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Investigation of ANN-GA and Modified Perturb and Observe MPPT Techniques for Photovoltaic System in the Grid Connected Mode

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Abstract

The output characteristics of Photovoltaic (PV) arrays are nonlinear and change with the cell's temperature and solar radiation. Maximum Power Point Tracking (MPPT) methods are used to maximize the PV array output power by tracking continuously the maximum power point (MPP). This paper presents 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. Data are optimized by GA and then these optimum values are used in neural network training. The obtained results show minimal error of MPP, optimal voltage (Vmpp) and superior capability of the suggested method in the MPPT. The simulation results are presented by using Matlab/Simulink and show that ANN–GA controller of grid-connected mode can meet the need of load easily and have fewer fluctuations around the maximum power point; also, this method has well regulated PV output power and it produces extra power rather than Modified Perturb & Observe (MP&O) method for different conditions. Moreover, to control both line voltage and current, a grid side P-Q controller has been applied.

Keywords: Genetic Algorithm, Neural Network, Photovoltaic, P-Q Control

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].

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 locates among PV systems and users, which switching operation of this converter is performed by the MPPT[3]. In the last few decades, different methods are utilized in order to achieve maximum power. The most prevalent technics are perturbation and observation algorithm (P&O)[3, 4] Incremental conductance (IC)[5, 6] fuzzy logic[7, 8] and ANN [9–11].

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 MPP even under steady state illumination which results in the loss of available energy[12–15]. However the fast variation of weather condition affects the output and these technics cannot track the maximum power.

Using fuzzy logic can solve the two mentioned problem dramatically. In fact, fuzzy logic controller can reduce the oscillations of output power around the MPPT and has faster respond than P&O and IC. Furthermore, convergence speed of this way is higher than two mentioned way. One the weak point of fuzzy logic comparing

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to neural network is oscillations of output power around the MPP[14, 15]

Nowadays, Artificial Intelligence (AI) 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 modelling PV module and MPPT controller in PV systems[16, 17].

ANN based controllers are applied to forecast optimum voltages corresponding to the MPP of PV system for different radiations and temperatures conditions. A review on AI methods applications in renewable energy was studied in these literatures[9, 18]. Neural networks are the best estimation for non-linear systems and by using ANN, oscillations of output power around the MPPT and time to reach the MPP are decreased[6].

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 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 MPP (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 detail of PV system is described. Part 3 is discussed steps to implement the GA and neural networks, respectively. In part 4 fuzzy logic 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, 3]. Features of PV system is described as following Equation (1)

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

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

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

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

Where, I is the output current, V is the output voltage, I_{pv} is the generated current under a given isolation, 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, R_s is the series loss resistance (.1 Ω), and R_p is the shunt loss resistance (161.34 Ω). 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 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 90 w modules; hence an array generates 3.2 kW.

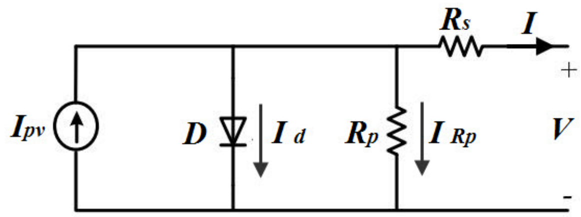


Figure 1. Equivalent circuit of one photovoltaic array.

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. MPPT - ANN and GA

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[19–21]. The procedure employed for implementing genetic algorithm is as follows[19, 22]:

1. Determining the target function
2. Determining the initial population size
3. Appraising the population using the target function
4. Conducting convergence test stop if convergence is provided.

The target function of GA is applied for its optimization by the following: finding the optimum $X = (X_1, X_2, X_3, ..., X_n)$ to determine the $F_{(X)}$ in the maximum value, where the number of design variables are regarded as 1. X is the design variable equal to PV system current and also, $F_{(X)}$ is the PV system output power that must be maximized[19, 20]. To determine the target function, the power should be set based on the PV system current (I_X). The genetic algorithm structures are presented in Table 2.

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

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

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

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

Table 2. Genetic algorithm parameters

Number of Design Variable	1
Population size	20
Crossover constant	80%
Mutation rate	10%
Maximum Generations	20

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

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[16,18]. 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[11].

Three layers can be considered for the proposed ANN. The input variables are temperature and solar irradiance and Vmpp corresponding to MPP is output variable of the neural network as shown in Figure 2 Proposed MPPT Scheme is illustrated in Figure 3.

