COMPARISON BETWEEN ANN-GA AND INCREMENTAL CONDUCTANCE CONTROL FOR SOLAR PV SYSTEM IN THE GRID CONNECTED MODE

Alireza Rezvani*[1], Maziar Izadbakhsh[1], Sohrab Mirsaeidi[1], Saeed vafaei[2]
[1]Young Researchers and Elite Club, Saveh Branch, Islamic Azad University, Saveh, Iran
[2]Department of Electrical Engineering, Saveh Branch, Islamic Azad University, Saveh, Iran
*Corresponding Author: Alireza Rezvani Email: alireza.rezvani.saveh@gmail.com

ABSTRACT: *In recent years, many different techniques have been applied in order to reach maximum power. Generally, the output power generation of the photovoltaic (PV) system relies on the intermittent solar insolation, cell temperature, efficiency of the PV panel and its output voltage level. Consequently, it is essential to track the generated power of the PV system and utilize the collected solar energy optimally. This paper proposes an integrated offline genetic algorithm (GA) and artificial neural network (ANN) to track the solar power optimally based on various operation conditions due to the uncertain climate change. Training data in ANN is optimized by GA. The proposed controller is simulated and studied using MATLAB software. The obtained results show minimal error of MPP, Vmpp and superior capability of the suggested method in MPP tracking. The ANN-GA algorithm can track accurately the MPP; also, this method has well regulated PV output power and it produces extra power rather than IC method for different conditions.*

***KEYWORDS*:** Photovoltaic, neural network, genetic algorithm, Incremental Conductance**.**

1. INTRODUCTION

Renewable energy sources play an important role in electricity generation. Different renewable energy sources such as a wind, solar, geothermal and biomass can be applied for generation of electricity and for meeting our daily energy needs. Photovoltaic generation is becoming increasingly important as a renewable source since it offers many advantages such as incurring no fuel costs, not being polluting, required little maintenance, and emitting no noise, among others.

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. Although, developing photovoltaic energy sources can reduce fossil fuel dependency, PV panels are low-energy conversion efficient [1].

In order to control maximum output power, using MPPT system is highly recommended. The output power of a PV module varies as a function of the voltage and also the MPP is change by variation of temperature and sun irradiation. A DC-to-DC converter is located between photovoltaic systems and consumers, which switching performance of this converter is done by the MPPT [2]. In recent years, many different technics are applied in order to reach maximum power. The most prevalent technics are perturbation and observation algorithm

(P&O) [2] Incremental conductance (IC), fuzzy logic and ANN [3].

According to above mentioned research, the benefits of perturbation and observation algorithm and incremental

conductance are1- low cost implementation 2- simple algorithm. And the depletion of these methods is vast fluctuation of output power around the maximum power point even under steady state illumination which results in the loss of available energy [4]. However the fast variation of weather condition affects the output and these technics cannot track the maximum power.

Nowadays, artificial intelligence techniques have numerous applications in determining the size of PV systems, MPPT control and optimal structure of photovoltaic systems. In most cases, multilayer perceptron (MLP) neural networks or radial basis function network (RBFN) have been employed for modeling PV module and MPPT controller in PV systems [5, 6].

ANN based controllers have been used to estimate voltages and currents corresponding to the maximum power point of PV module for radiations and variable temperatures. A review on artificial intelligence (AI) techniques applications in renewable energy production systems has been presented in these literatures [7]. Neural networks are the best approximation (modeling) for non-linear systems and problems such as oscillations of output power around the maximum power point and time to reach the maximum point are reduced.

In [8-10], GA is used for data optimization and then, the optimum values are utilized for training neural networks and the results show that, the GA technic 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 photovoltaic system performance, which is not considered.

In this paper first, temperature and irradiance as inputs data are given to genetic algorithm and optimal voltages (Vmpp) corresponding to the maximum power point (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 photovoltaic module is described. Part 3 is discussed steps to implement the GA and neural networks, respectively. In part 4 the IC method is presented. In part 5 p-q controller is described and in part 6 the results are presented based on current study.

