JOURNAL OF ENERGY SYSTEMS

2023, 7(1)

2602-2052 DOI: 10.30521/jes.1053423 Research Article

Design and implementation of a robust ANN-PID corrector to improve high penetrations photovoltaic solar energy connected to the grid

Gueye Daouda*
Alioune Diop University, Efficiency and Energetic System, Physics Department, Bambey, Senegal, daouda.gueye2@uadb.edu.sn
Ndiaye Alphousseyni
Alioune Diop University, Efficiency and Energetic System, Physics Department, Bambey, Senegal, alphousseyni.ndiaye@uadb.edu.sn
Diao Amadou
Cheikh Anta Diop University, Faculty of Science and Technic, Physics Department, Dakar, Senégal, ama_diao@yahoo.fr

Submitted: 11.01.2022
Accepted: 27.01.2023
Published: 31.03.2023

* Corresponding Author

Abstract: The best quality of PV energy into the grid is now problematic that is why this paper focuses on the design and implementation of a robust Proportional Integral Derivative based on Artificial Neural Network (ANN-PID). This technique used to ensure the regulation of the Boost Converter (BC) output voltage and the Three Phase Inverter (3 PI) output currents of a photovoltaic solar system (PVS) connected to the grid. The mathematical model of the DC bus and the 3-PI is presented. Applications under Matlab/Simulink justify the efficiency of the neural regulator. In comparison with the conventional one, the proposed method presents the best follow-up of the DC link voltage reference and a maximum overshoot of 3.16 %. In addition, despite the long time put in transient mode, the proposed method keeps better robustness and ensures an injection of current of a total harmonic distortion (THD) of 0.96 % against 2.18 % of the classical PID regulator.

Keywords: *Robust ANN-PID;DC bus; THD and PVS*

Cite this paper as: Daouda, G., Alphousseyni, N., & Amadou, D., Design and implementation of a robust ANN-PID corrector to improve high penetrations photovoltaic solar energy connected to the grid. Journal of Energy Systems 2023; 7(1): 121-131, DOI: 10.30521/jes.1053423

Nomenclature	
GHG	Greenhouse gases
THD	Total Harmonic Distortion
PID	Proportional Integral Derivative
3-PI, BC	Three Phase Inverter, Boost Converter
k_p, k_i, k_d	Proportional gain, Integral gain, Derivative gain
V_{dc}, I_{dc}, C_{dc}	DC link voltage, DC link current, DC link capacity
E_{abc}, U_{abc}, I_{abc}	Grid voltage, Inverter output voltage, Injected current
L, R	Inductance and Resistance of the inverter filter
E_{dq}, U_{dq}, I_{dq}	Active and reactive voltage, active and reactive current
E_{cc}, E_{cs}	Inputs of hidden layer neurons and output layer neurons
S_{cc}, S_{cs}	Outputs of hidden layer neurons and output layer neurons

1. INTRODUCTION

The global energy crisis, marked by a rise in the price of oil, has long compromised, the effects of several developing countries, notably Senegal [1]. This problem is on top of an already delicate situation for most utilities. Faced with the latter, Senegal, in 2014, implemented a new economic policy called Plan Senegal Emergent, which focuses on inexhaustible sources of energy on a human scale and less polluting: Renewable Energies [2]. The share of renewable energies, reaching 600 MW of total electricity production capacity in 2020, is 13 % hydropower, 13 % solar photovoltaic and 8 % wind power [2]. However, photovoltaic solar energy is able to partially meet current energy needs and overcome the year after year of fossil sources reduction and the emitting aspect of greenhouse gases (GHG) [3,4,5,6,7,8]. It represents an incontestable solution to meet Senegal's energy requirements thanks to its position (5.7 kWh / m^2 per day) and the law No. 2010-21, orientation law on renewable energies [1]. Based on this law, various photovoltaic solar power plants have been built since 2016. These are those of Bokhol, Malicounda, Kahone, of Sakal. Thanks to these investments, Senegal can benefit, from 2021, a power of 265 Megawatts solar photovoltaic systems autonomously or by injection into the grid [9].