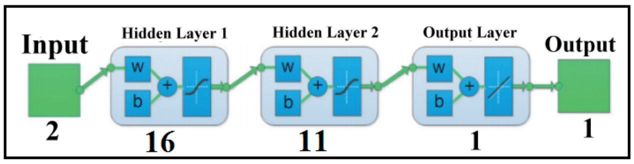


Figure 2. Feed forward neural network for MPPT.

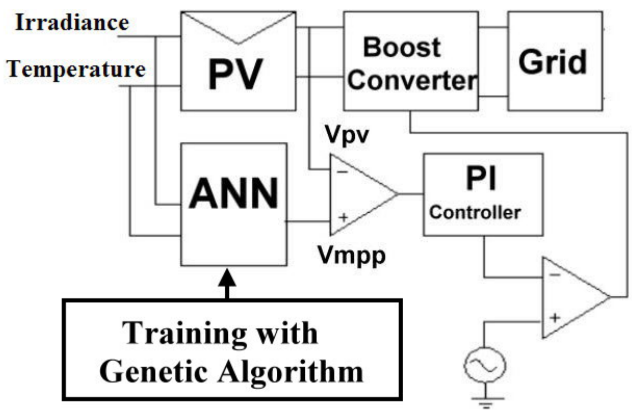


Figure 3. Proposed MPPT Scheme.

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 500 data as shown in Figure 4 (irradiance between 0.05 to 1 watt per square meter (W/m^2) and temperatures between –5 °C to 55 °C) and also, a set of 500 Vmpp corresponding to MPP is obtained by GA as shown in Figure 5.

In order to implementation of 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 Train lm. 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 close to optimum output from GA. Figure 6 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 7 illustrate the output of the neural network test with the amount of target which showing a negligible training error percentage of about 0.3%.

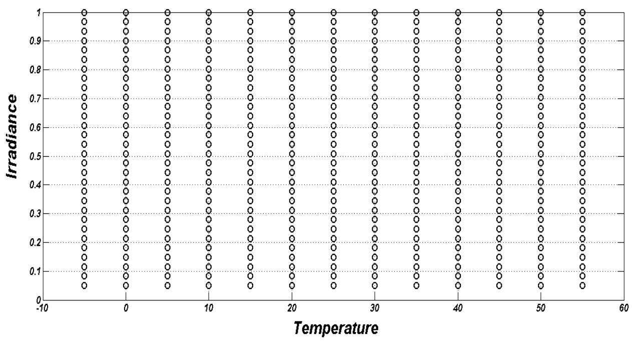


Figure 4. Inputs data of irradiation and temperature.

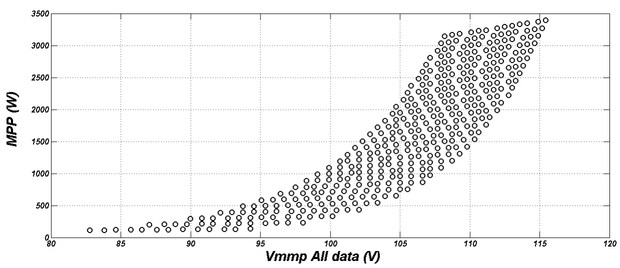
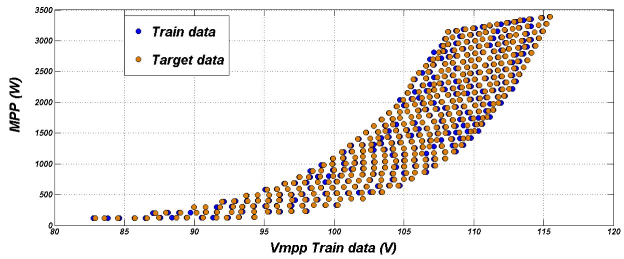
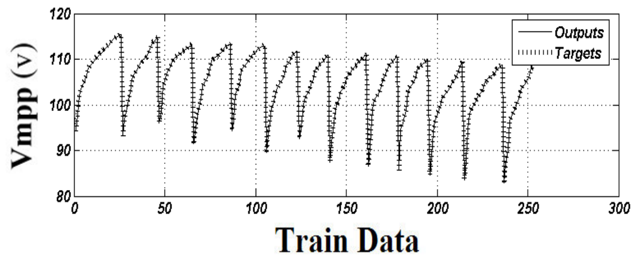