2. PHOTOVOLTAIC CELL MODEL

Figure.1 shows equivalent circuit of one photovoltaic array [2], Characteristic of one solar array is explained in Equation (1)

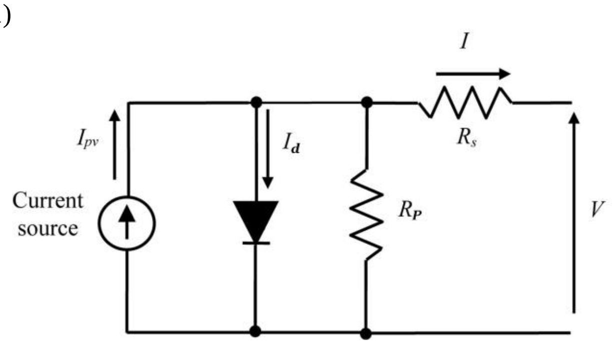


Figure. 1. Equivalent circuit of one photovoltaic array

$$I = I_{pv} - I_0\left[\exp\left(\frac{V+R_S I}{V_t n}\right)-1\right]-\frac{V+R_s I}{R_P}$$

(1)

Where, I is the output current, V is the output voltage, I_{pv} is the generated current under a given insolation, I_0 is the diode reverse saturation current, n is the ideality factor for a p-n junction, R_s is the series loss resistance, and R_{sh} is the shunt loss resistance. V_{th} is known as the thermal voltage. Red sun 90 w is taken as the reference module for simulation and the name-plate details are given in Table 1. The array is the combination of 6 cells in series and 6 cells in parallel of the 90w module; hence an array generates 3.2kW.

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. NEURAL NETWORK AND GENETIC ALGORITHM TECHNIC

3.1 The Steps of Implementing Genetic Algorithm

In order to pursue the optimum point for 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 training ANN [8-10]. The procedure employed for implementing genetic algorithm is as follows [11]: 1. defining the objective function and recognizing the design parameters, 2. defining the initial production population, 3. evaluating the population using the objective 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 the following: finding the optimum X= (X_1, X_2, X_3,..., X_n) to put the F(X) in the maximum value, where the number of design variables are considered as 1. X is the design variable equal to array current and also, F(X) is the array output power which should be maximized [8]. To determine the objective function, the power should be arranged based on the current of array (IX). The genetic algorithm parameters are given in Table 2.

Table 2: Genetic algorithm parameters

Number of Design Variable	1
Population size	25
Crossover constant	75%
Mutation rate	14%
Maximum Generations	16

$$F_{(X)} = V_X * I_X \tag{2}$$

$$0 < I_X < I_{SC} \tag{3}$$

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

3.2 Combination of Proposed Neural Network with Genetic Algorithm

Neural networks are most appropriate for the approximation (modeling) of nonlinear systems. Non-linear systems can be approximated by multi-layer neural networks and these multi-layer networks have better result in comparison with the other algorithm. In this paper, feed forward neural network for MPPT process control is used. The important section of this technic is that, the required data for training process must be obtained for each PV module and each specific location [7].

The proposed neural network has three layers which the temperature and solar irradiance as input variables and output variable of the neural network is Vmpp corresponding to MPP as shown in Figure 2. Also, a simple block diagram of the PV system with the proposed MPPT is shown in the Figure 3.

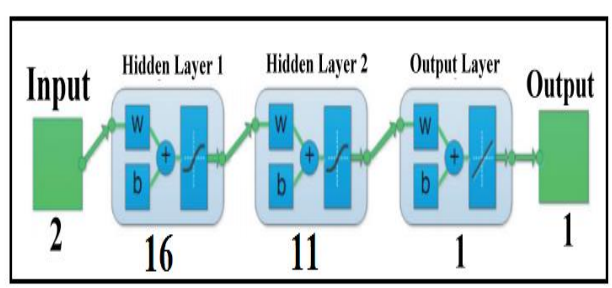


Figure. 2. Feed forward neural network for MPPT

The output characteristic of arrays are changed during time and environmental conditions. Therefore, for periodic training of the neural network in order to increase precision is essential, training of the neural network is a set of 500 data (temperatures between -5 °C to 55 °C and irradiance between 0.05 to 1 watt per square meter (W/m^2)) and also, a set of 500 Vmpp corresponding to MPP is achieved by GA.

