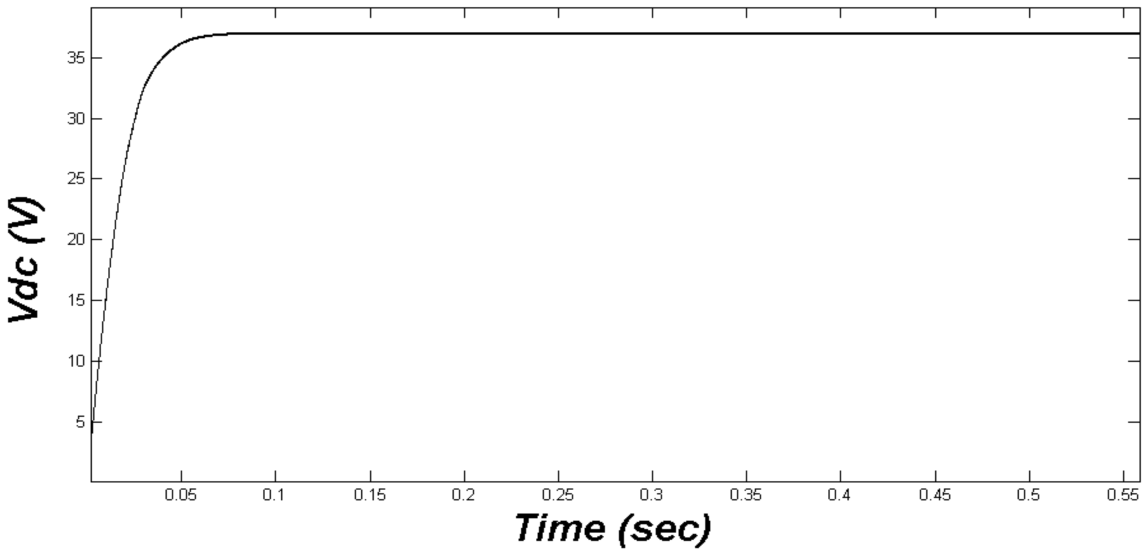


Fig. 11. Output voltage of PV

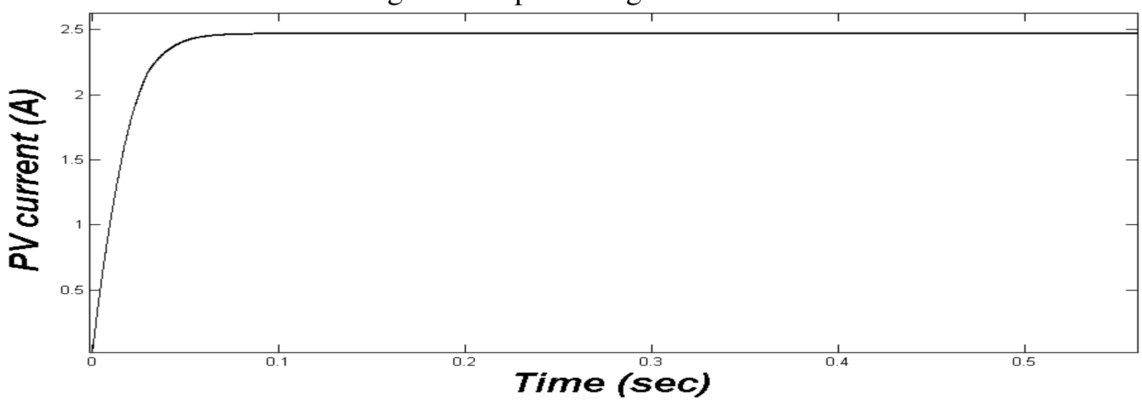


Fig. 12. Output Current of PV

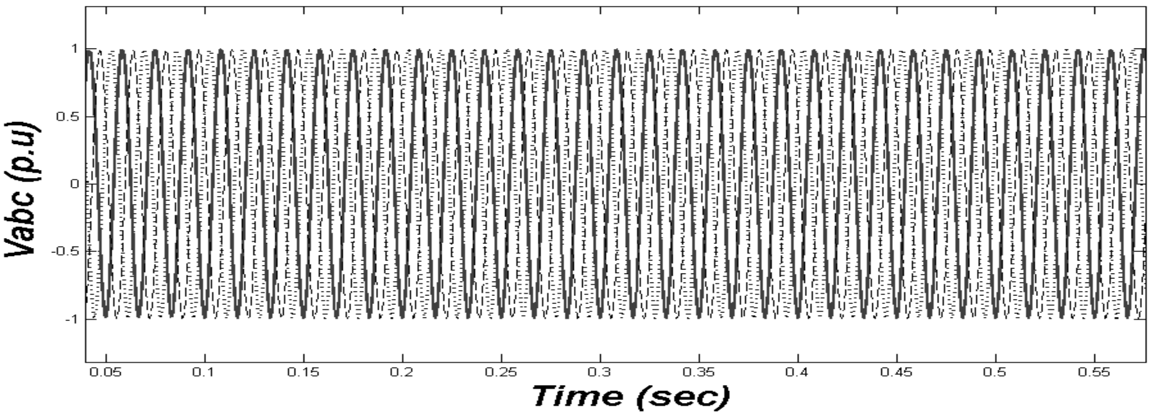


