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Active and reactive power neurocontroller for grid-connected photovoltaic generation system

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Many researchers have contributed to the development of a firm foundation for analysis and design of control applications in grid-connected renewable energy sources. This paper presents an intelligent control algorithm fond on artificial neural networks for active and reactive power controller in grid-connected photovoltaic generation system. The system is devices into two parts in which each part contains an inverter with control algorithm. A DC/DC converter in output voltage established by control magnitude besides maximum power point tracker algorithm always finds optimal power of the PV array in use. A DC/AC hysteresis inverter designed can synchronize a sinusoidal current output with the grid voltage and accurate an independent active and reactive power control. Simulation results confirm the validation of the purpose. Neurocontroller based active and reactive power presents an efficiency control that guarantees good response to the steps changing in active and reactive power with an acceptable current/voltage synchronism. In this paper the power circuit and the control system of the presented grid-connected photovoltaic generation system is simulated and tested by MatLab/Simulink.

Keywords: Artificial neural network; power grid; photovoltaic system; hysteresis inverter.

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1. Introduction

Solar photovoltaic (PV) generator is one of the most widely used renewable energy for produce electricity in industrial applications, that is essentially due to their; high reliability, relatively low cost, non-polluting, and modest maintenance requirements [1]-[2]. So, solar PV systems are an ideal renewable energy source. PV panels can be used either offline or online. In offline applications, PV panels supply local loads which can be residential or commercial. In online applications, these modules not only supply local loads, but also are connected to the utility grid. In the last case, the system would be called “grid-connected PV system”. Power inverters used to ensure the combination of grid with solar sources in which the generated DC power from PV modules converted to AC power provide to electric equipments. Inverter is therefore very important for grid connected photovoltaic systems. In grid connected solar inverter scheme, closed loops controls are traditionally implemented by fixed gain PID (proportional integral derivative) controllers [3-6]. Conventional PID control laws provide good results in case of linear systems with constant parameters. Moreover, these control laws are limited in robustness and effectiveness. However, in the control systems, the robustness is of particular importance. Recently, intelligent control acts are better than conventional controls. Artificial intelligent techniques classed on three big branches: fuzzy logic, neural network and evolutionally algorithms where the more popular used are genetic algorithms and particle swarm optimization. These

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proceeds has exhibited particular superiorities and used widely in electrical control systems like electrical machines control and the integrations of grid-power sources.

Artificial neural networks (ANNs) present an ideal solution for solving many problems in many applications of electrical systems as control, identification and classification. Many successes in the applications of this technique have been presented in the literature [7-9].

In this paper, an efficiency application of neural networks control to decoupling active and reactive power in grid-connected photovoltaic generation system is presented. After developing a reasonable model of the proposed power generation system under description analytic solutions, a decoupling control for active and reactive power via NN control algorithm is obtained. These greatly improve the design PV connected grid system quality. Simulation results using MatLab/Simulink verify the potential of the proposed intelligent control in grid connected-photovoltaic conversion system.

2. System description

The configuration of the proposed grid-connected PV generator system is depicted in Figure 1. The system connected with the utility power is mainly composed of photovoltaic power generation system and three phase grid. PV systems ensure the conversion of the solar energy into electrical power. Output voltage of the PV generator is not regular, which present a difficulty for the application. So, PV system does not provide the required output. Hence power converter is necessary to enable the no regular voltage of PV array to be used. DC/DC converter is used where PV array operates electrically at a certain voltage which corresponds to the maximum power point under different climatic conditions. To do this, various maximum power point tracking (MPPT) techniques have been proposed [10-13]. A fairly simple maximum power point tracking algorithm called perturbation and observation (P&O) heavily used in solar energy systems. This method requires a few mathematical calculations [14]. For this reason, P&O was used in this particular work. A generate PWM signal based MPPT ensure the control of the DC/DC converter. A power conversion unit composed of DC/DC converter and DC/AC inverter grantee the transfer of the total generated power from the PV generator to the grid. A transformer steps up the alternative voltage to the nominal value of the grid. Another role of the transformer using is to providing electrical isolation between the DC part and the AC part of the system. The harmonics reduction inductor filter eliminates the harmonic components.

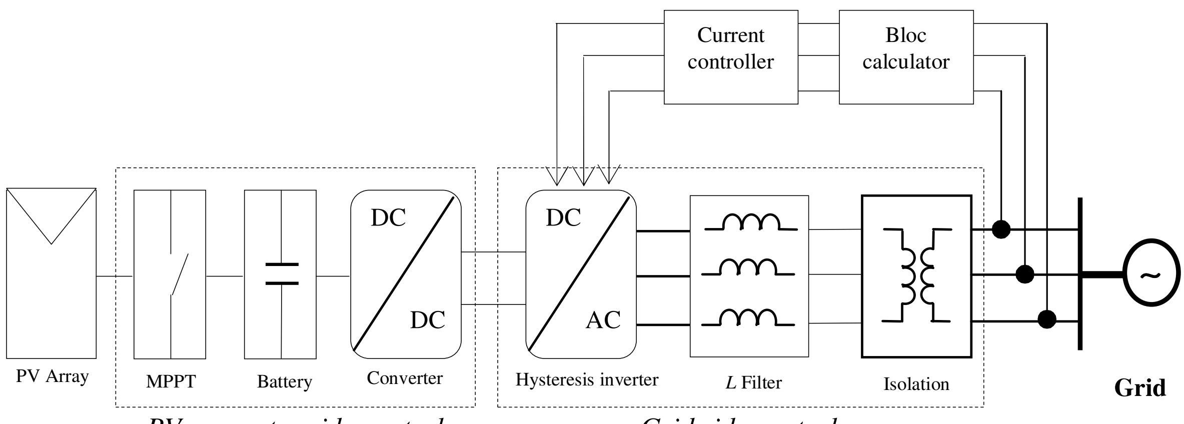


Figure. 1: Structure of the proposed grid-connected PV generation system.