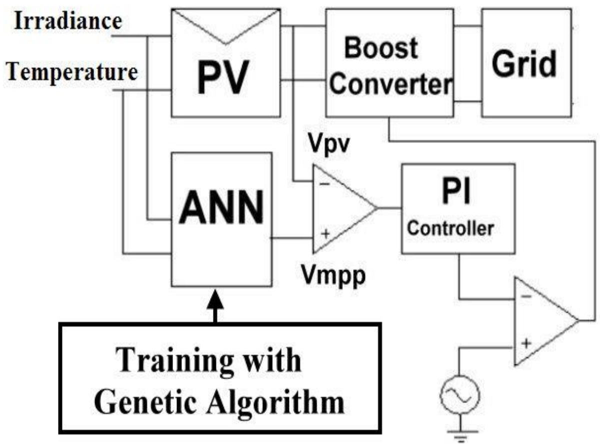
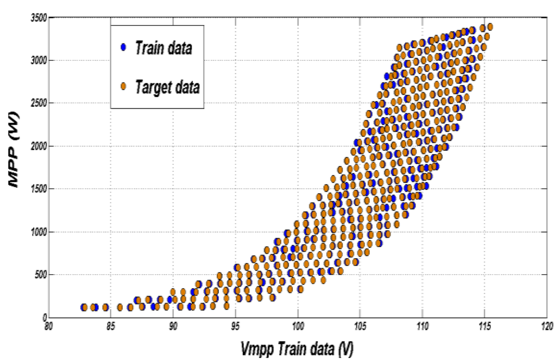
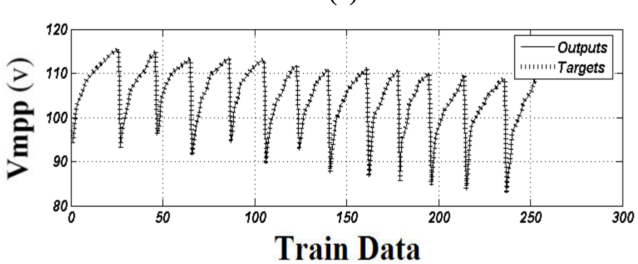


Figure. 3. Proposed MPPT Scheme

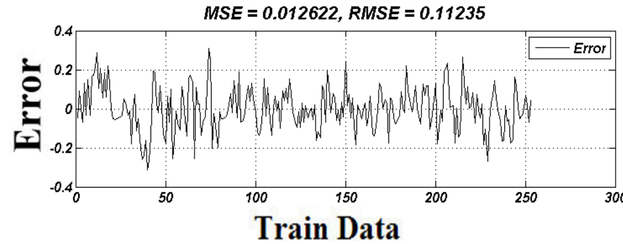
In order to implement the ANN for MPPT, first it should be determined the number of layers, number of neurons in each layer, transmission function in each layer and type of training network. The proposed ANN in this paper has three layers which first and second layers have respectively 16 and 11 neurons and third layer has 1 neuron. The transfer functions for 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 850 iterations, will converge to a desired target. After training, the output of training network should be



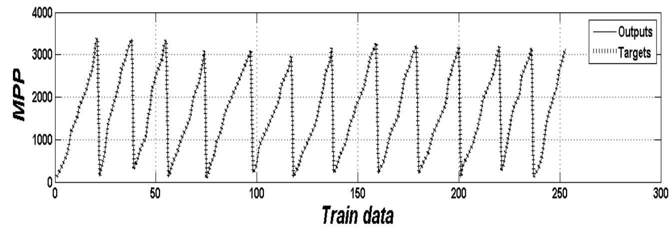
4(a)



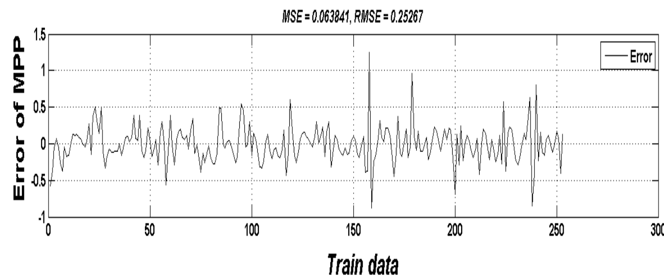
4(b)



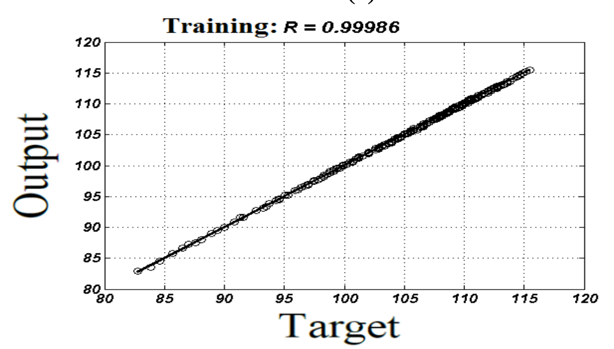
4(c)



4(d)