Fig. 13. Output voltage of grid

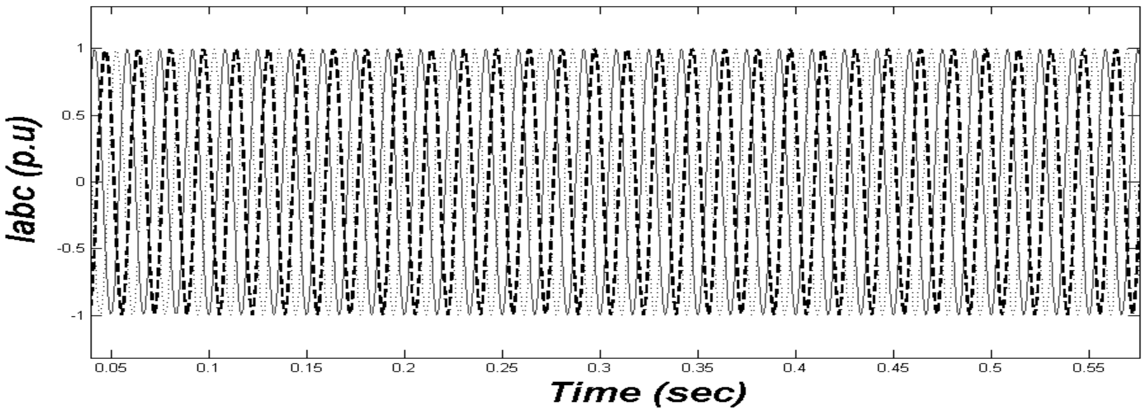


Fig. 14. Output current of grid

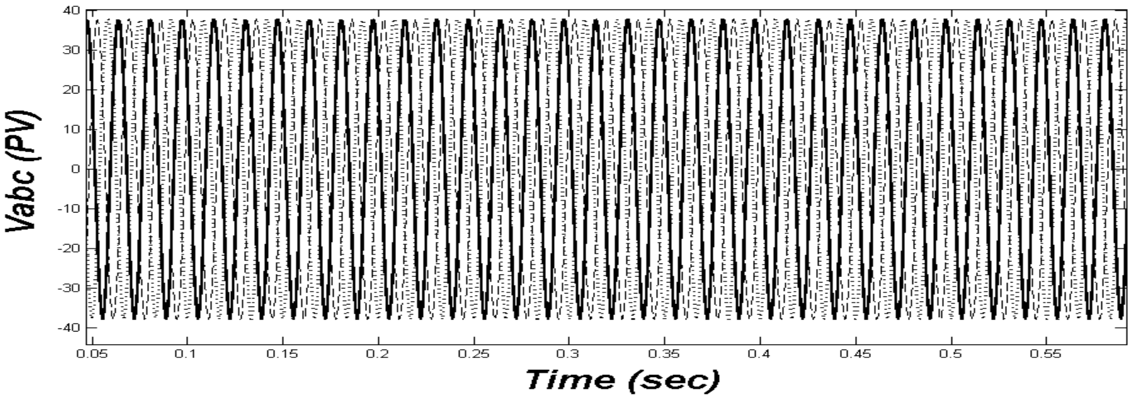


Fig. 15. Output voltage of PV (after filter)