3. P/Q neurocontroller

3.1 Presentation of ANN

Principal of an artificial neural network estimate to the biological nervous system of the human brain and supply a mathematical application from an input space $\mathfrak{R}^n$ into an output space $\mathfrak{R}^m$ [15]. Its properties include function approximation, learning, generalization, classification, identification, control, etc. A neural network composed of many simple and similar processing elements that cool a processing unit, characterized by sets of inputs, outputs, biases, weights and a nonlinear transfer function. Nowadays, ANN applied to address some of the very practical control problems caused of their enormous parallelism and capability to learn any type of nonlinearity [16]-[17].

The processing elements each have a number of interior parameters called weights. Changing the weights of an element will alter the behavior of the system. The aim here is choose the weights of the network to accomplish a desired input/output association. This procedure is known as training the network. The network can be considered memory less in the sense that, if one keeps the weights constant, the output vector depends only on the current input vector and in independent of past inputs [15]. ANN architecture performs a specific form of the adaptive control with the controller taking the form of a multi layer network and the adaptable parameters being distinct as the adaptable weights. An artificial neural network stores the information concerning the problem in terms of weights of inter-connections. The operation of determining the global process information called training. The Error Back Propagation method is one of the general approaches for training neural networks [18]. In this technique, model output error is passed through the plant, and updating law of the weights is accomplished. When this step is over, model performance is confirmed.

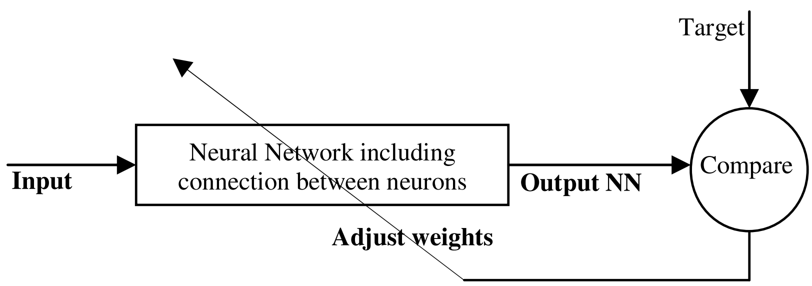


Figure. 2: Simplified schematic of the ANN training process.

3.2 Measurement, identification and calculation

To apply the proposed intelligent control algorithm it is necessary to identify some parameters and to apply some transformations, measurement and calculation. So, to provide reference phase angle θ by using the phase locked loop (*PLL*) to obtain v_d and v_q voltage also the i_d and i_q current grid with applying Park transformation and lastly, estimate the real active (P) and reactive (Q) power.

Measurement and calculation unit is illustrating in figure 2. The object is to senses the three phase inverter current i_a, i_b, and i_c, the three phase inverter voltage v_a, v_b, and v_c, to calculate inverter voltage and to identify the active and the reactive power.

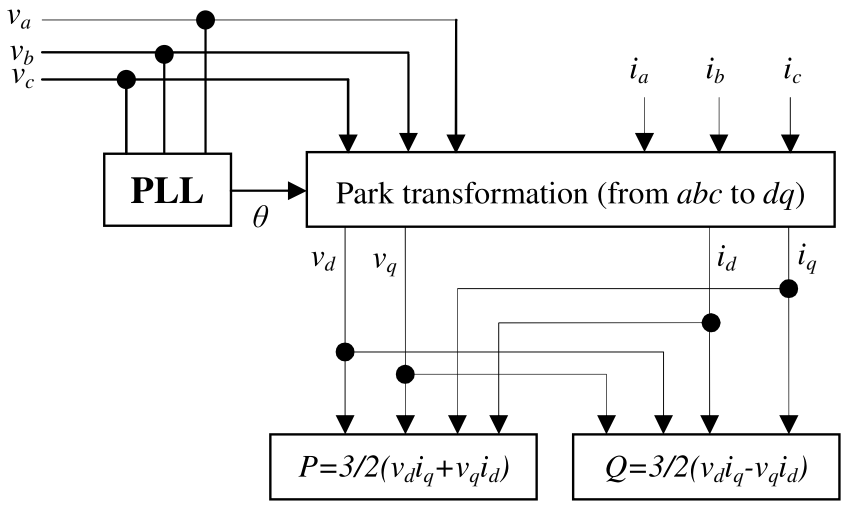


Figure. 3: Measurement and calculation of θ, P and Q.

P and Q in the dq plant obtained as follows:

$$\begin{cases} P = \frac{3}{2}\left(v_d i_q + v_q i_d\right) \\ Q = \frac{3}{2}\left(v_d i_q - v_q i_d\right) \end{cases} \tag{1}$$

Conventional mathematical-model-based analysis techniques and control methods require PID controllers applied in electrical systems control are very complex and limited in performances. In parallel the new technologies for renewable energy based inverters applications demands a good control performance.

In the proposed system, a neurocontrol algorithm do not require any mathematical modelling of the system used to ensure a perform P/Q control in the grid connected PV generator with a relatively strong degree of one can be obtained considering proportionality to a linear combination of the errors of the state variables. Therefore, we define P and Q errors, e_P and e_Q respectively, and so, the aim is to minimize the possible the active and the reactive power errors are given as:

$$\begin{cases} e_P = P_{ref} - P \\ e_Q = Q_{ref} - Q \end{cases} \tag{2}$$

3.3 Power grid neurocontroller model

The proposed intelligent control aimed to maintaining the desired active and reactive power of the grid with their references. Considered for the neural controller output were the references current components in *dq* frame that would present an action intervention for hysteresis control inverter after transformation in real three phase reference farm and comparing with the real currents of grid.