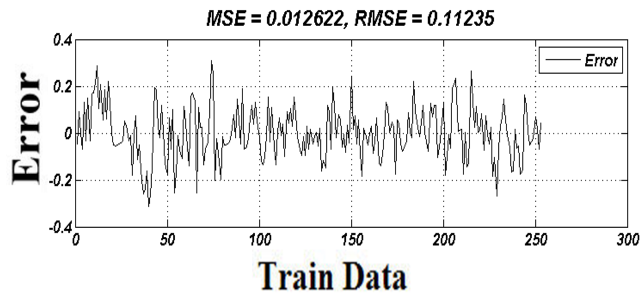
Figure 5. The output of $V_{mpp} – M_{pp}$ optimized by (GA)



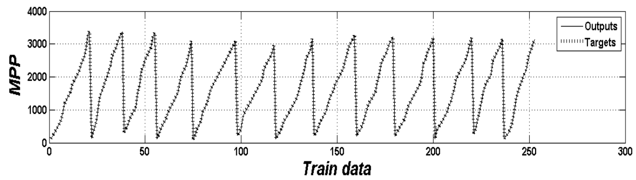
6(a)



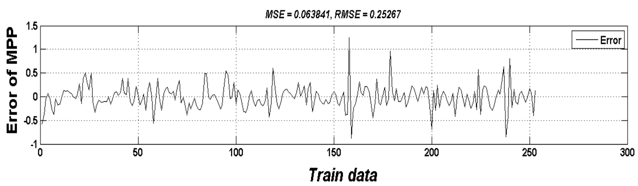
6(b)



6(c)

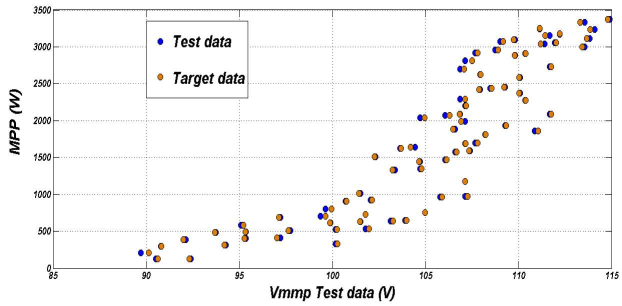


6(d)

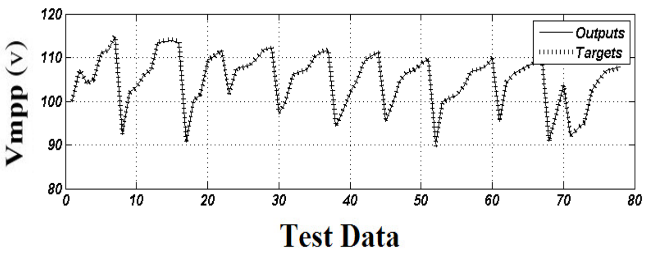


6(e)

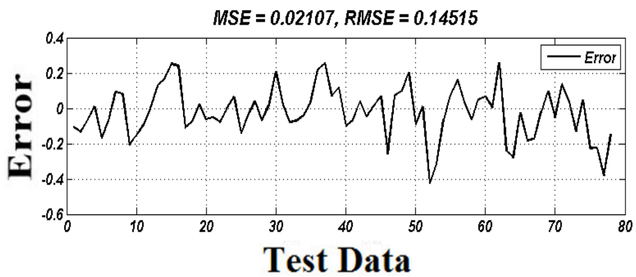
Figure 6. Shown the output of the neural network by fallowing: (a) The output of the neural network training with the amount of target data; (b) The output of the neural network of Vmpp with the amount of data; (c) total error percentage of the Vmpp; (d) The output of the neural network of MPP with the amount of target data;(e) total error percentage of the MPP.



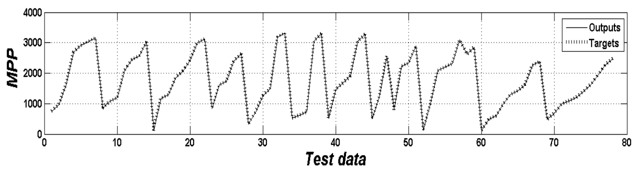
7(a)



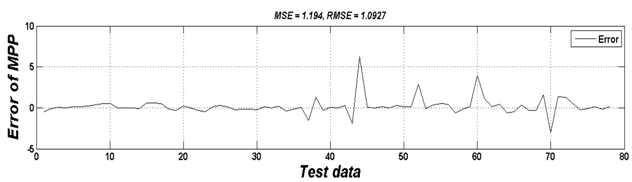
7(b)



7(c)



7(d)



7(e)

Figure 7. 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.

