Predictive Direct Power Control of Shunt Active Power Filter Associated to PV System and ANN-Backstepping MPPT

Meraouah Mustapha[1], Kaddari Faiza[2], Hassaine Said[1], Mihoub Youcef[1], Heroual Samira[1]
Khenfar Noureddine[3]
[1] Electrical Engineering Department, Ibn Khaldoun University
Tiaret, Algeria
[2] Higher School of Electrical and Energy Engineering
Oran, Algeria.
[3] Electrical Engineering Department, University of Djilali Liabes
Sidi Bel Abbas, Algeria
[*]Corresponding author; Email: mustapha.meraouah@univ-tiaret.dz

Article Info

Article history:

Received , 15/03/2024
Revised , 15/05/2024
Accepted , 05/06/2024

Keywords:

Shunt active power filter
Predictive direct power control
Artificial Neural network
Backstepping
PV system

ABSTRACT

An enhanced predictive direct power control of a three-phase shunt active power filter (SAPF) is required to eliminate power ripples with low current distortion and lower the maximum overshoot and undershoot of the DC-link voltage fluctuation in compliance with IEEE Std. 519–2014, solar energy is a very important renewable energy that can complete the increase of power demand and used it associated with SAPF; in this work, we propose an effective MPPT based on the combination of artificial neural network and non-linear control type backstepping, the total energy obtained from the PV system injected to the grid with predictive direct power control to eliminate the harmonics and inject the totality of energy generated, the system was implemented under MATLAB/Simulink to verify the efficacy and the robustness of the results.

I. Introduction

The demand for electricity in the contemporary industrial world is constantly increasing, whether for residential utilities or commercial sectors. Energy distribution methods based on renewable energies are becoming more and more economically and technologically fascinating. Various technical and environmental concerns have increased the level of integration of these sources. Solar photovoltaic (PV) systems are one of the many ways to obtain energy from renewable energy sources, and they have generated a lot of interest due to their unique advantages, such as ease of allocation, absence of fuel costs, and wide distribution on the planet. In addition, governments and several companies strongly encourage the use of photovoltaic (PV) systems for electricity production[1]. The DC/DC boost power converter connects the photovoltaic panels to the electrical grid. The converter acts as a maximum power point tracker (MPP) [2]. The voltage and current characteristics of photovoltaic panels vary according to their irradiation and their temperature. Maximum power tracking algorithms (MPPT) have been used to track the maximum power of a photovoltaic module. Disorder and observation (P&O), incremental and conductance (I&C), fractional open-circuit voltage and fractional short-circuit current are some of the many MPPT strategies that have been developed and implemented [3]. Due to the disadvantages of conventional techniques, researchers are now more attracted to soft computing techniques, also known as bio-inspired and artificial intelligence methods. In addition, many control applications develop adaptive and robust control algorithms. A well-known control algorithm, sliding mode control (SMC) and backstepping control, is designed in comprehensive case studies to guarantee the previously mentioned control objectives. However, high-frequency oscillations can be dangerous for the conventional SMC and backstepping in real-world applications. Fuzzy logic controllers (FL) and artificial neural networks (ANN) are techniques based on artificial intelligence used to reach the power point of photovoltaic modules. The advantages of these methods include working with variable inputs, the absence of accurate mathematical modelling, self-convergence and self-learning abilities. They are adaptable to the non-linear behaviour of the systems. ANN-based MPPT techniques have recently become more and more popular. An ANN-based MPPT technique is proposed due to its fast-tracking speed and low computational requirement [4]. In addition, due to the rapid progress in the field of power electronics, the electrical network has been subjected to significant disturbances, such as harmonics and unbalanced currents, due to the intensive use of non-linear loads. This wide range of power conversion systems, control electronics, and non-linear loads include adjustable speed driving, domestic machinery, transformer saturation, etc.

Recently, active power filters have been proposed as one of the most common solutions to the harmonics problem. The SAPF injects the compensation current into the PCC to eliminate the harmonics and provide a sinusoidal source current [5], [6]. Research has shown that various shunt active power filter topologies are effective in various applications where various control techniques are used, such as direct power control and instantaneous active and reactive power control. One is based on direct power control, while the other is on direct control of the protective power supply. The robustness and the simplicity of implementation of the control are some of the advantages of this method [7].

This paper is presented in 4 sections; the first section explains the PV system and the MPPT proposed to extract the maximum power named NN-backstepping because it is based on the combination of the two methods; the second section presents the predictive direct power control for the calculation of the reference current. The third section presents the total Simulink results obtained from MATLAB/Simulink and Concludes this work.