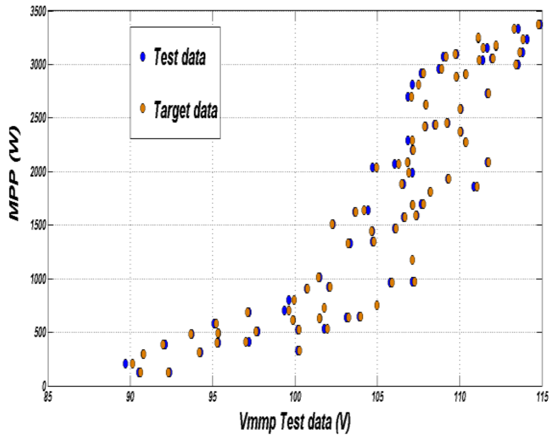
4(e)



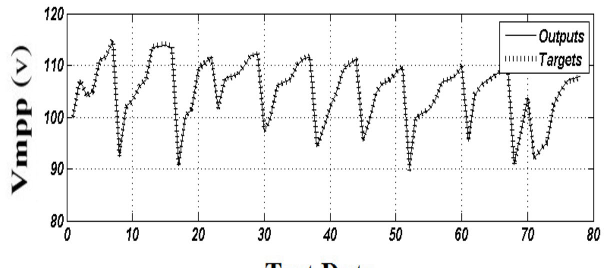
4(f)

Figure. 4. shown the output of the neural network by fallowing: (a) The output of the neural network training with the amount of target data; (b) The output of the neural network of Vmpp with the amount of data; (c) total error percentage of the Vmpp; (d) The output of the neural network of MPP with the amount of target data;(e) total error percentage of the MPP; (f) Train output versus target data.

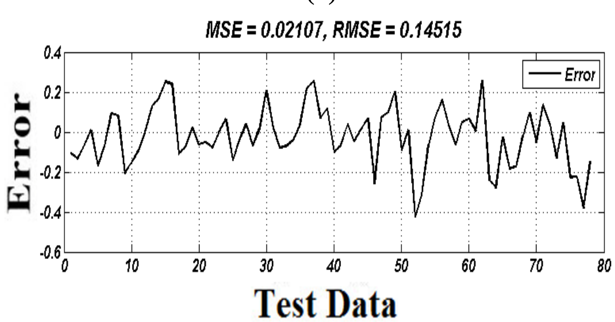
close to optimum output from GA. Figure 4 show the output of the neural network training with the amount of target. A set of 80 data is used for the ANN test. Figure 5 illustrate the output of the neural network test with the amount of target which showing a negligible training error percentage of about 0.4%.



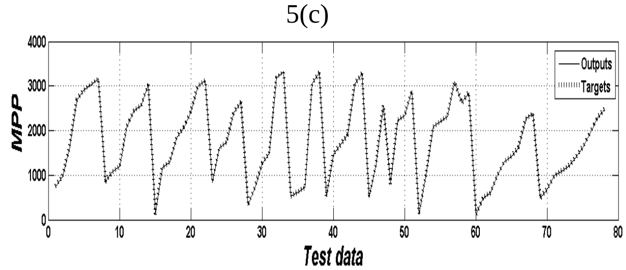
5(a)



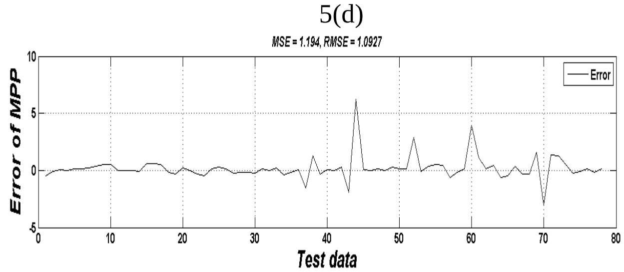
5(b)



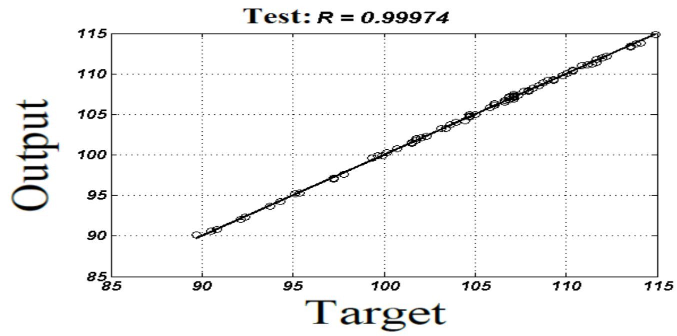
5(c)



5(d)



5(e)



5(f)

Figure. 5. shown the output of the neural network test by following: (a) The output of the neural network test with the amount of target data; (b) The output of the neural network test of Vmpp with the amount of test target data; (c) Percentage error of test data Vmpp; (d) The output of the neural network test of MPP with the amount of target data; (e) Percentage error of MPP test data. (f) Test output versus target