The injection of photovoltaic solar energy into the grid is becoming a development technology because it allows participating in the reduction of GHG emissions. Despite their advantages, it is difficult in realization and possible that by the use of converters as BC and 3-PI. However, the intermittent nature of the photovoltaic source is a real problem [10,11,12,13]. The latter influences the BC output voltage through meteorological changes (temperature and / or sunshine) through the BC output current. In add, the voltage dip or short-circuit at the 3-PI also perturb the BC output voltage. The 3-PI influences the quality of the injected energy because of high level of THD in current and the total efficiency of the system. These disturbances caused by significant switching losses and conduction losses, which are due to the properties of the type of transistor. In order to overcome these problems, three methods can be considered. The first is the use of modulation techniques, the second is to reduce the transistor current or voltage and the third is to use a DC bus.

It is in this context that various methods based on the 3-PI control have been proposed in the literature. Hysteresis control, thanks to its simplicity, is used to control current with a PI regulator to control the DC bus voltage [14,15]. The simulation results give a response time of nearly 0.25 s of the bus in the presence of variations in illumination and a THD of 2.61% [9]. Contrary to Ref. [16], it is used for the control of the active and reactive powers. However, the unstable of the switching frequency is still its real problem. The latter leads to a reduction in efficiency due to the large switching loss [14,15,16]. In Ref. [17], using the fractional order PI as regulator of the BC output voltage, a reactive power compensation and low THD (while basing on IEEE 519 standard) are achieved. A modified PID regulates BC output voltage and 3-PI currents in base of Park [18]. Applications exhibit a tracking of the BC output voltage and a good sinusoidal shape of the injected current injected. In spite of these advantages like simplicity, performances and so for, the manual adjustment always remains a major drawback of the corrector. A PI regulator in the Park base gives a THD lower than international standards [19]. In Ref. [20], an adaptive PI regulator is proposed for controlling the currents of the 3-PI connected to the grid. An algorithm based on the power, the voltage and the modulation index automatically adjusts it. The simulation and experimental results in view of the climate variations, the response time is improved up to 20 to 25 ms. On this same lance, a linear quadratic regulator is used as a digital controller of the inverter connected to the grid [21]. This method, compared to the classical technique, is faster, more robust with regard to perturbations and gives low THD. In add, experimental tests proved its performances. In Ref. [22], a robust technique based on the approach of the theory of H∞ is proposed. This technique is compared to the resonant proportional regulator for controlling a PV grid-connected. The applications prove the H∞ technique superiority with a THD of 0.67% in simulation and 1.78 % experimentally.

The best form of currents into the grid is obtained using intelligent techniques. Hybrid neuro-fuzzy control has been proposed in order to overcome the limitations of classical controls in order to improve THD [23]. It injects a current of a THD of 3.02% with a precision and an appreciable speed compared to PI regulator. The simplicity of the PI controller pushed the author towards a comparative study of meta-heuristic techniques like Whales Optimization Algorithm, Grey Wolf Optimization algorithm, Antlions Optimization algorithm and Moth Flame Optimization algorithm) [24]. These meta-heuristic techniques determine the optimal gain of PI regulator, which enable to increase efficiency of the inverter PV system grid-connected and to ensure stability, unit power factor and low THD. However, the obtained results attained through Matlab/Simulink prove that the Whales Optimization Algorithm technique is better than the three others studied meta-heuristic techniques in terms of inverter efficiency, stability, power factor and THD. In Ref. [25], the parameters K_p and K_i of the PI corrector are provided by the radial function of neural networks to solve the problems of active or reactive power. The same neural network is used to improve the PID parameters in order to regulate the BC output voltage of a 3-PI through a photovoltaic system [26]. The application results show better tracking of the BC output voltage reference using the proposed method. In comparison with the classical PID, overshoots of 0.54% against 15.9% are obtained in transient. Dynamic control based on ANN is proposed for controlling a single-phase inverter in order to ensure an energy quality to the grid through a photovoltaic system [27]. Application results, compared to the resonant proportional regulator, show the best performances of the neural technique in terms of DC bus voltage stability and total harmonic distortion of 3.83%. A PI regulator based on ANN is respectively offered for controlling the BC output voltage and the currents of the 3-PI connected to the grid [28]. This technique is used for improving the system output transient mode. Compared to the classic PI regulator, the applications show a fast response time and elimination of static errors of the BC output voltage and from the direct and quadratic axes of the current. In addition, it presents a significant reduction in THD by 1.97% against 5.06% of the classic PI regulator. In Ref. [29], a review based on the artificial neural networks in order to pay attention of the artificial neural network users like microgrid, supervisory control and optimization. Different techniques were elaborated which one note multilayer perceptron, Elman neural network, radial basis function network.