II. System Description

This section presents a description of the studied system. The shunt active power filter, the DC-DC converter connected to the photovoltaic sources and the injection of energy into the network are all functions of the system [8]. Fig. 1 shows its schematic diagram. The system is composed of three main parts, as can be seen in the figure below.

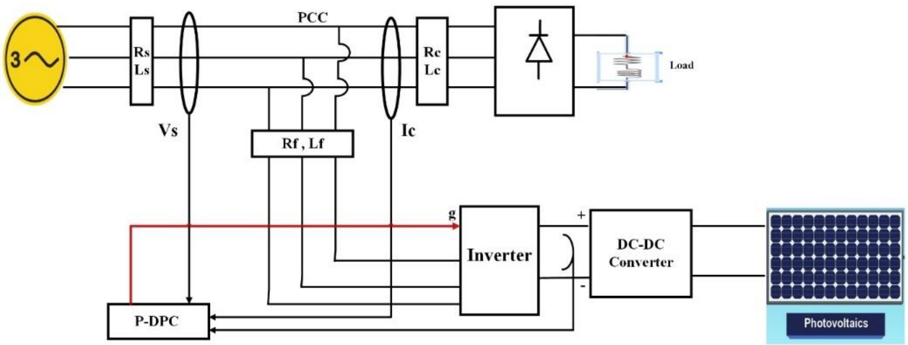

Figure 1. Shunt active power filter topology associated with the PV system.

A photovoltaic network transforms solar energy into electricity. Then, the DC-DC step-up converter amplifies the voltage of the photovoltaic grid to follow the highest point of the photovoltaic grid. The DC connection capacitor is connected to the three phases VSI in series [9].

III. PV System

The most critical component of a PV is the PV cell. A photovoltaic module is a set of cells connected to form a photovoltaic panel; a photovoltaic array comprises many panels [10]—voltage and current produced by the photovoltaic generator. Fig. 2 represents the solar cell's operational electrical circuit and the inverted diode.

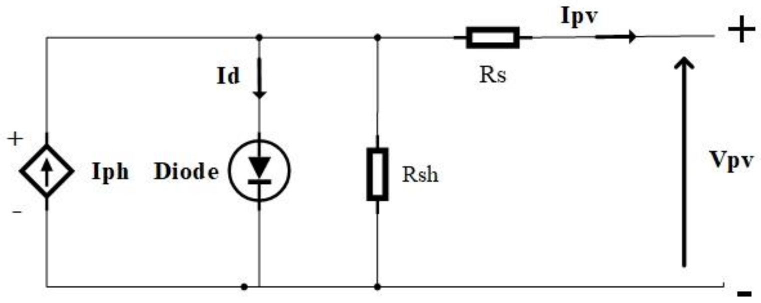

Figure 2. PV cell model.

The formula Eq(1) can be used to express the photon current model of the solar cell :

$$I_{ph} = [I_{rs} + K_i.(\mathrm{T} - \mathrm{Tr}].\frac{G}{G_r} \tag{1}$$

The current of the photovoltaic cell can be measured in this way:

$$I_{pv} = I_{ph} - I_{sat}\left(e^{\frac{q(V_{pv}+R_s.I_{pv})}{n.K.TNs}} - 1\right) - \mathrm{Np}\left(\frac{qV_{pv} + qR_s.I_{pv}}{R_{sh}\,R_s}\right) \tag{2}$$

The dynamic equations of the converter are derived from the inductance current and the voltage of the photovoltaic generator, where the state model is:

$$\begin{cases} \dot{x}_1 = \dfrac{1}{C_1} i_{pv} - \dfrac{1}{C_1} x_2 \\ \dot{x}_2 = \dfrac{1}{L} x_1 - \dfrac{1}{L}(1-D)V_{out} \end{cases} \tag{3}$$

Where $[x_1 \;\; x_2]^T = [V_{pv} \;\; I_L]^T$

I.1. Artificial neural network-based backstepping MPPT control

In this work, the MPPT controller based on the ANN-backstepping approach is proposed, which is designed using the Lyapunov theory; the output voltage of the panel must be controlled and conveindices V_{pvref} value given by the ANN controller to obtain the maximum power of the photovoltaic power board for different irradiation change[11].