4. INCREMENTAL CONDUCTANCE (IC)

This method is based on the fact that the slope of the PV array power curve is zero at the MPP, positive for values of output power smaller than MPP, and negative for values of the output power greater than MPP [4]. This is shown in Equations (4) to (8).

$$P = V * I \tag{4}$$

Differentiating equation (6) with respect to dv:

$$\frac{dP}{dV} = I + V * \frac{dI}{dV} \tag{5}$$

From equation (5), the basic equations of this method are as follows:

$$\frac{dI}{dV} = -\frac{I}{V} \ldots\ldots\ldots\ldots\ldots\ldots \frac{dP}{dV} = 0 \quad \text{at MPP} \tag{6}$$

$$\frac{dI}{dV} > -\frac{I}{V} \ldots\ldots\ldots\ldots\ldots\ldots \frac{dP}{dV} > 0 \quad \text{Left of MPP} \tag{7}$$

$$\frac{dI}{dV} < -\frac{I}{V} \ldots\ldots\ldots\ldots\ldots\ldots \frac{dP}{dV} < 0 \quad \text{Right of MPP} \tag{8}$$

The MPP can thus be tracked by comparing the instantaneous conductance (I/V) to the incremental conductance (I/V) as shown in the flowchart given in Figure. 6.

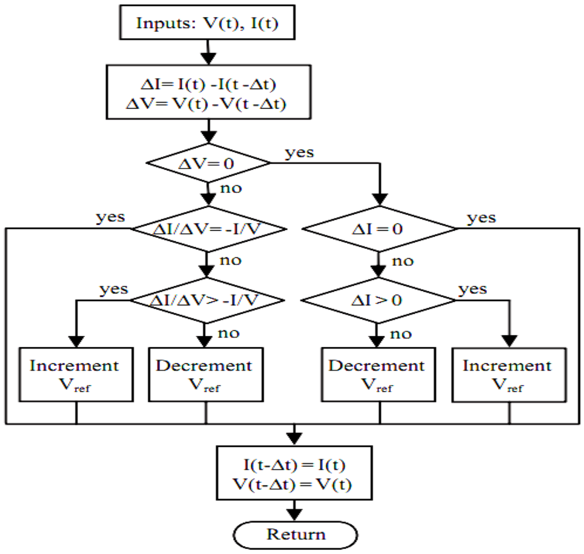


Figure 6.The flow diagram of the incremental conductance method

5. CONTROL STRATEGY (P-Q)

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 [12]. Also, internal control-loop which is responsible for power quality such as low 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.

6. SIMULATION RESULTS

In this section, simulation results under different terms of operation use with Matlab /Simulink is presented. System block diagram is shown in Figure. 7. Detailed model descriptions are given in Appendix A.

6.1 Variation of Irradiance and Temperature

In order to compare the accuracy and efficiency of the two MPPT algorithms selected in this paper, Matlab/Simulink is used to implement the tasks of modeling and simulation. The main objective of this case is investigated comparative study of MPPT algorithms under variations of irradiance and temperature in PV system. The system is connected to the main grid that includes 3200W photovoltaic system and the amount of load is 3200 W. There is no power exchange between photovoltaic system and grid in normal condition.

The following simulation is presented for different insolation levels at fixed temperature of 25°C as shown in Figure 8(a). The output voltage and the current of PV are depicted in Figures 8(b) and 8 (c), respectively. When irradiance is increased at t=4 and t=8, it lead to increase in the output current of PV as shown in Figure 8(c).