Although the system inverse model plays an important part in the theory of control, the achievement of its systematic form is pretty strenuous. Expecting that a dynamic system can be described by the differential equation:

$$Y(i+1) = f\left[Y(i),\ldots,Y(i-n+1),U(i),U(i-n+1)\right] \tag{3}$$

Where the system output *Y(i+1)* depends on the preceding *n*-output values, the system inverse model can be generally presented in the following form:

$$U(k) = f^{-1}\left[r(i+1),Y(i)\ldots,Y(i-n+1),U(i),U(i-n+1)\right] \tag{4}$$

Here *Y(i+1)* is an unknown value, and hence can be alternated by the output quantity desired value *r(i+1)*. The simplest way to arrive at a system inverse NN model is it to train process to approximate the system inverse model.

The Feed Forward Time-Delay Neural Network [19] architecture contains a set of delays at the input layer that allows retention of the evolution of the inputs in time, and enhances the ability of the NN for time series applications. The number of delays can be different for each input, which allows the network to pact with the differences in the time evolution of the inputs. Figure 4 shows a diagram for the proposed intelligent control based ANN with two inputs, two delays for one input and one for the other input, two nonlinear neurons in the input layer and one linear neuron in the output layer.

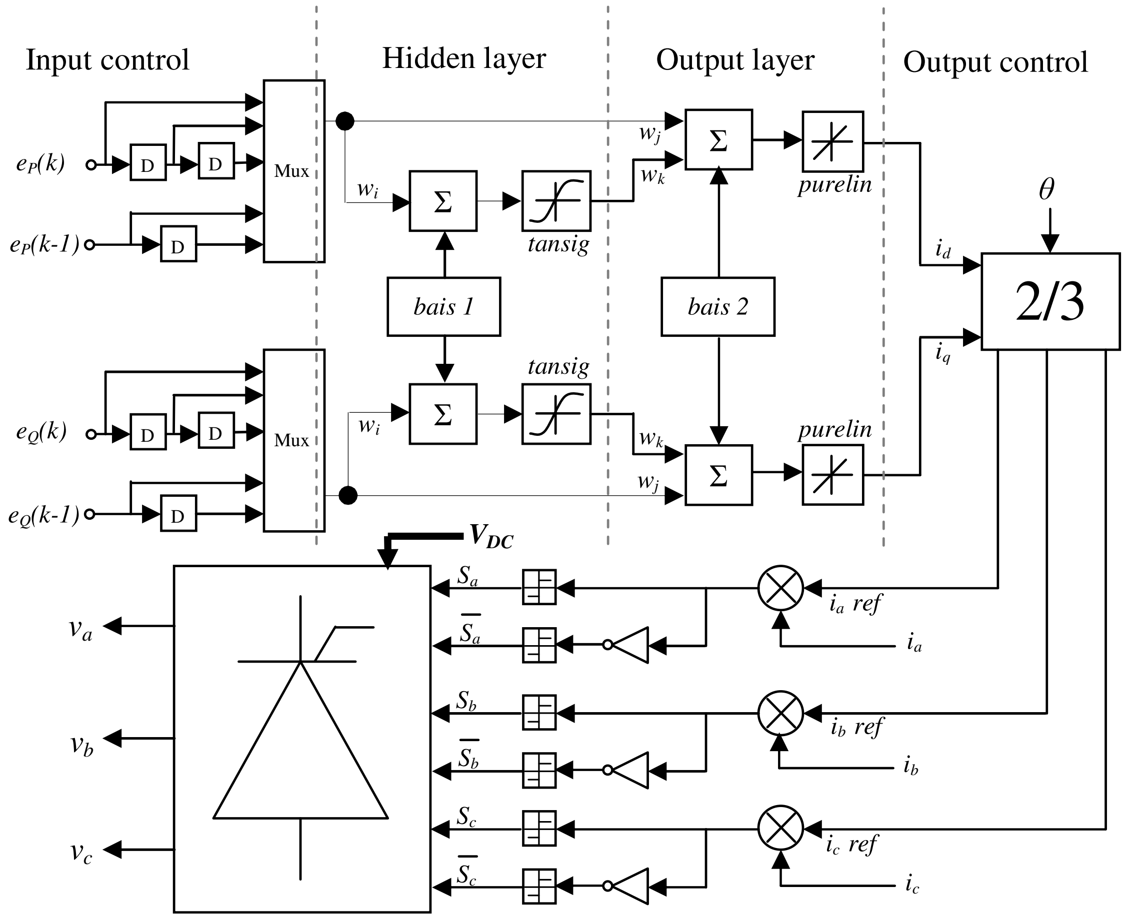


Figure. 4: Proposed neurocontroller of *P* and *Q* in grid connected-photovoltaic generation system based on hysteresis inverter.

4. Simulation results

Table 1 summarizes the important required parameters of the PV generator and the utility grid with different accessories of the simulation model. At irradiation of 1000W/m^2 and temperature of 25^{0}C, solar array is generating 440V DC voltage. The generated DC voltage is converted to the grid using two-level DC/AC hysteresis inverter after filtrate using inductor filter. The switching frequency of the hysteresis inverter is 2kHz.

Table 1: Simulation parameters

	Parameter	Index	Value	Unite
PV generator	Open-circuit voltage	V_{OC}	21.7	V
	Voltage at the maximum power point	V_{mp}	19.8	V
	Short circuit current	I_{SC}	5	A
	Current at the maximum power point	I_{mp}	3.28	A
	Number of modulus in parallel	N_P	10	--
	Number of modulus in series	N_S	22	--
Grid	Grid Inductor	L_g	10^{-5}	H
	Grid Resistor	R_g	0.01	Ω
	Max of active power grid	P_{Max}	10	KW
	Max of reactive power grid	Q_{Max}	1	$KVAR$
	RMS phase	V_g	380	V
Filter	Filter Inductor	L_f	0.002	H

A digital simulation was carried out using MatLab Simulink interface for the proposed system and was run for 3s which show the results obtained for voltage and current waveforms, active and reactive powers on the AC side supplied to the grid. The maximum of active power injected in grid is 10kW and the maximum of reactive power is 1kVAR.