1) Backstepping control

The first error variable is:

$$e_1 = x_1 - V_{pvref} \tag{4}$$

Using the system (4,5), the tracking error derivative is written as follows:

$$\dot{e}_1 = \dot{x}_1 - \dot{V}_{pvref} = \frac{1}{C_1}(i_{p_v} - x_2) - \dot{V}_{pvref} \tag{5}$$

The candidate Lyapunov function is considered:

$$V_1(e_1) = V_1 = \frac{1}{2}e_1^2 \tag{6}$$

This function is positive definite, the derivative versus time using equation (6) is:

$$\dot{V}_1 = e_1\dot{e}_1 = e_1\left(\frac{1}{C_1}(i_{p_v} - x_2) - \dot{V}_{pvref}\right) \tag{7}$$

relevant choice of α_1 allows to write $\dot{e}_1 \doteq -\lambda_1 e_1^2$, $\dot{V}_1$is negative semi-definite function for that its must be:

$$\alpha_1 = i_{p_v} + C_1\left(\lambda_1 e_1 - \dot{V}_{pvref}\right) \tag{8}$$

In order to guarantee the stability of the subsystem, λ_1 is a positive constant that represents a design parameter of the rollover controller.

The second error variable, which is defined as the difference between the state x_2 and its desired value α_1, is expressed as:

$$e_2 = x_2 - \alpha_1 \tag{9}$$

After deducing the equations of the system in the error space (e_1, e_2) below:

$$\begin{aligned} \dot{e}_1 &= i_{pv} + \frac{1}{C_1}(\alpha_1 + e_2) + \frac{1}{C_1} i_{pv} - \dot{V}_{pvref} \\ \dot{e_2} &= \frac{1}{L}(x_1 - (1 - D_1)V_{out}) - \dot{\alpha}_1 \end{aligned} \tag{10}$$

The new Lyapunov function:

$$V_2(e_1, e_2) = V_1 + \frac{1}{2} e_1^2 \tag{11}$$

The derivative function expressed by:

$$\begin{aligned} \dot{V_2}(e_1, e_2) &= \dot{V_2} \\ \dot{V_2} &= e_1\left(\frac{1}{C_1} e_2 - \lambda_1 e_1\right) + e_2\left(\frac{1}{L}(x_1 - (1 - D_1)V_{out}) - \dot{\alpha_1}\right) \\ \dot{V_2} &= -\lambda_1 e_1^2 + e_2\left(-\frac{1}{C_1} e_1 + \frac{1}{L}(x_1 - (1 - D_1)V_{out}) - \dot{\alpha_1}\right) \end{aligned} \tag{12}$$

In this step, the command choosing D_1 to obtain the following expression:

$$\left(-\frac{1}{C_1} e_1 + \frac{1}{L}(x_1 - (1 - D_1)V_{out}) - \dot{\alpha_1}\right) = -\lambda_2 e_2 \tag{13}$$

the backstepping controller produces the expression of command D_1 by this:

$$D_1 = 1 - \frac{1}{V_{out}}\left[x_1 - L\dot{\alpha_1} - L\left(\frac{1}{C1} e_1 - \lambda_2 e_2\right)\right] \tag{14}$$

With $\lambda_2 > 0$ leads to semi negative derivative of the Lyaponov function:

$$\dot{V_2} = -\lambda_1 e_1^2 - \lambda_2 e_2^2 \tag{15}$$

This ensures that the error variables (e_1, e_2) converge asymptotically towards the origin, which implies that x_2 converges asymptotically towards the origin (V_{pvref}), thus allowing the maximum power extraction from the PV system.

2) Reference voltage with artificial neural network

ANNs are well known for solving complex problems with non-linearities. Artificial neural network works like an A biological neural network. It is mainly made up of closely related neurons, such as brain cells. The layers generally comprise an input layer, an emission layer and one or more concealed layers. The interconnection weights wij ultimately connect each layer to the adjacent layers, as shown in Fig 3. The neural network must be properly trained to perform the intended task correctly. The parameters of the photovoltaic module such as Voc and Isc, the irradiation and the temperature can be the inputs, or any corresponding configuration. The start cycle is usually used as the converter input for the maximum power point[12].