4. Modified Perturb and Observe (MP&O) Algorithm

One of the disadvantages of P&O is that it cannot determine when it has actually reached the MPP. As well as, it oscillates around the MPP. The Modified Perturb and Observe (MP&O) algorithm was presented to solve the deviation problem by decoupling the PV power fluctuations caused by hill-climbing process from those caused by the irradiance. This algorithm adds an irradiance changing estimate process in each perturb process to evaluate the amount of power change caused by the change of atmospheric condition and then compensates it using a perturb process. Figure 8 shows the flow chart of the MP&O method. The details of the proposed method were presented in refs[12] and[13].

5. Control Strategy (P-Q)

Inverter control model is illustrated in Figure 9 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

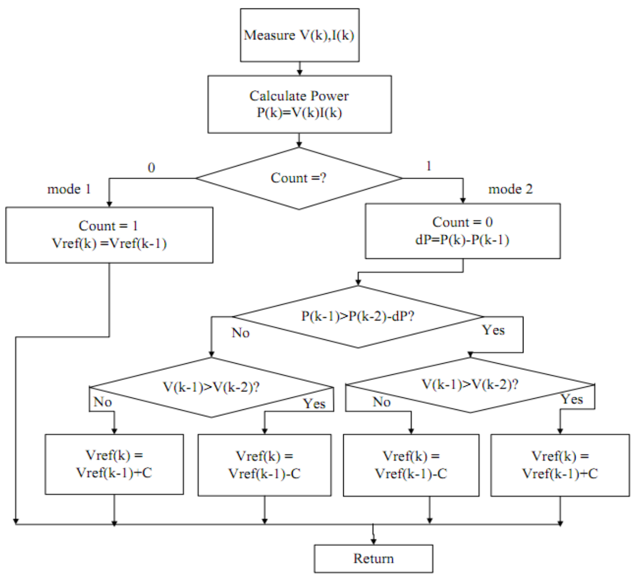


Figure 8. Structure of MP&O algorithm.

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 10 Detailed model descriptions are given in Appendix A.

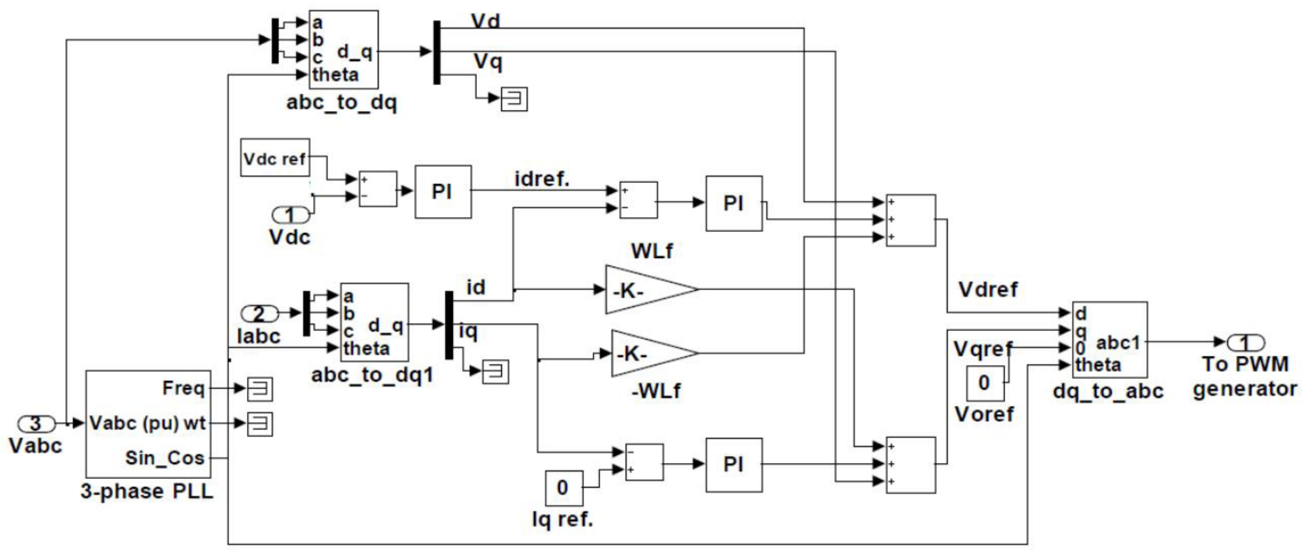


Figure 9. The inverter control model.