For analyzing the performance of the grid connected solar system with the proposed intelligent active and reactive power controller various active power and reactive power injected into the grid for nine generation conditions selected all possibilities of active and reactive power variation in grid with percent for the maximum power injected by the photovoltaic generation system to the grid were the total injected power is absorbed by the load. Nine steps of changes load are describes in table 2.

Table 2: P and Q injected into the grid with 9 generation conditions

t(s)	0→0.5	0.5→0.75	0.75→1	1→1.25	1.25→1.5	1.5→1.75	1.75→2.25	2.25→2.5	2.5→3
P (%)	100	50	50	0	0	100	100	100	0
Q (%)	0	0	50	50	100	100	50	0	0

Figure 5 shows the output grid voltage of the phase "*a*" of the solar inverter before filtering and an enlarged waveform. For making the inverter output voltage into pure sinusoidal AC voltage an *L* filter is used. The numeric value of the filter inductance (L_f) is 20mH. Figure 6 shows the solar inverter output of the three phase voltage after filtering with enlarged waveforms as well the phase "*a*" using the *L* filter.

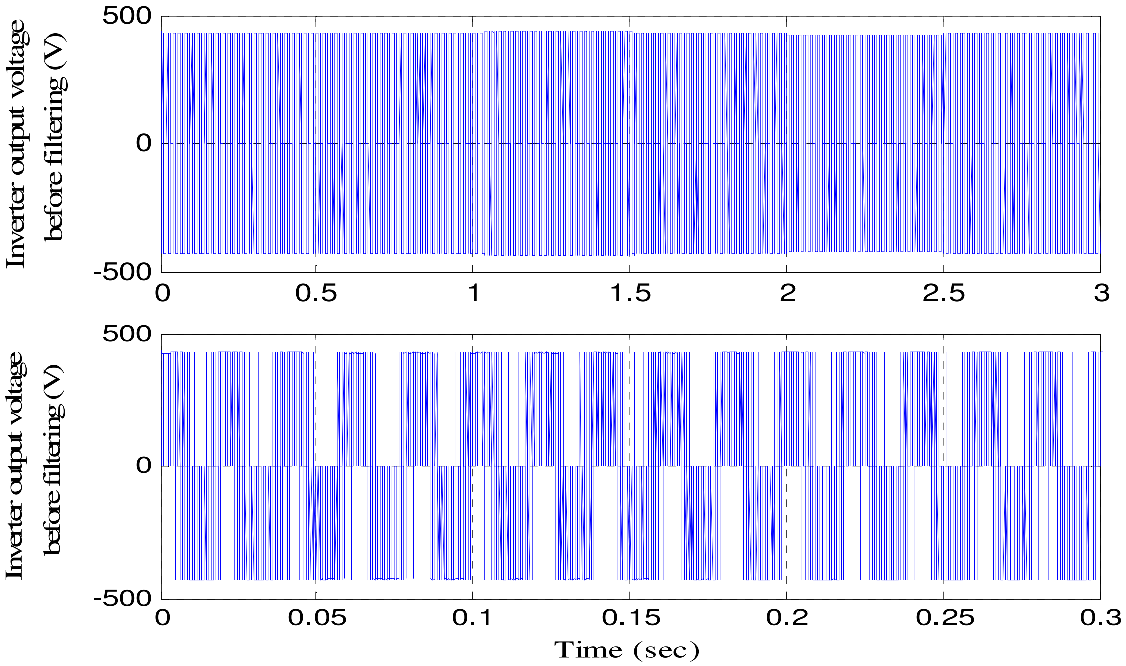


Figure. 5: Zoom of inverter output voltage of phase “*a*” before filtering.