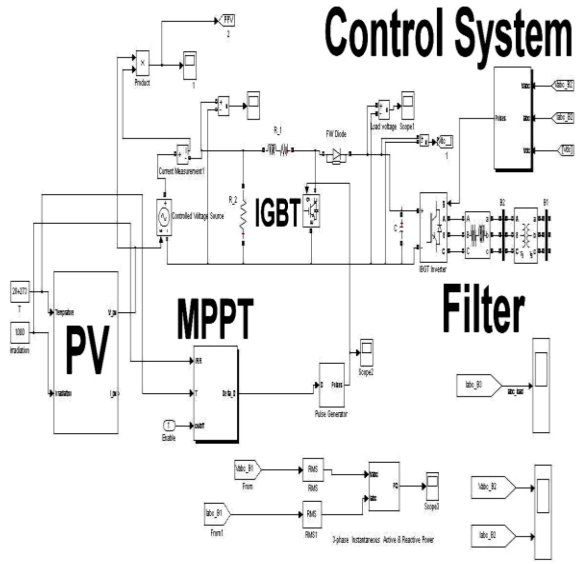


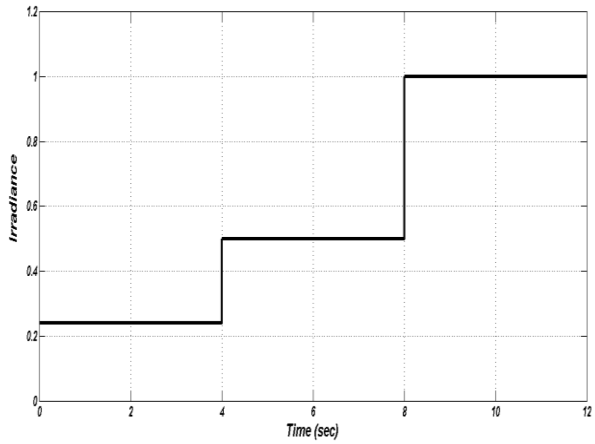
Figure. 7. Case study system

The evaluation of the proposed controller is compared and analyzed with the IC. The proposed MPPT algorithm can track accurately the MPP when the irradiance changes continuously; also, this method has well regulated PV output power and it produces extra power rather than aforementioned method as indicated in Figure 8(d). Therefore, the injected power from main grid to photovoltaic system is decreased as demonstrated in Figure 8(e). The IC method performs a fluctuated PV power even after the MPP operating has been successfully tracked.

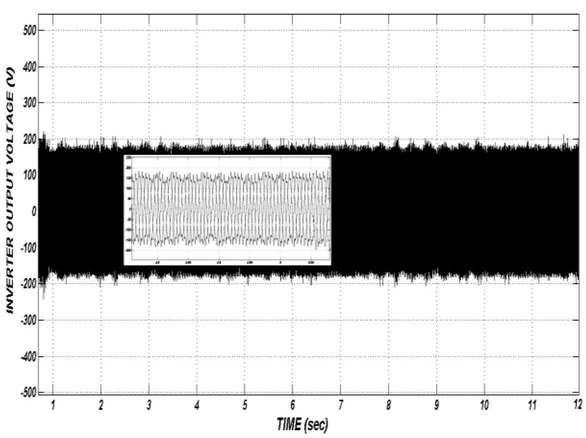
In order to realize a precise analysis of the performance of the ANN-GA technique, different temperature levels at fixed insolation of 1000 W/m^2 as shown in Figure 9(a). The grid voltage is indicated in Figure 9(b). Figure 9(c) shows the variation of the output current of PV. The ANN-GA method shows smother power, less oscillating and better stable operating point than IC method. It has more accuracy for operating at MPP also, it generates exceeding power and it possesses faster dynamic response rather than mentioned technique as depicted in Figure 9(d). Consequently, the grid power injection to the photovoltaic system is declined as illustrated in Figure 9(e). In the view of power stabilization, the PV power which is controlled by ANN-GA is more stable than the conventional method.

7. CONCLUSIONS

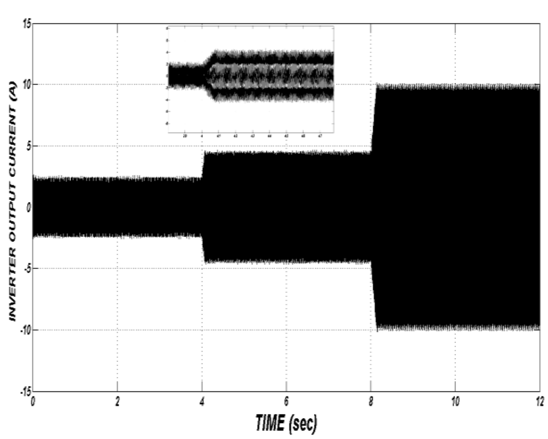
An integrated scheme for optimal power tracking was proposed in this paper. With the aid of this method, the PV system was able to perform and to enhance the production of the electrical energy at an optimal solution under various operating conditions. To extract the maximum power from the PV system ANN-GA technique was used. The GA based offline trained ANN was used to provide the reference voltage corresponding to the maximum power for any environmental changes .Then; optimized values were used for training the ANN. The simulation results showed that The ANN-GA algorithm cloud track accurately the MPP; also, this method had well regulated PV output power and it produced extra power rather than IC method for different conditions. The proposed algorithm was verified and it was found that the error percentage of Vmpp between 0.05% to 1.46%. This error could be reduced by increasing the number of the training data for ANN.