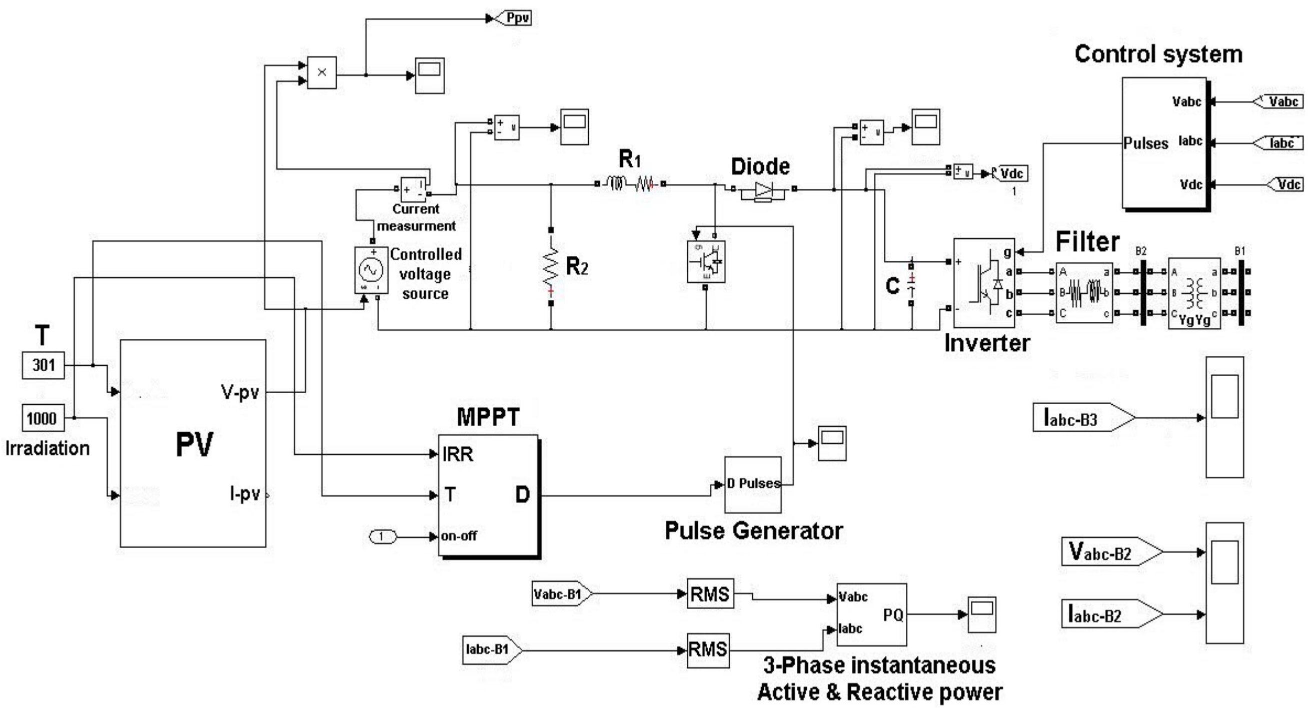


Figure 10. Case study system.

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 11(a). The output voltage and the current of PV are depicted in Figures 11(b) and 11 (c), respectively. When irradiance is decreased at t = 3.5 and t = 7, it lead to decrease in the output current of PV as shown in Figure 11(c). The evaluation of the proposed controller is compared and analyzed with the MP&O and P&O controllers. 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 11(d). Therefore, the injected power from main grid to photovoltaic system is decreased as demonstrated in Figure 11(e). MP&O and P&O methods perform a fluctuated PV power even after the MPP operating has been successfully tracked.