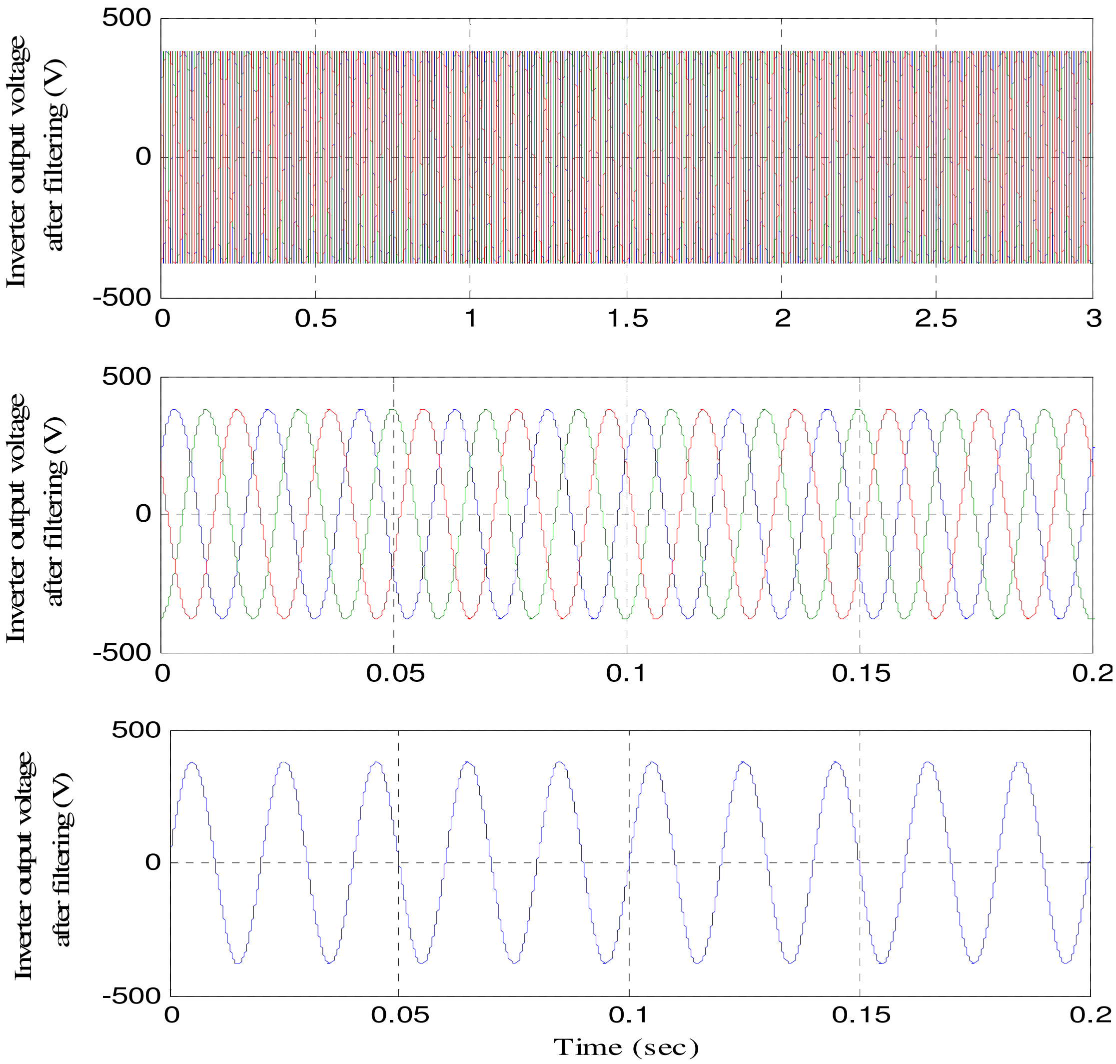


Figure. 6: Inverter output voltage, enlarged waveform of inverter output voltage and enlarged waveform of the phase “*a*” after filtering.

Figure 7 show active and reactive power with their references that prove a good control performance. P and Q follows their references are done in table 2. As observed that, when P is reduced, the control is adjusted to increase Q. Hence, the values of inverter current (Figure 8) can get the rate values. Injected power from PV system to the grid devised into active and reactive power side grid presents a reasonable system response. Presented system receives the advantage of ability of the compensation of reactive power. Many enlarged waveforms of grid current illustrates by figure 9. It is clear that the grid current has a sinusoidal form varied with the active power variation but not an important influence with the reactive power variation.

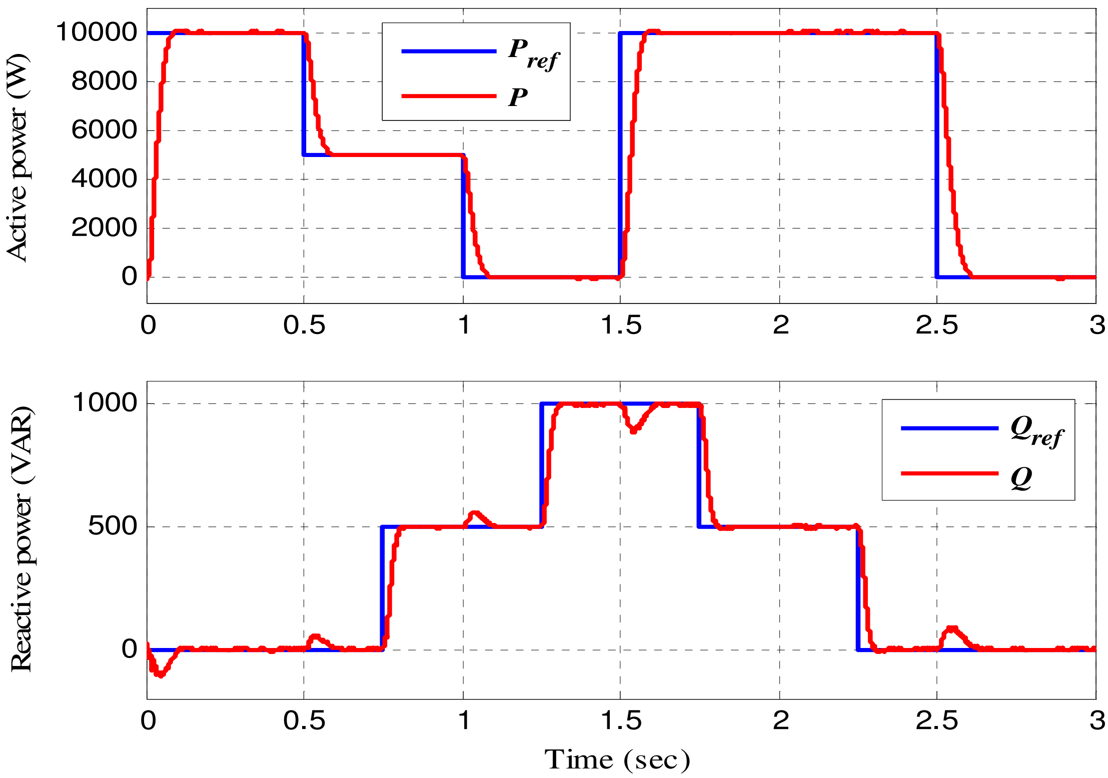


Figure. 7: Active and reactive power variation of grid.

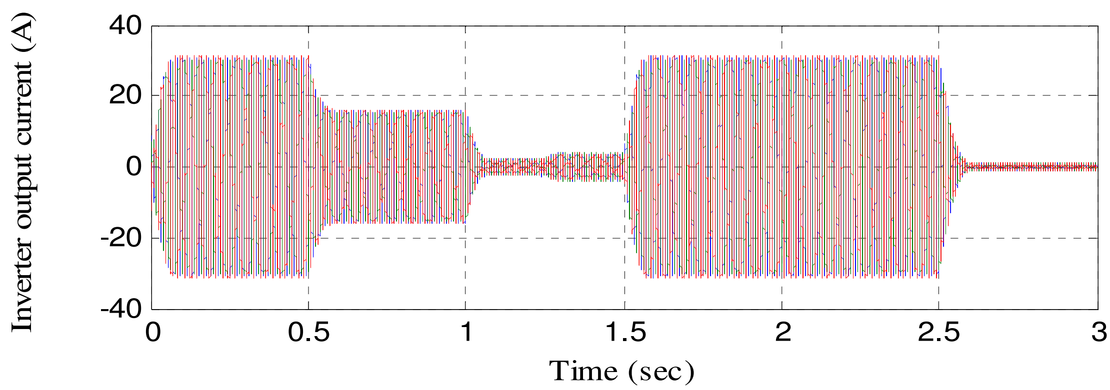


Figure. 8: Three phase inverter output current.