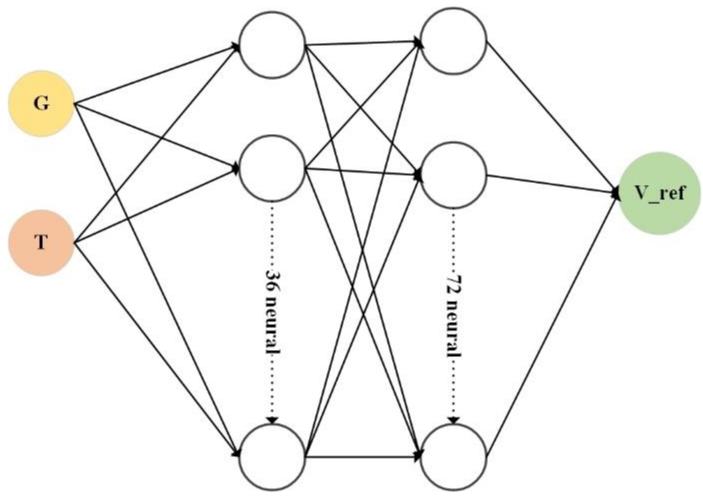

Figure 3. Artificial neural network structure.

In this work, we used the structure of a neural network containing 1 input layer, 2 hidden layers (first with 36 neural, second 72 neural) and one output layer. Logh and Hardlims are used as activation functions.

The neural network proposed to extract the reference voltage for the PV system was trained based on the data shown in Figure 4.

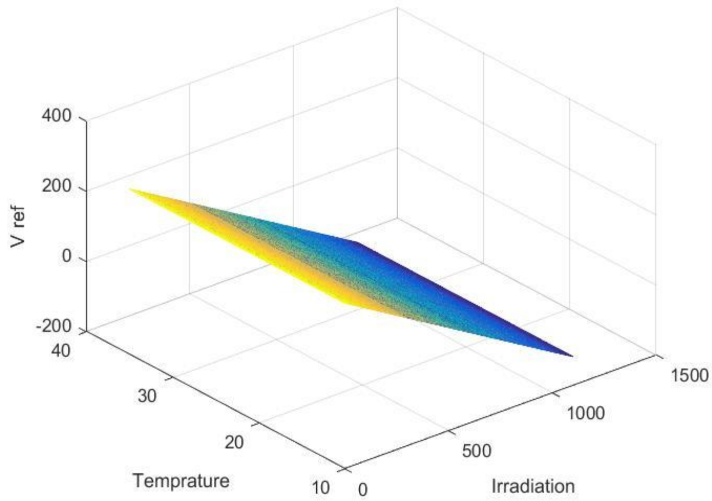

Figure 4. 3-D plane of ANN proposed.

The training was stopped at 503 epoch with the best validation and performance, as shown in Figure 5.

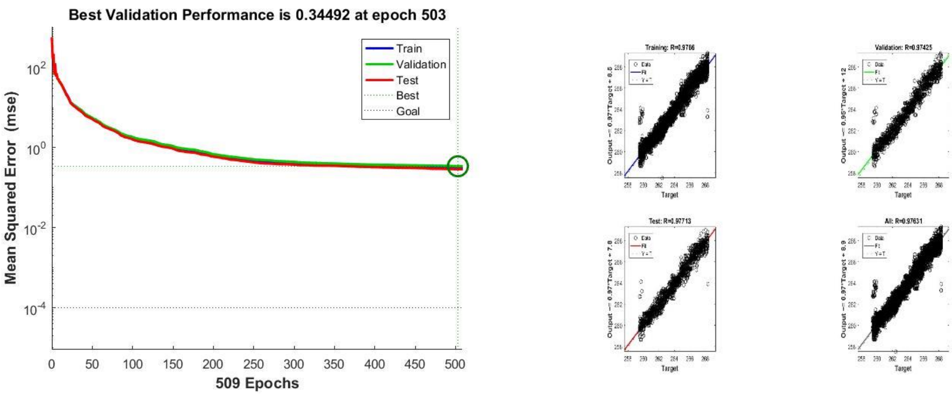

Figure 5. Performance and regression of training.

IV. Predictive direct power control of SAPF

The predictive direct power control needs the model of the global system wish is giving by the following equation:

$$\begin{aligned} e_{sa} &= R_s\, i_{sa} + L_s \frac{di_{sa}}{dt} + V_{sa} \\ e_{sb} &= R_s\, i_{sb} + L_s \frac{di_{sb}}{dt} + V_{sb} \\ e_{sc} &= R_s\, i_{sc} + L_s \frac{di_{sc}}{dt} + V_{sc} \end{aligned} \tag{16}$$

Predictive control needs the equation of the model in the discrete time for that, the current derivative is given by Euler as:

$$\frac{di_s}{dt} = \frac{i(k+1) - i(k)}{T_s} \tag{17}$$

Where T_s is the sampling time.