However, by limiting to the injection of PV energy, the general objective of this paper is to design and implement a robust corrector to improve the PV energy penetration to the grid. Today, the most used controls in PV systems connected to the grid are the classic ones thanks to their simple implementation. These commands have limitations with respect to the variations in weather conditions and do not prevent the creation of harmonics. It is thereby the object of realizing adaptive control techniques based on ANN in order to ensure a flexible injection to the grid. To achieve this, a neural control of the 3-PI is performed. The latter is split into two loops with a PID regulator based on the ANN: one for regulating the BC output voltage and another for the 3-PI output currents.

2. MODELLING AND APPROACHES

2.1. Modelling of the Controlled System

2.1.1. DC bus modelling

The DC bus is, in our case, an interface between the BC and the 3-phase inverter. The DC bus plays a role of energy storage but also of filtering. Its mathematical model is obtained thanks to the relation between the current (I_{dc}) which crosses it, the voltage (V_{dc}) and the equivalent capacity (C_{dc}). This relation is given as in Eq. (1).

$$I_{dc} = C_{dc}\frac{dV_{dc}}{dt} \quad (1)$$

The constancy of the BC output voltage is very important for performances of the 3 PI. It is sometimes disturbed by the BC output current and the injected saturation currents. It is in this context that its regulation remains necessary to maintain it constantly and to discharge the energy previously stored.

2.1.2. Modelling of the three-phase inverter

The three-phase inverter is a static device used to convert direct to alternating energy. It represents a very essential element in the photovoltaic system injected energy to the grid. However, it influences the waveform of injected currents through high total harmonic distortion but also on the overall efficiency of the system through switching and conduction losses. Its mathematical model is defined by the differential equations obtained through the application of the mesh law. These equations highlight the relationship between the output voltages of the inverter (U_{abc}), injected currents (I_{abc}), grid voltages (E_{abc}) and filter components (R, L) as given in Eq. (2).

$$U_{abc} = L\frac{dI_{abc}}{dt} + RI_{abc} + E_{abc} \tag{2}$$

However, the Park transform remains necessary because output currents of the 3-PI are regulated using linear techniques. This transformation makes it possible to simplify the three-phase model into a two-phase model. The application of the latter gives as in Eq. (3).

$$U_{dq} = L\frac{dI_{dq}}{dt} + RI_{dq} + E_{dq} \pm L\omega I_{dq} \tag{3}$$

2.2. Approaches Used for System Control

With its classic nature, the PID controller has limitations in a PVS where the regulated systems depend on weather conditions. Added to this is the limit on the experimental Ziegler-Nichols adjustment of the corrector parameters when the studied system is slow. These problems direct the work towards other techniques that will take into account or face unexpected changes in the regulated system. This idea pushed us in this paper to use a method based on ANN to generate the optimal parameters of the PID corrector according to the corrected error in order to improve the performance of the 3-PI. Thus, we will present in this part the PID regulator based on ANN. This approach is proposed for regulating the BC output voltage and the output currents of the 3-PI.