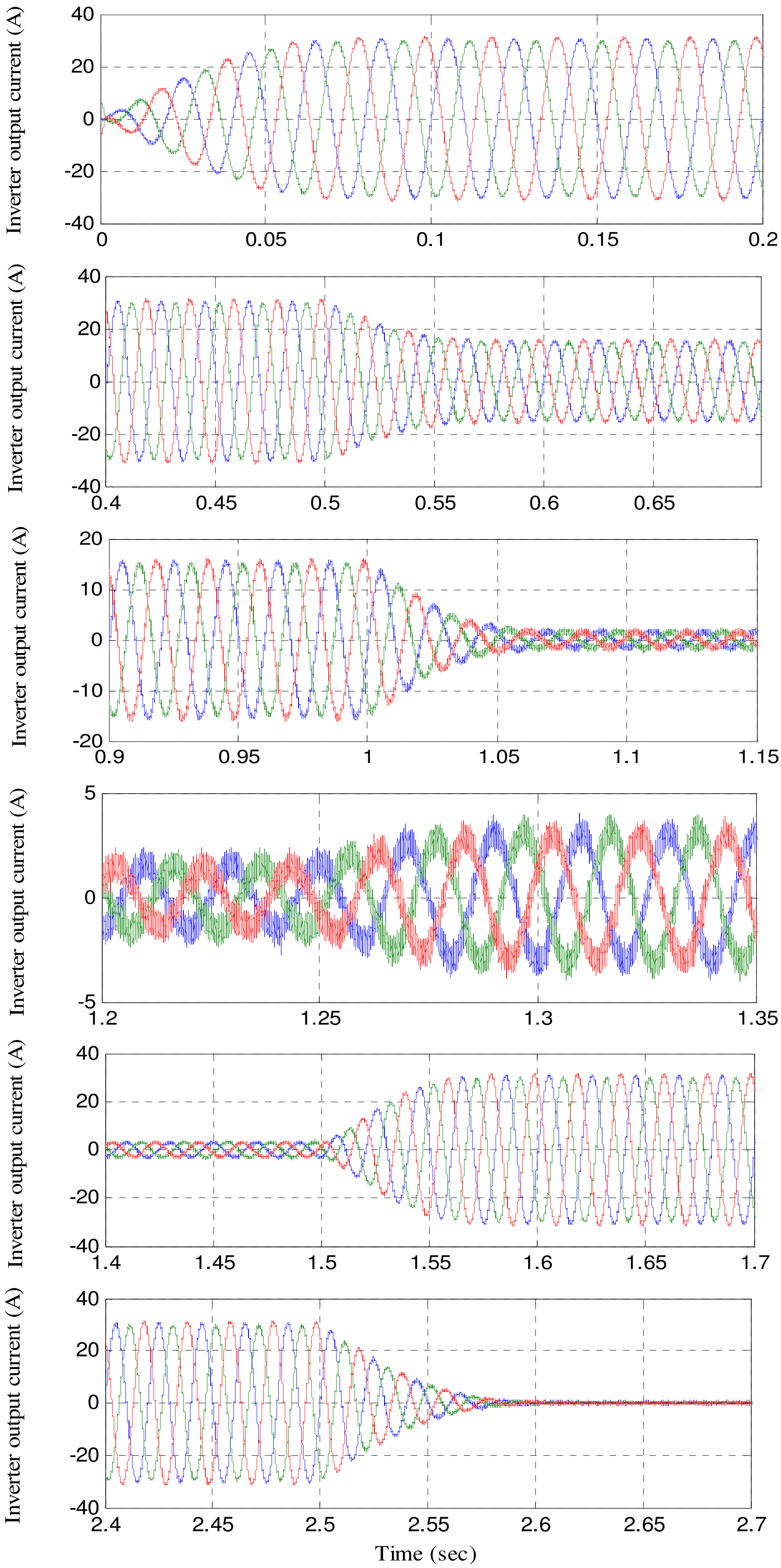


Figure. 9: Enlarged waveforms of inverter output current.

Figure 10 shows the voltage and current of the active and reactive power neurocontroller for hysteresis inverter of the grid-connected PV generation system, the simulation is done under different active and reactive power steps changing. Load changed via different ladder signified all possibilities are varied as:

- Active power: from heavy to medium load; from medium to no load; from no load to heavy load; from heavy to no load.
- Reactive power: from no load to medium; from medium to heavy load; from heavy to medium load; from medium to no load.

The results under different step load (active and reactive power) changes are given to examine the load variation effect. It is observed that a good synchronism of the output current and the grid voltage that more obvious via many zooms are done by figure 11.