The shunt active power filter controlled by PDPC As shown in Fig. 6, the PI controller is used for control the DC bus voltage and generate the active power reference for the power control strategy [13]; the predicted power is generated and the cost function used to minimise the error and locate the corresponding victor of SAPF to eliminate the reactive power and inject the power of the PV system and enhanced the quality of the source current.

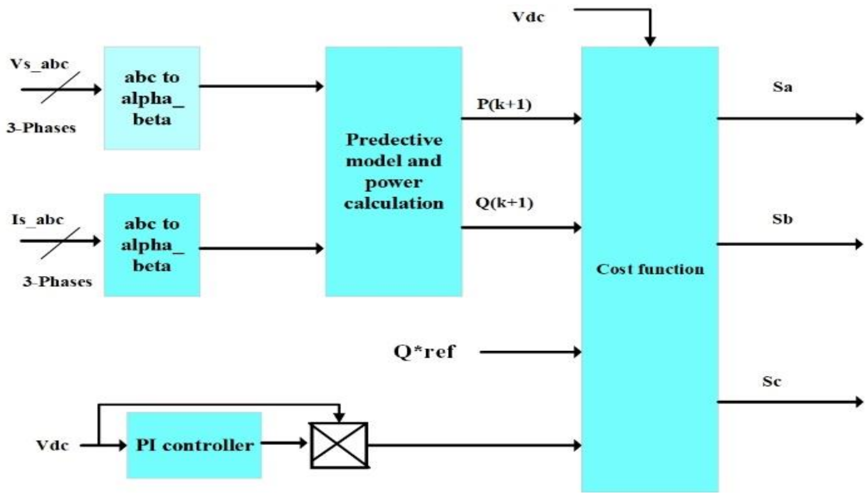

Figure 6. Diagram block of predictive direct power control.

IV.1. Vectors of voltage for 2-Level VSI

Figure 7 provides eight voltage vectors for a voltage source inverter (VSI) of 2 Level [14]. The vectors V_1 and V_8 are zero, while the other vectors are active voltage vectors.

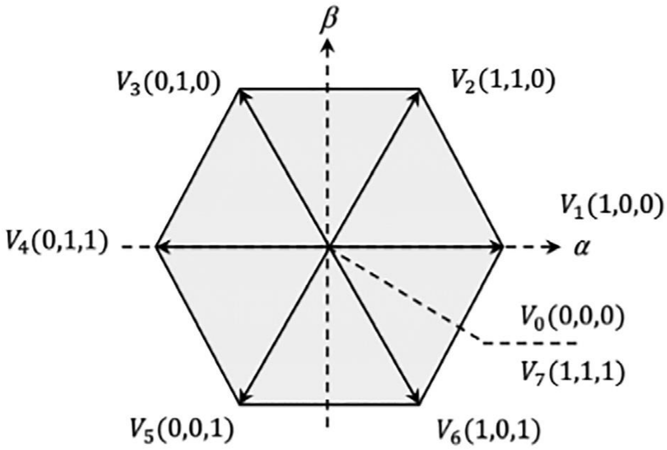

Figure 7 . Voltage vectors according to the switching states.

V. Simulink result

The system proposed was verified and tested by MATLAB/Simulink under fast irradiation change, as shown in Figure 8 and the parameter of the system is presented in Table 2. The result is presented in Figure 9,10.

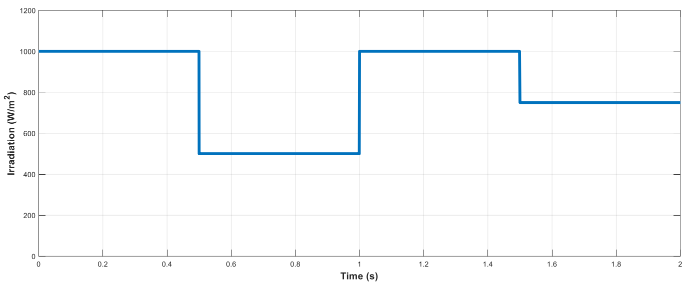

Figure 8. Irradiation profile.