2.2.1. Proportional-Integral-Derivative

The PID corrector is a linear regulator. It improves the stability and precision of a system. It remains a regulator widely used in the industry despite the complication of certain systems. Its transfer function (Ft) is defined as given in Eq. (4).

$$F_t(s) = k_p + \frac{k_i}{s} + \frac{sk_d}{1+\tau s} \tag{4}$$

2.2.2. Neural regulator (ANN-PID)

The neural regulator is the combination of the classical PID corrector and artificial neural networks (ANN). The ANN, depending on the error to be corrected, determines the parameters of the PID. This structure, represented in Fig 1, is generally made up of three types of layers: an input layer represented by the neurons, which receive the initial information, an output layer, which represents the conclusions obtained by the network, or the response to input signals, and hidden layers that represent the intermediate layers between the input and output of the network.

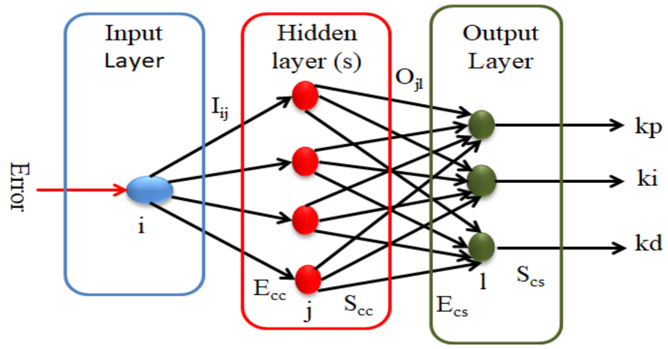

Figure 1. Structure of the neural PID.

Activation functions as sigmoid and hyperbolic tangent are respectively used to activate neurons in the hidden layer and output layer. They are noted *G(Ɛ)* and *H(Ɛ)*, and given as in Eqs. (5,6). The sigmoid function has the advantage of giving intermediate values unlike the threshold and linear functions which return either to "0" or to "1". It also has the advantage of being differentiable. Given the outputs of the neural network must positive parameters, therefore the activation function of the output layer neurons is non-negative. This is how the tangent function is chosen. There are other activation functions such as the ReLU function, which is generally used in convolutional neural networks or the Gaussian function.

$$G(\varepsilon) = \frac{1}{1+e^{-\varepsilon}} \tag{5}$$

$$H(\varepsilon) = \frac{1}{2}(1 + \tanh\varepsilon) \tag{6}$$

Starting from these functions, neurons in the hidden layer are obtained in Eqs. (7,8). From these results, the inputs and outputs of neurons of the output layer are calculated as in Eqs. (9,10).

$$E_{cc} = \sum I_{ij}\, Error \tag{7}$$

$$S_{cc} = G(E_{cc}) \tag{8}$$

$$E_{cs} = \sum O_{jl}\, S_{cc} \tag{9}$$

$$S_{cs} = H(E_{cs}) \tag{10}$$

A learning supervised algorithm is used to learn the neural network. With the cost or error function (*F*), the algorithm adjusts synaptic weights (I_{ij}) and (O_{jl}). Adjustment and error functions are respectively given in Eqs. (11,12).

$$F(\rho) = \frac{1}{2}(Ref(\rho) - Measure(\rho))^2 \tag{11}$$

$$\omega(\rho+1) = \omega(\rho) - \gamma\frac{\partial F(\rho)}{\partial\omega(\rho)} + \delta F(\rho) \tag{12}$$

With γ and δ are respectively the step of training and the inertia coefficient. The variable ω is synaptic weights, which can take I_{ij} or O_{jl}. The step summarizing the operating principle of ANN-PID is given below and the overall control scheme of the system is given in Fig. 2.