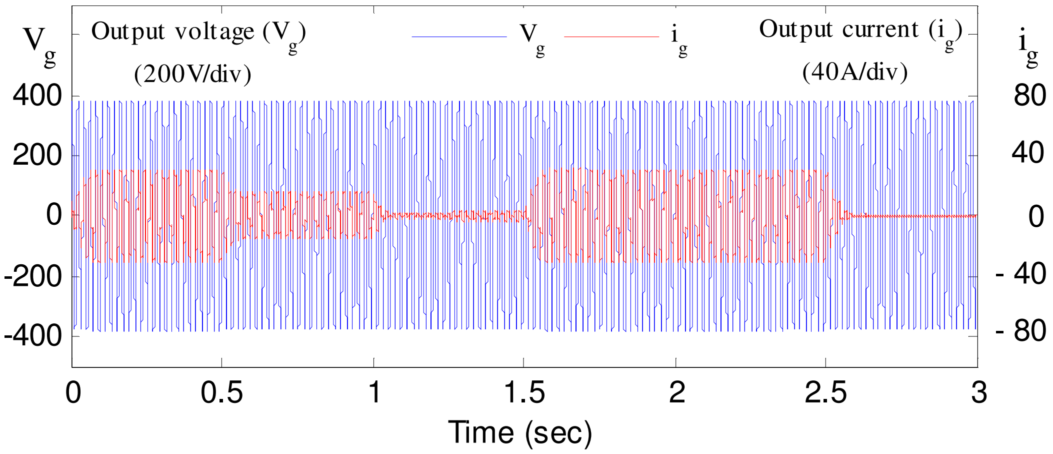
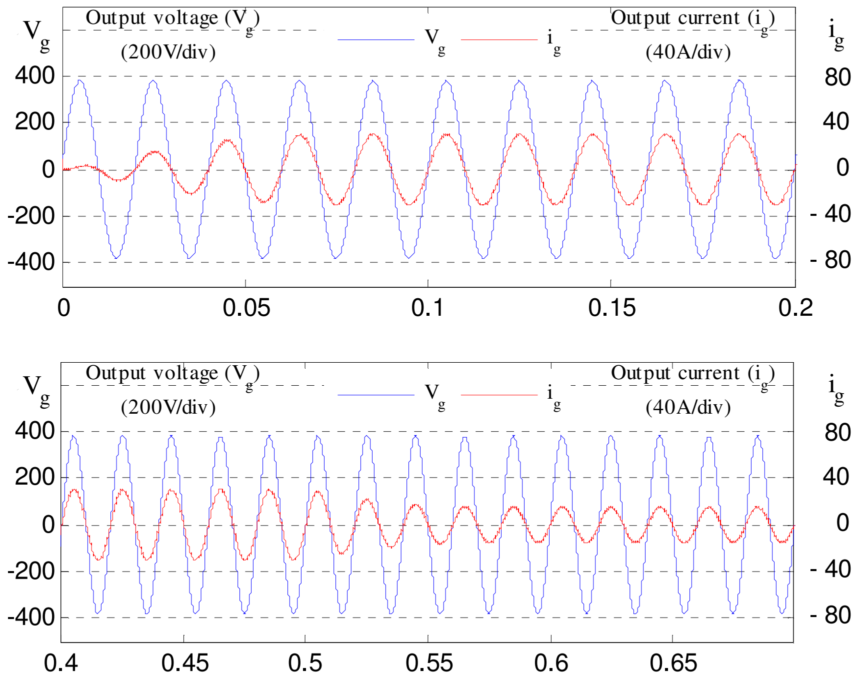


Figure. 10: Synchronism of inverter output current with grid voltage.



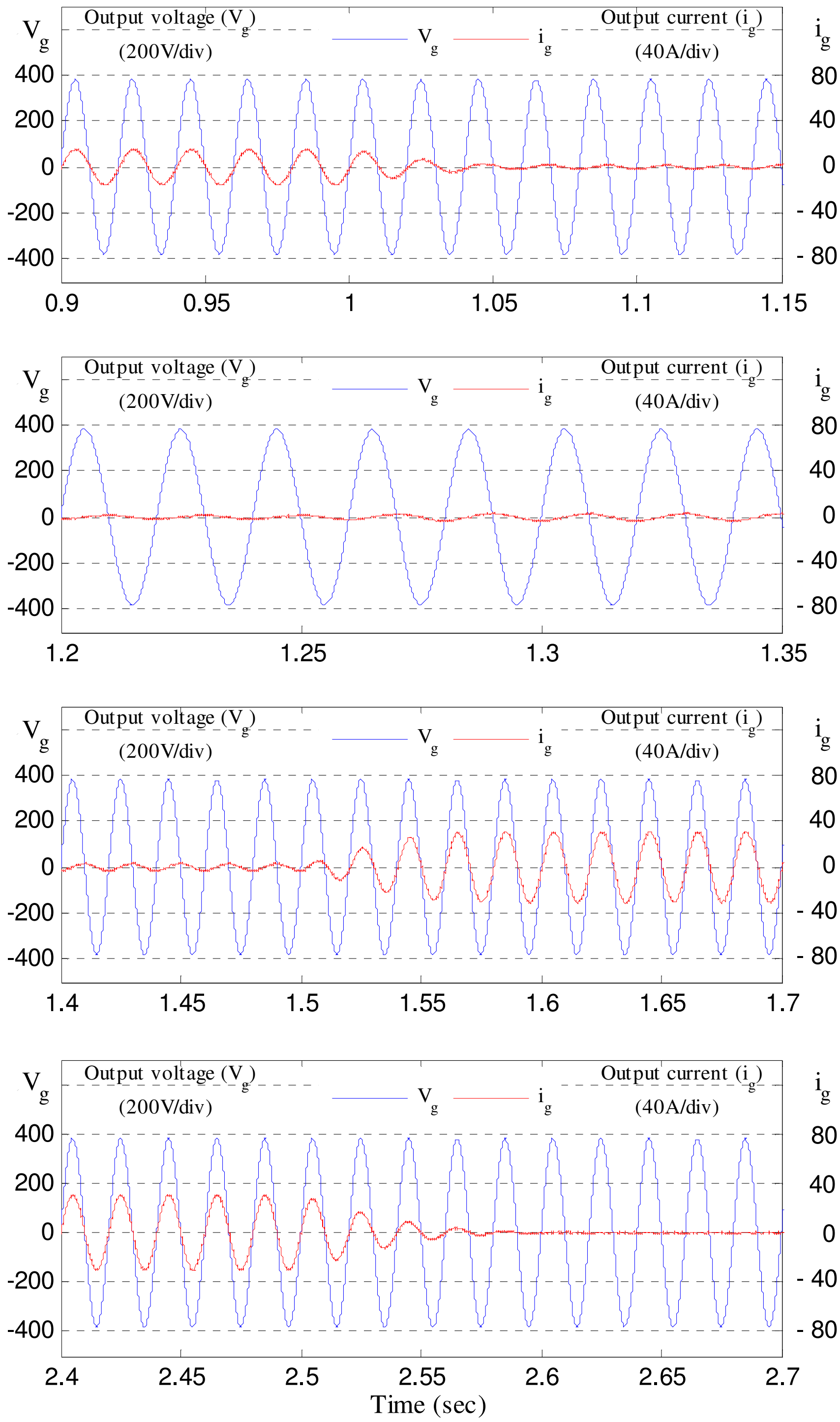


Figure. 11: Enlarged waveforms of inverter output current in phase with the grid voltage.