Vsrms	Rs	Ls	Rc	Lc
220 V	3.5 mΩ	0.023 mH	0.82 mΩ	0.4 mH
Rf	**Lf**	**Rd**	**Ld**	**Vdc**
0.5 Ω	1 mH	3.15 Ω	2.5 mH	700 V
Pmax	**Vco**	**Icc**	**Vmpp**	**Impp**
200.143 W	32.9 V	8.21A	26.3 V	7.61 A

For this system, we use 5 parallel and 10 series strings type KYOCERA SOLAR KC200GT PANEL to generate at G=1000 w/m^2 power equal to 10Kwatt.

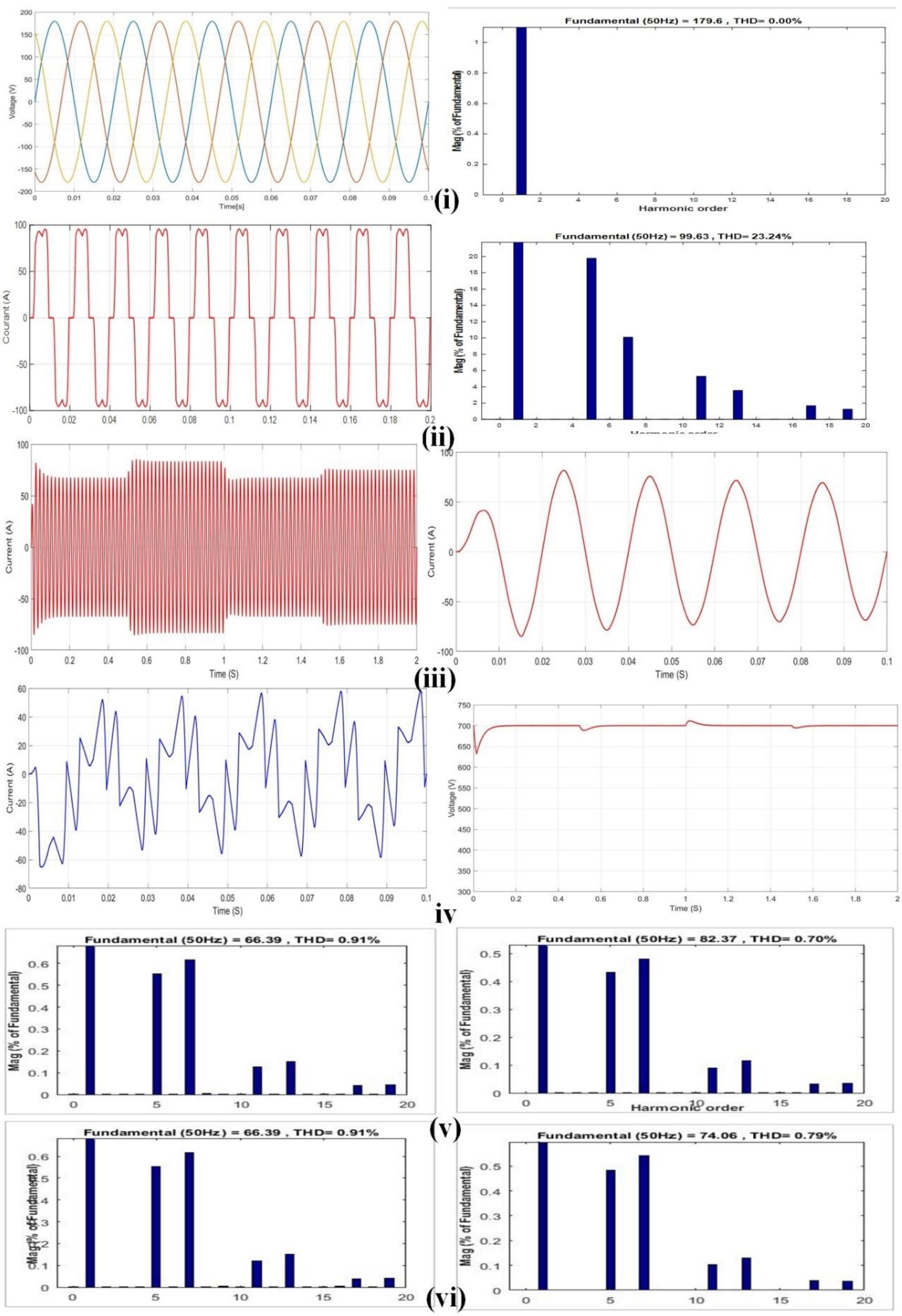

Figure 10. Simulation results of fast irradiation change: (i) three-phase source voltages and frequency spectrum of the source voltage of phase a (ii) load currents phase a and frequency spectrum of load current of phase-a, (iii) source current of phase-a , (iv) filter current of phase-a and the DC bus voltage, (v) frequency spectrum of source current of phase a in the first and second case,.(vi) frequency spectrum of source current of phase a in the third and fourth case.