***Step 1** Initialization of I_{ji} (ρ), O_{lj} (ρ), η and α for the iteration ρ= 1;*

Step 2 *Collect the measurement and reference value and calculate the error at iteration ρ ($F(\rho)$);*
Step 3 *Calculate the input and output of each neuron and obtain the PID parameter (K_p, K_i and K_d);*
Step 4 *Calculate the PID output;*
Step 5 *Online learning: Adjust synaptic weights of neurons in the network through the back propagation of gradient descent in order to ensure adaptive tuning. This step is made using Eq. (12);*
Step 6 *if the fixed condition for the error is reached, the program is finished else one turns over at the step 2 and pass to the iteration ρ+1.*

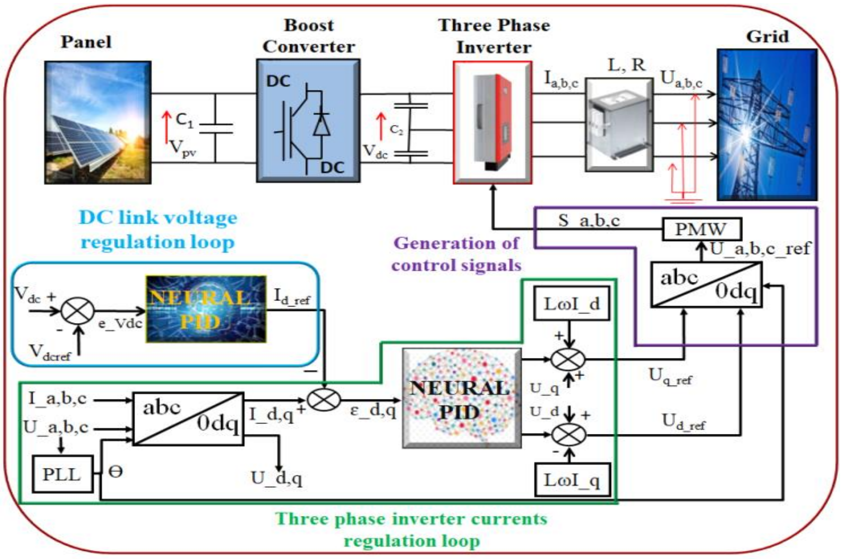

Figure 2. Overall control scheme of the system

3. RESULTS AND DISCUSSIONS

To study the behavior of the proposed technique, simulations of the system illustrated in Fig. 2 are carried out using the Matlab/Simulink environment. It has undergone climatic variations illustrated in Fig. 3. These data are obtained through the experimental bench of the Higher Polytechnic School (HPS) in Dakar. This school is located in the Dakar region of latitude and longitude respectively equal to 14° 41'37 " North and 17° 26'38" West.

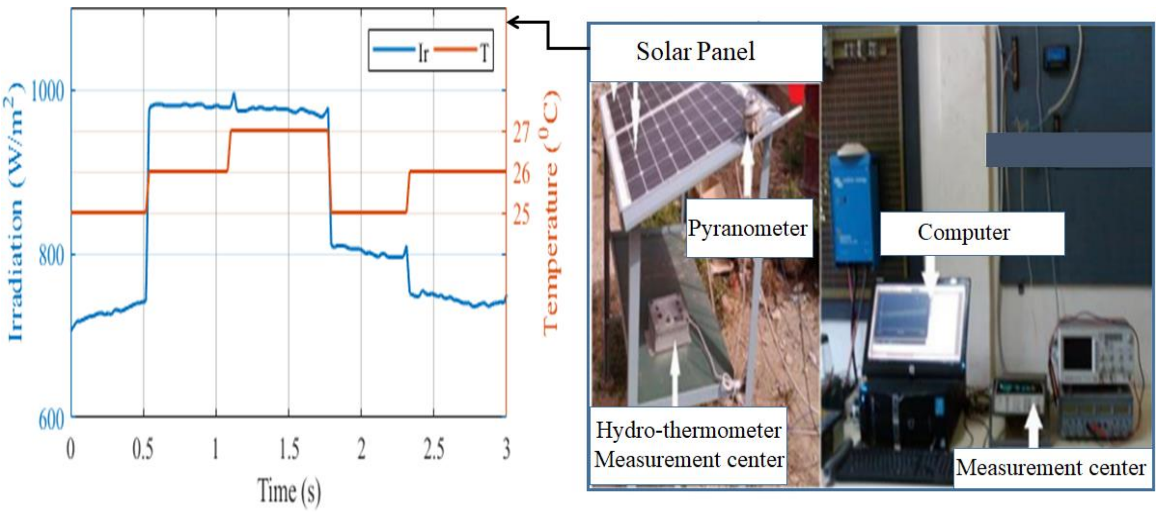

Figure 3. The irradiation, temperature profiles and setup.