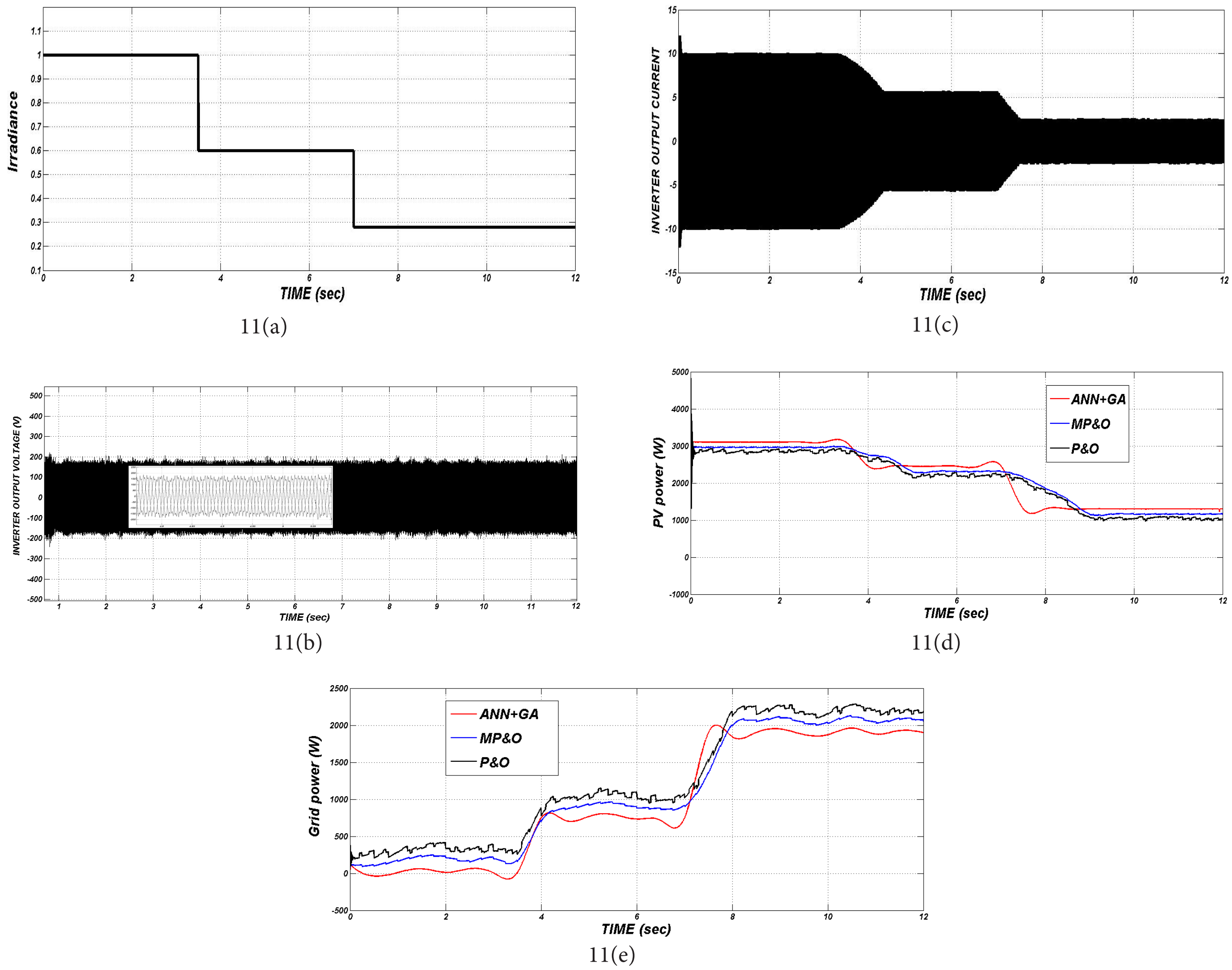


Figure 11. Simulated results for PV (Variation of Irradiance) in case 1: (a) Irradiance; (b) Inverter output voltage; (c) Inverter output current; (d) PV power; (e) Grid power.

In order to realize a precise analysis of the performance of the ANN-GA technique, different temperature levels at fixed insolation of 1000 W/m2 as shown in Figure 12(a). The grid voltage is indicated in Figure 12(b). Figure 12(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 MP&O and P&O methods. 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 12(d). Consequently, the grid power injection to the photovoltaic system is declined as illustrated in Figure 12(e). In the view of power stabilization, the PV power which is controlled by ANN-GA is more stable than the conventional method.