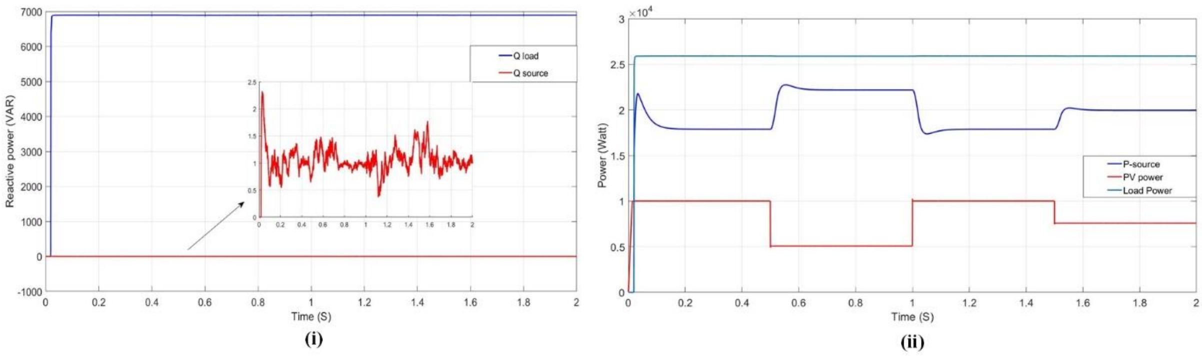

Figure 11. Power result :(i) Reactive power of the load consummation and the reactive power of the source, (ii) Active control of the source photovoltaic and the load active power consummates.

1) Case a

The figure and show that the source voltage without any harmonics, and the shunt active power enhance the Total harmonics distortion of the source current with good THD (0.91%) knowing that before inserting the SAPF the THD was 23.24%, reduce the magnitude of it, and inject the total power generated by the PV system (10Kwatt) in the grid to reduce the generation of the source power to 17.89 Kwatt and compensate the total reactive power of the source and the PI controller maintain the DC bus voltage at constant value with small oscillation band.

2) Case b

The figure and show that the source voltage without any harmonics, and the shunt active power enhance the Total harmonics distortion of the source current with good THD (0.7%) knowing that before inserting the SAPF the THD was 23.24%, reduce the magnitude of it, and inject the total power generated by the PV system (5.05Kwatt) in the grid to reduce the generation of the source power to 22.19 Kwatt and compensate the total reactive power of the source and the PI controller maintain the DC bus voltage at a constant value with small oscillation band.

3) Case c

The figure and shows that the source voltage without any harmonics, and the shunt active power enhance the Total harmonics distortion of the source current with good THD (0.91%) knowing that before inserting the SAPF the THD was 23.24%, reducing the magnitude of it, and inject the total power generated by the PV system (10Kwatt) in the grid to reduce the generation of the source power to 17.89 Kwatt and compensate the total reactive power of the source and the PI controller maintain the DC bus voltage at a constant value with small oscillation band.

4) Case d

The figure and shows that the source voltage without any harmonics, and the shunt active power enhance the Total harmonics distortion of the source current with good THD (0.79%) knowing that before inserting the SAPF the THD was 23.24%, reducing the magnitude of it, and inject the total power generated by the PV system (7.584Kwatt) in the grid to reduce the generation of the source power to 20 Kwatt and compensate the total reactive power of the source and the PI controller maintain the DC bus voltage at a constant value with small oscillation band.

VI. Conclusion

In this paper, the Predictive direct power control technique is investigated for improving the performance of a grid containing non-linear load with SAPF associated with a PV system controlled by NN-backstepping MPPT, and a study with fast irradiation change is presented. The numerical results of the PDPC method show the proposed system give good performance and, filtering the total harmonics distortion, and inject the total energy generated by the PV system in the grid. Furthermore, the NN-backstepping extracts the PV system's maximum power (Pmpp) with minimal rate time and almost no oscillation. In addition, simulation results show improving performance for NN-backstepping MPPT and PDPC.