The results of the carried out regulation of the DC link voltage are illustrated as in Fig. 4. These results are obtained by the use of the neural and conventional PID. Vdc_{PID} and $Vdc_{ANN\text{-}PID}$ respectively are the BC output voltage using the conventional PID and neural regulator, and Vdcref is the reference BC output voltage.

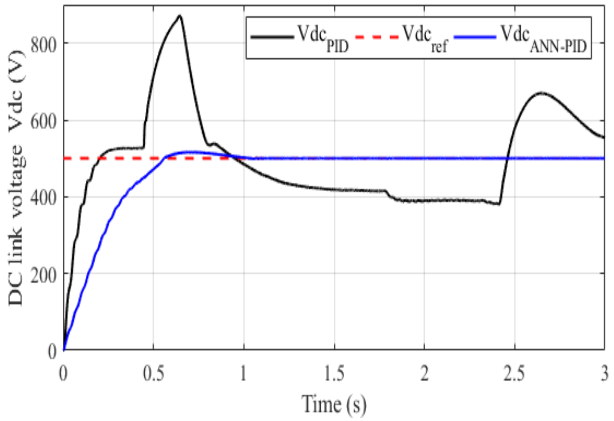

Figure 4. DC link voltage.

The curves of Fig. 4 justify the efficiency of the neural regulator, in comparison with the conventional one, by a clear follow-up of the DC link voltage reference and a maximum overshoot (O) of 3.16 %. It goes through a transient regime of one second before following its reference. Unlike the classic PID regulator, the neural regulator proves its robustness to climate change.

The superiority of the neural technique over the classical one is also proven by a comparative study in terms of errors (Root Mean Square Error (RMSE), Mean Absolute Percent Error (MAPE) and Mean Absolute Error (MAE)), response time (R_t). These results are illustrated in the Table 1. This table shows that the neural method presents better precision basing on the RMSE that allows taking account the impacts of infrequent important errors contrary to MAPE and MAE. The system is precise, the smaller is the RMSE.

Table 1. Comparative study on the DC link voltage.

Methods	R_t (s)	O (%)	RMSE	MAPE (%)	MAE
PID	0.550	74.86	3.35	0.42	0.0042
ANN-PID	0.278	3.16	0.91	0.055	$5.5\ 10^{-4}$

The output current regulation of the three-phase inverter is performed on the Park's base. In other words, a regulation of the active and reactive currents is made. The results obtained with the proposed technique and the conventional one are presented as in Fig. 5 and 6.