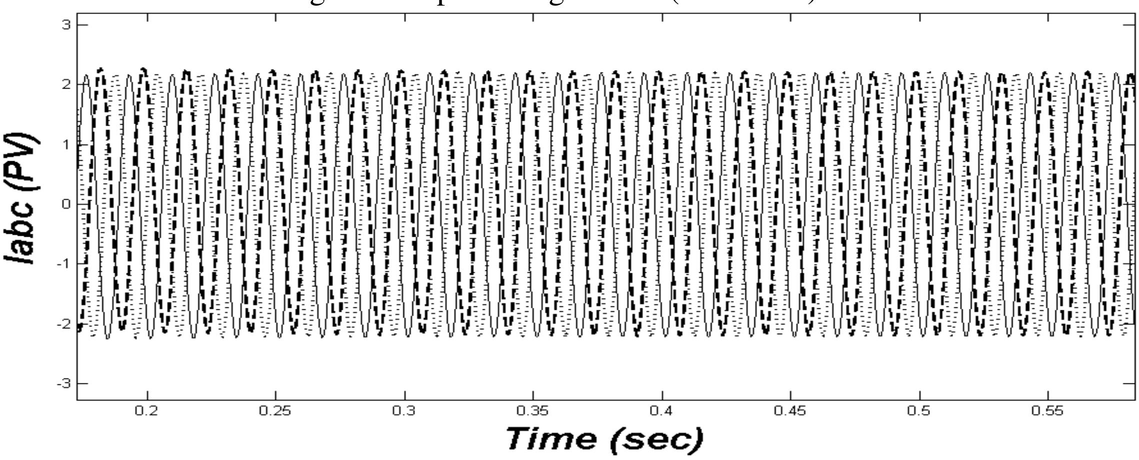


Fig. 16. Output current of PV (after filter)

6.2. Case study 2:

In this case the amount of load is 90 W that is connected to grid in different irradiation level. Fig.17 depicts irradiation levels. It is worth to mention that, PV system can track accurately the MPP when the irradiance changes continuously and active power exchange between grid and PV system can be easily done, while the load is supplied completely.