7. Conclusion

The presented study is a kind of modelling and analysis of the PV system under fault circumstances by using ANN-GA. 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. The GA is used to provide the reference voltage corresponding to the maximum power for any environmental changes. The simulation results show that using ANN-GA controller can dramatically reduce the disadvantages of previous approaches and also, it can decrease oscillations of power output around the MPP and can increase convergence

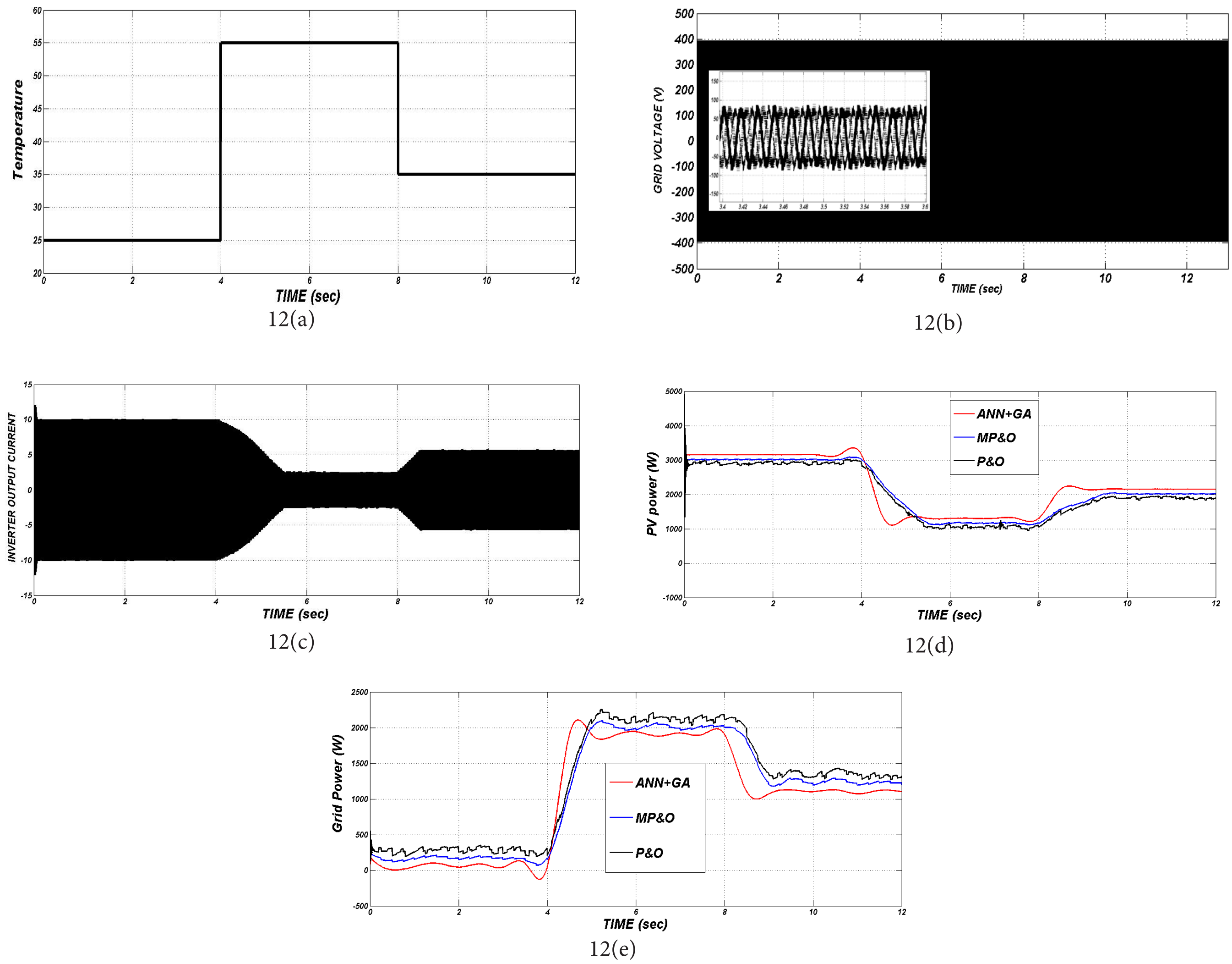


Figure 12. Simulated results for PV (Variation of Temperature) in case 1: (a) Temperature; (b) Grid voltage; (c) Inverter output current; (d) PV power; (e) Grid power.

speed to achieve the MPP in comparison with MP&O and P&O methods; also, this method had well regulated PV output power and it produced extra power rather than MP&O for different conditions.

8. 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: $K_{pVdc} = 3.5$, $K_{iVdc} = 7.3$, $K_{pId} = 8.4$, $K_{iId} = 343$, $K_{pIq} = 8.4$, $K_{iIq} = 343$.