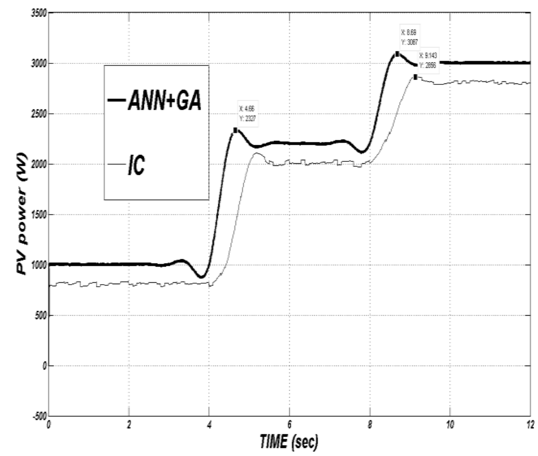
8(a)



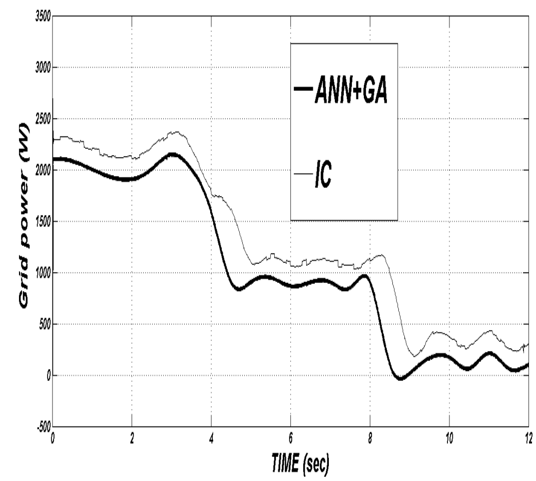
8(b)



8(c)

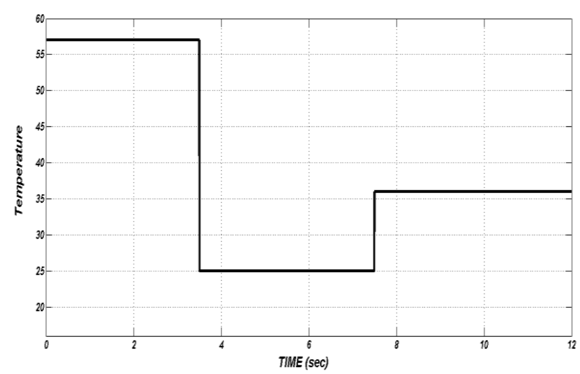


8(d)

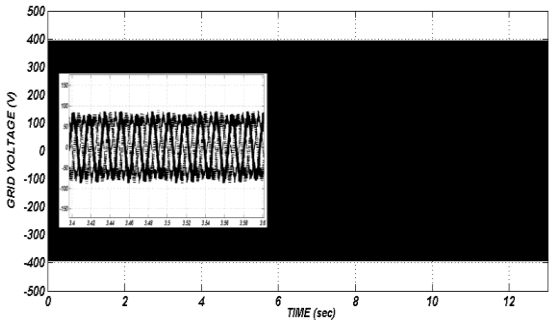


8(e)

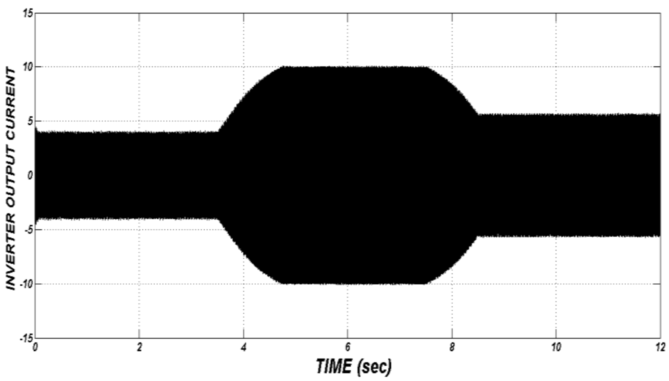
Figure 8. Simulated results for PV (Variation of Irradiance) in case 1: (a) Irradiance; (b) Inverter output voltage; (c) Inverter output current; (d) PV power; (e) Grid power.