5. Conclusion

In this paper, performance analysis of grid-connected photovoltaic generator via hysteresis inverter using active and reactive power neurocontroller under load variation has been done. The proposed intelligent power grid control enabled the control independently of active and reactive power with the possibility of doing the compensation of the reactive power. Also, the proposed control system allows maintaining the output current approximately in phase with the utility voltage.

References

[1] J. Wang, Y. LiSu, J. Cherng, and J. Jiang, "High-accuracy maximum power point estimation for photovoltaic arrays", *Solar Energy Materials & Solar Cells*, vol. 95, pp. 843–851, 2011.

[2] R. J. Wai, and W. H. Wang, "Grid-Connected Photovoltaic Generation System", *IEEE Transactions on circuits and systems*, vol. 55, no. 3, pp. 953-964, 2008.

[3] Y. Yong, Z. Binbin, and W. liang, "Multistring Power Conditioning System For Grid-connected Photovoltaic Inverters", *J. Electrical Systems*, vol. 9, no. 4, pp. 392-400, 2013.

[4] J. Shen, H. Jou, J. Wub, and K. Wua, "Single-phase three-wire grid-connected power converter with energy storage for positive grounding photovoltaic generation system", *Electrical Power and Energy Systems*, vol. 54, pp. 134-143, 2014.

[5] K. H. Chua, Y. S. Lim, P. Taylor, S. Morris, and J. Wong, "Energy Storage System for Mitigating Voltage Unbalance on Low-Voltage Networks With Photovoltaic Systems", *IEEE Transactions on power delivery*, vol. 27, no. 4, pp. 1783-1790, 2012.

[6] B. Zhu, Y. Yang, A. Ji, X. Tao, M. Xie, and F. Cao, "A Novel Control Strategy for Single- Phase Grid-Connected PV Generation System with the Capability of Low Voltage Ride Through", *J. Electrical Systems*, vol. 10, no. 4, pp. 370-380, 2014.

[7] X. Maa, Z. Tao, Y. Wang, H. Yu, and Y. Wang, "Long short-term memory neural network for traffic speed prediction using remote microwave sensor data", *Transportation Research*, vol. 54, pp. 187-197, 2015.

[8] N. Wang, and H. Adeli, "Self-constructing wavelet neural network algorithm for nonlinear control of large structures", *Engineering Applications of Artificial Intelligence*, vol. 41, pp. 249-258, 2015.

[9] K. Mathiyalagan, J. H. Park, and R. Sakthivel, "Synchronization for delayed memristive BAM neural networks using impulsive control with random nonlinearities", *Applied Mathematics and Computation*, vol. 259, pp. 967–979, 2015.

[10] N.A. Ahmed, M. Miyatake, and A.K. Al-Othman, "A stand-alone hybrid generation system combining solar photovoltiac and wind turbine with simple maximum power point tracking", *Electric Power Components Syst*, vol. 37, no. 1, pp. 43–60, 2009.

[11] N.A. Ahmed, M. Miyatake, and A.K. Al-Othman, "Power fluctuations suppression of stand-alone hybrid generation combining solar photovoltaic/wind turbine and fuel cell systems", *Energy Conversion Manage,* vol. 49, no. 10, pp. 2711–2719, 2008.

[12] T. Noguchi, S. Togashi, and R. Nakamoto, "Short-current pulse-based maximum power point tracking method for multiple photovoltaic-and-converter module system", *IEEE Trans. Ind. Electron,* vol. 49, no. 1, pp. 217–223, 2002.

[13] T V.V.R. Scarpa, S. Buso, and G. Spiazzi, "Low-complexity MPPT technique exploiting the PV module MPP locus characterization", *IEEE Trans. Ind. Electron,* vol. 56, no. 5, pp. 1531–1538, 2009.

[14] W. Xiao, M. G. J. Lind, W. G. Dunford, and A. Capel, "Real-Time Identification of Optimal Operating Points in Photovoltaic Power Systems", *IEEE Trans. Ind. Electron,* vol. 53, no. 4, pp. 1017–1026, 2006.

[15] F.L. Lewis, "Neural Networks in Feedback Control Systems", *Mechanical Engineer's Handbook,* John Wiley, New York, 2005.

[16] H. D. Patiño, R. Carelli, and B. R. Kuchen, "Neural Networks for Advanced Control of Robot Manipulators", *IEEE Transactions on Neural Networks,* vol. 13, no. 2, pp. 343–354, 2002.

[17] K. P. Tee, S. S. Ge, and F. E. H. Tay "Adaptive Neural Network Control for Helicopters in Vertical Flight", *IEEE Transactions on Control Systems Technology,* vol. 16, no. 4, pp. 753–762, 2008.

[18] G. V. Puskorius, and L. A. Feldkamp, "Neurocontrol of Nonlinear Dynamical Systems with Kalman Filter Trained Recurrent Networks", *IEEE Transactions on Neural Networks,* vol. 5, pp. 279-297, 1994.

[19] D. Pérez, and R. Bevilacqua, "Neural Network based calibration of atmospheric density models", *Acta Astronautica,* vol. 110, pp. 58-76, 2015.