9. References

1. Izadbakhsh M, Gandomkar M, Rezvani A, Ahmadi A. Short-term resource scheduling of a renewable energy based micro grid. Renew Energ. 2015; 75:598–606.
2. Rezvani A, Gandomkar M, Izadbakhsh M, Ahmadi A. Environmental/economic scheduling of a micro-grid with renewable energy resources. Journal of cleaner production. 2014; DOI: 10.1016/j.jclepro.2014.09.088.
3. Salas V, Olias E, Barrado A, Lazaro A. Review of the maximum power point tracking algorithms for stand-alone photovoltaic systems. Sol Energ Mater Sol Cell. 2006; 90(11):1555–78.
4. Villal MG, Gazoli JR, Filho E. Comprehensive Approach to Modeling and Simulation of Photovoltaic Arrays. IEEE Trans Power Electron. 2009; 24(5):1198–208.
5. Chu CC, Chen CL. Robust maximum power point tracking method for photovoltaic cells: a sliding mode control approach. Solar Energy. 2009; 83(8):1370–8.
6. Liu FF, Duan S, Liu B, Kang Y. A variable step size INC MPPT method for PV systems. IEEE Trans Ind Electron. 2008; 55(7):622–2628.
7. Shafy A, Nafeh A, Fahmy FH, Abou El-Zahab EM. Maximum-power operation of a stand-alone PV system using fuzzy logic control. Int J Numer Model Electron Network, Dev Field. 2002; 15(4):385–98.
8. Bouchafaa F, Hamzaoui I, Hadjammar A. Fuzzy Logic Control for the tracking of maximum power point of a PV system. Energy Procedia. 2011; 6(1):152–9.
9. Veerachary M, Senjyu T, Uezato K. Neural-network-based maximum-power-point tracking of coupled inductor interleaved-boost-converter-supplied PV system using fuzzy controller. IEEE Transactions on Industrial Electronics. 2003; 50(4):749–58.
10. Rai AK, Kaushika ND, Singh B, Agarwal N. Simulation model of ANN based maximum power point tracking controller for solar PV system. Sol Energ Mater Sol Cells. 2011; 95(2):773–78.
11. Cernazanu C. Training Neural Networks Using Input Data Characteristics. Adv Electr Comput Eng. 2008; 8(2):65–70.
12. Liu C, Wu B, Cheung R. Advanced algorithm for mppt control of photovoltaic systems. Proceeding of the Canadian Solar Buildings Conference; 2004; Montreal.
13. Hohm DP, Ropp ME. Comparative Study of Maximum Power Point Tracking Algorithms. Progress in photovoltaics: research and applications. 2003; 11:47–62.
14. Simoes MG, Franceschetti NN. Fuzzy Optimization Based Control of A Solar Array System. Electric Power Applications. 1999; 146(5):552–58.
15. Lee S, Kim J, Cha H. Design and Implementation of Photovoltaic Power Conditioning System using a Current-based Maximum Power Point Tracking. Journal of Electrical Engineering & Technology. 2010; 5(4):606–13.
16. Hiyama T, Kouzuma S, Imakubo T, Ortmeyer TH. Evaluation of Neural Network Based Real Time Maximum Power Tracking Controller Far PV System. IEEE Trans Energ Convers. 1995; 10(3):543–8.
17. Hiyama T, Kitabayashi K. Neural Network Based Estimation of Maximum Power Generation from PV Module Using Environment Information. IEEE Trans Energ Convers. 1997; 12(3):241–7.
18. HajirKarimi H, Dastranj J. Artificial Neural network-based genetic algorithm to predict natural gas consumption. Energy Systems. 2014; 5(3):571–81.
19. Rezvani A, Gandomkar M, Izadbakhsh M, Vafaei S. Optimal power tracker for photovoltaic system using ann-ga. International Journal of Current Life Sciences. 2014; 4(9):107–11.
20. Vincheh MR, Kargar A, GHA. A Hybrid Control Method for Maximum Power Point Tracking (MPPT) in Photovoltaic Systems. Arabian Journal for Science and Engineering. 2014; 39(6):4715–25.
21. Ramaprabha R, Gothandaraman V, Kanimozhi K, Divya R, Mathur BL. Maximum power point tracking using GA-optimized artificial neural network for Solar PV system. Electrical Energy Systems (ICEES). 2011; 264–8.
22. Yang J, Honavar V. Feature subset selection using a genetic algorithm. IEEE Intelligent Systems. 1998; 13(2):44–9.
23. Blaabjerg F, Teodorescu R, Liserre M, Tim-bus AV. Overview of Control and Grid Synchronization for Distributed Power Generation Systems. IEEE Trans Ind Electron. 2006; 53(5):1398–409.