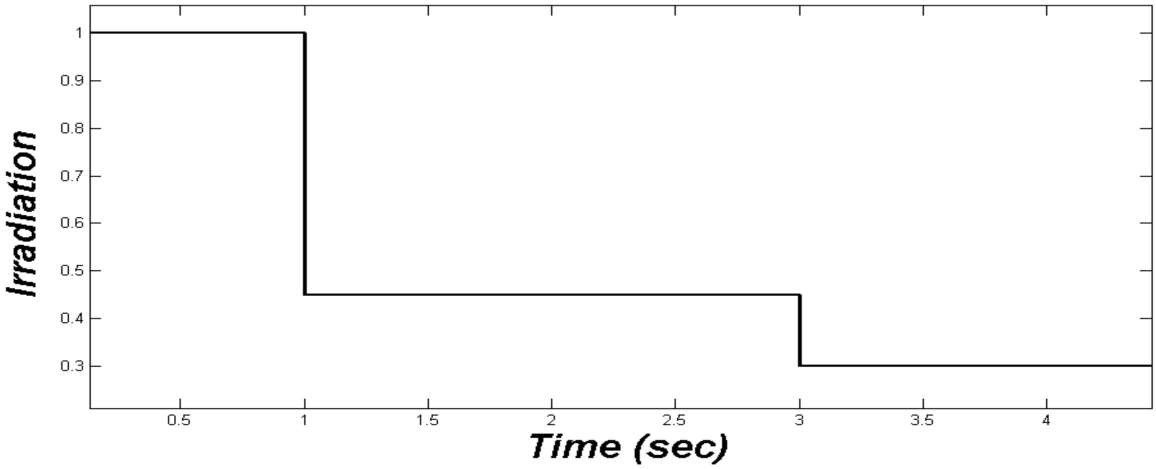


Fig. 17. Irradiation

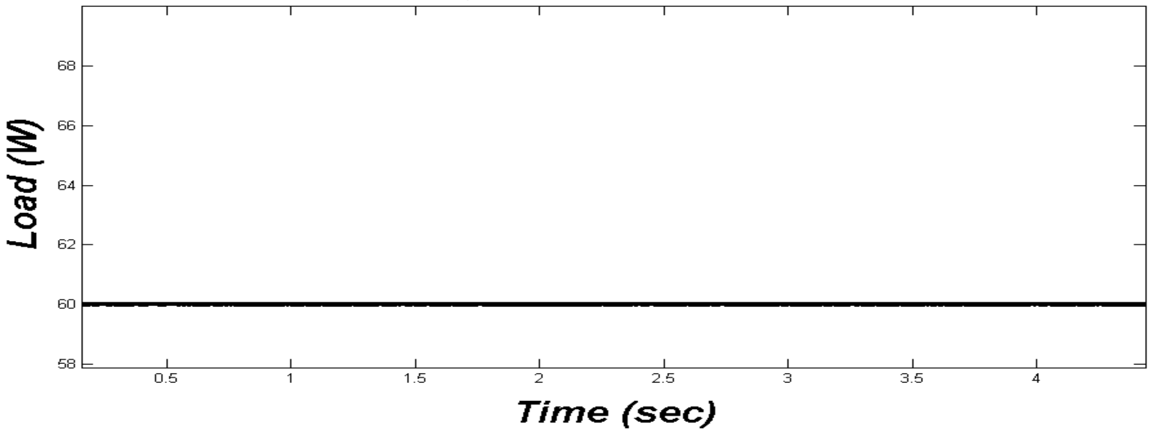


Fig. 18. Load

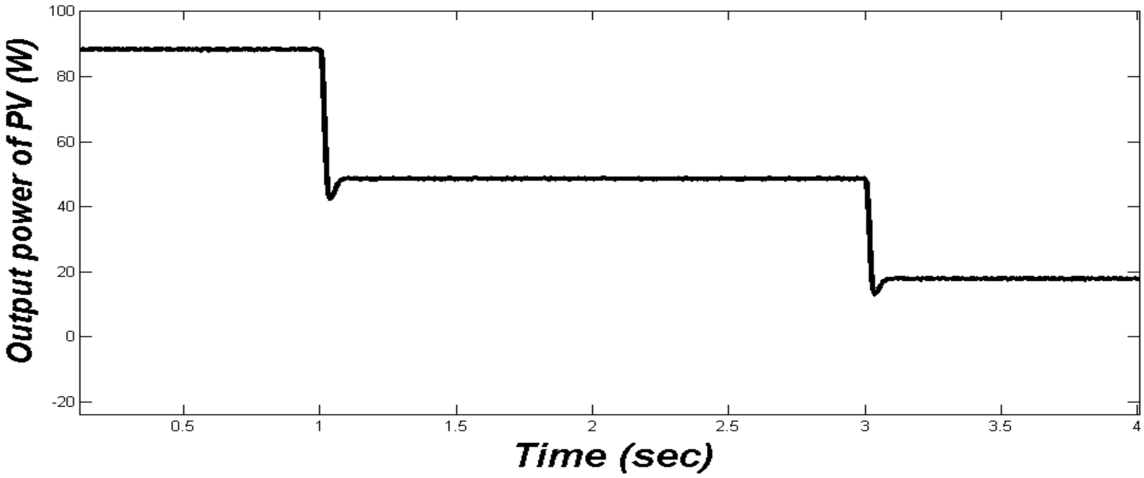


Fig. 19. PV Power

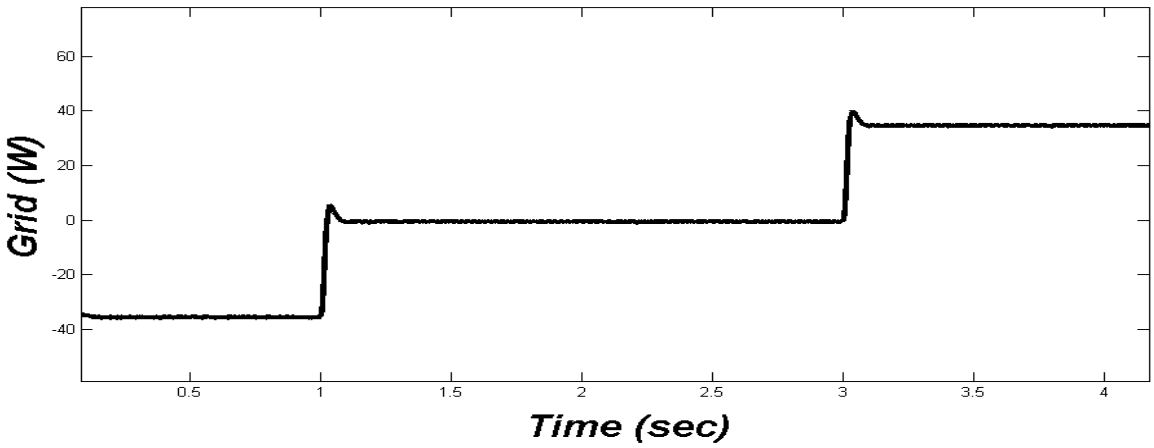


Fig. 20. Grid Power

7.Conclusion

The goal of this paper is to simulate and control of a photovoltaic source in grid-connected and stand-alone mode using ANN-GA controller. The simulation results show that using ANN-GA controller can dramatically reduce the disadvantages of previous approaches. In fact, this research suggests in grid-connected mode using ANN-GA controller can decrease oscillations of output power around the MPP and can increase convergence speed to achieve the MPP. In order to control the grid current and voltage, a grid-side controller, has been applied. Inverter adjusts the dc link voltage and active power is fed by d-axis and reactive power is fed by q-axis using PQ control method. Finally, by applying the appropriate controller the PV system can be connected to load in both stand-alone and grid-connected mode, and also can meet the need of load assuredly.

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