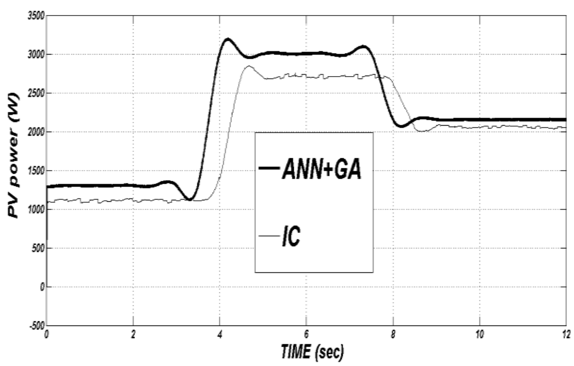
9(a)



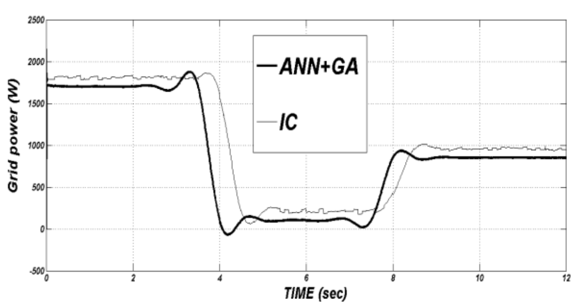
9(b)



9(c)



9(d)



9(e)

Figure 9. Simulated results for PV (Variation of Temperature) in case 1: (a) Temperature; (b) Grid voltage; (c) Inverter output current; (d) PV power; (e) Grid power.

Appendix A: Description of the Detailed Model

PV parameters: output power = 3.2kW, Carrier frequency in V_{MPPT} PWM generator: 4.3 kHz and in grid-Sid controller: 5 kHz, boost converter parameters: L= 3.5mH, C= 630μF, PI coefficients in grid-side controller: K_{pVdc}= 3.5, K_{iVdc}= 7.3, K_{pId}= 8.4, K_{iId}= 343, K_{pIq}= 8.4, K_{iIq}= 343.

REFERENCES

[1] M. G. Villalva, J. R. Gazoli, and E. R. Filho, "Comprehensive Approach to Modeling and Simulation of Photovoltaic Arrays," Power ElectronicsIEEE Transactions on, vol. 24(5),pp.1198-1208, 2009

[2] V. Salas, E. Olias, A. Barrado, A. Lazaro, Review of the maximum power point tracking algorithms for stand-alone photovoltaic systems, Solar Energy Materials and Solar Cells, 90(11), pp.1555-1578, 2006.

[3] C.C. Chu, C.L. Chen, Robust maximum power point tracking method for photovoltaic cells: a sliding mode control approach, Solar Energy, 83(8), pp. 1370-1378, 2009.

[4] L. Fangrui, et al., A Variable Step Size INC MPPT Method for PV Systems, IEEE Trans. on Industrial Electronics, 55(7), pp.2622-2628, 2008.

[5] T. Hiyama, S. Kouzuma, T. Imakubo, T.H. Ortmeyer, Evaluation of Neural Network Based Real Time Maximum Power Tracking Controller Far PV System, IEEE Transaction On Energy Conversion, 10(3), pp.543-548, 1995.

[6] T. Hiyama, K. Kitabayashi, Neural Network Based Estimation of Maximum Power Generation from PV Module Using Environment Information, IEEE Transaction on Energy, Conversion, 12(3), 1997, pp.241-247.

[7] E. Karatepe, M. Boztepe, M.C olak, Neural network based solar cell model, Energy Conversion and Management, 47(9) , pp.1159-1178, 2006.

[8] A. Rezvani , M. Izadbakhsh, M. Gandomkar. Enhancement of hybrid dynamic performance using ANFIS for fast varying solar radiation and fuzzy logic controller in high speeds wind. Journal of Electrical Systems, 11(1), pp 11-26, 2015.

[9] R.M. Vincheh , A. Kargar, Gh.A. Markadeh, A Hybrid Control Method for Maximum Power Point Tracking (MPPT) in Photovoltaic Systems, Arabian Journal for Science and Engineering. 39(6): 4715-4725, 2014.

[10] M. Izadbakhsh, A. Rezvani , M. Gandomkar. Improvement of microgrid dynamic performance under fault circumstances using ANFIS for fast varying solar radiation and fuzzy logic controller for wind system , Archives of Electrical Engineering. 63(4), pp.551–578, 2014.

[11] J. Yang, V. Honavar, Feature subset selection using a genetic algorithm, IEEE Intelligent Systems,. 13(2), pp.44-49, 1998.

[12] F. Blaabjerg, R. Teodorescu, M. Liserre, A. V. Tim-bus, Overview of Control and Grid Synchronization for Distributed Power Generation Systems, IEEE Transactions on Industrial Electronics, 53(5) , pp.1398-1409, 2006.