Reference

[1] B. E. Youcefa, A. Massoum, S. Barkat, and P. Wira, 'Backstepping Predictive Direct Power Control of Grid- Connected Photovoltaic System Considering Power Quality Issue', vol. 14, no. 1, 2020.

[2] Z. Hekss, A. Abouloifa, I. Lachkar, F. Giri, S. Echalih, and J. M. Guerrero, 'Nonlinear adaptive control design with average performance analysis for photovoltaic system based on half bridge shunt active power filter', *International Journal of Electrical Power & Energy Systems*, vol. 125, p. 106478, Feb. 2021, doi: 10.1016/j.ijepes.2020.106478.

[3] R. Kumar and H. O. Bansal, 'Real-time implementation of adaptive PV-integrated SAPF to enhance power quality', *Int Trans Electr Energ Syst*, vol. 29, no. 5, p. e12004, May 2019, doi: 10.1002/2050-7038.12004.

[4] I. U. Haq *et al.*, 'Neural network-based adaptive global sliding mode MPPT controller design for stand-alone photovoltaic systems', *PLoS ONE*, vol. 17, no. 1, p. e0260480, Jan. 2022, doi: 10.1371/journal.pone.0260480.

[5] S. Ouchen, H. Steinhart, J.-P. Gaubert, M. Benbouzid, and F. Blaabjerg, 'Improvement of PV Grid Connected System Associated with Active Power Filter Based on Fuzzy-Predictive Direct Power Control', 2019.

[6] A. Yousfi, Y. Bot, F. Mehedi, and A. Chaker, 'Current model predictive control for three-phase active power filter using cascaded H-bridge multilevel converter', vol. 21, no. 2, 2021.

[7] A. Benzahia, R. Boualaga, A. Moussi, L. Zellouma, M. Meriem, and B. Chaima, 'A PV powered shunt active power filter for power quality improvement', *Global Energy Interconnection*, vol. 2, no. 2, pp. 143–149, Apr. 2019, doi: 10.1016/j.gloei.2019.07.001.

[8] Z. Hekss *et al.*, 'Advanced nonlinear controller of single-phase shunt active power filter interfacing solar photovoltaic source and electrical power grid', *Int Trans Electr Energ Syst*, vol. 31, no. 12, Dec. 2021, doi: 10.1002/2050-7038.13237.

[9] N. Hamouda, B. Babes, S. Kahla, Y. Soufi, J. Petzoldt, and T. Ellinger, 'Predictive Control of a Grid Connected PV System Incorporating Active power Filter functionalities', in *2019 1st International Conference on Sustainable Renewable Energy Systems and Applications (ICSRESA)*, Tebessa, Algeria: IEEE, Dec. 2019, pp. 1–6. doi: 10.1109/ICSRESA49121.2019.9182655.

[10] N. F. Ibrahim *et al.*, 'A new adaptive MPPT technique using an improved INC algorithm supported by fuzzy self-tuning controller for a grid-linked photovoltaic system', *PLoS ONE*, vol. 18, no. 11, p. e0293613, Nov. 2023, doi: 10.1371/journal.pone.0293613.

[11] A. Taouni, A. Abbou, M. Akherraz, A. Ouchatti, and R. Majdoul, 'MPPT design for photovoltaic system using backstepping control with boost converter', in *Proceedings of 2016 International Renewable and Sustainable Energy Conference, IRSEC 2016*, 2017, pp. 469–475. doi: 10.1109/IRSEC.2016.7983920.

[12] F. Berrezzek, K. Khelil, and T. Bouadjila, 'Efficient MPPT scheme for a photovoltaic generator using neural network', in *020 1st International Conference on Communications, Control Systems and Signal Processing (CCSSP)*, EL OUED, Algeria: IEEE, May 2020, pp. 503–507. doi: 10.1109/CCSSP49278.2020.9151551.

[13] S. Ouchen, J.-P. Gaubert, H. Steinhart, and A. Betka, 'Energy quality improvement of three-phase shunt active power filter under different voltage conditions based on predictive direct power control with disturbance rejection principle', *Mathematics and Computers in Simulation*, vol. 158, pp. 506–519, Apr. 2019, doi: 10.1016/j.matcom.2018.11.024.

[14] Y. Bekakra, L. Zellouma, and O. Malik, 'Improved predictive direct power control of shunt active power filter using GWO and ALO – Simulation and experimental study', *Ain Shams Engineering Journal*, vol. 12, no. 4, pp. 3859–3877, Dec. 2021, doi: 10.1016/j.asej.2021.04.028.