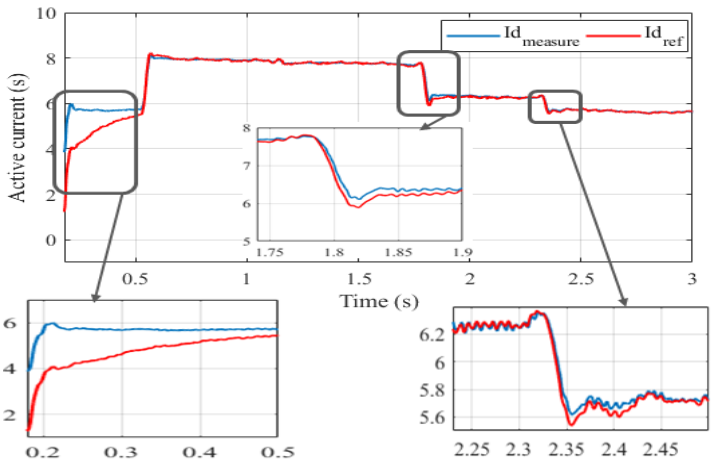

Figure 5. Active current using PID

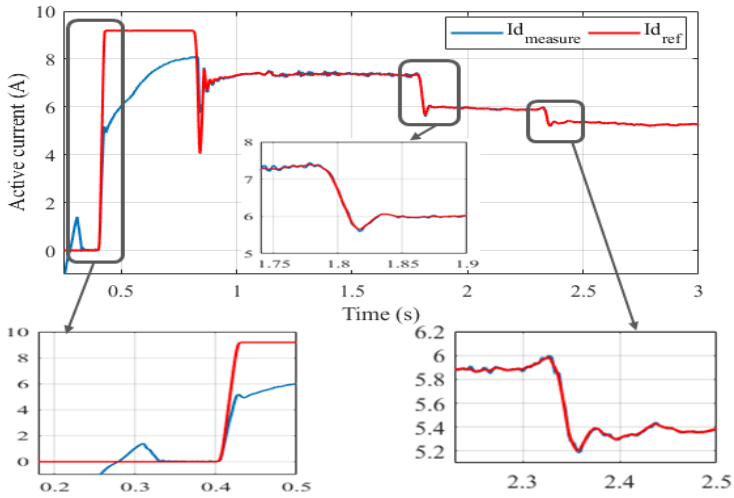

Figure 6. Active current using ANN-PID

The curves in Figs. 5,6 prove the effectiveness of the both techniques used. The neural regulator, despite the long-time put in transient mode, keeps better robustness with respect to disturbances as shown in the zoomed parts. In the absence of transient rapidity, the performance criteria proving the effectiveness of the neuronal technique are given in Table 2. Like the Table 1, the Table 2 proves the precision of the neural basing on the RMSE.

Table 2. Comparative study on the DC link voltage.

Methods	RMSE	MAPE (%)	MAE
PID	0.071	0.73	0.0073
ANN-PID	0.029	0.27	0.0027

Moreover, thanks to the inverse Park transformation, the sinusoidal currents injected to grid and obtained by the neural regulator are illustrated in Fig. 7. These last underwent a study of total harmonic distortion compared to that of the conventional regulator. The smaller the THD, the better is the signal quality. These results, given as in Figs. 8 and 9, prove the quality of the injected energy and justify the superiority of the proposed technique on the classical method.

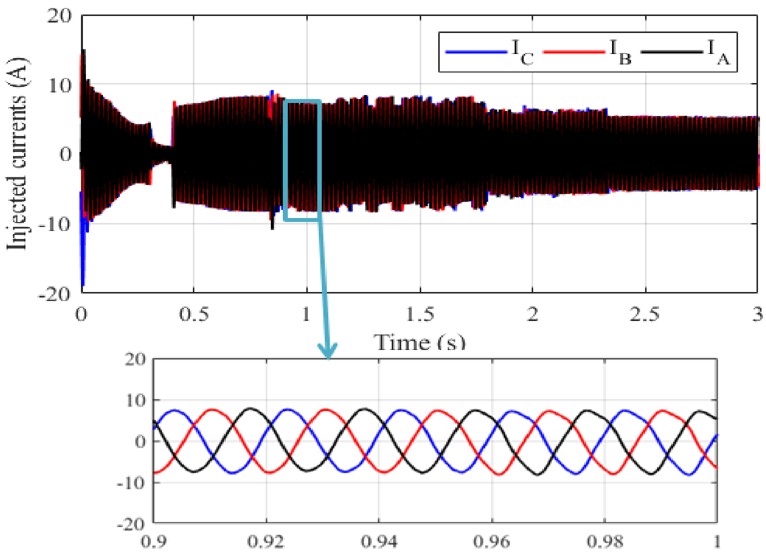

Figure 7. Injected currents using ANN-PID.

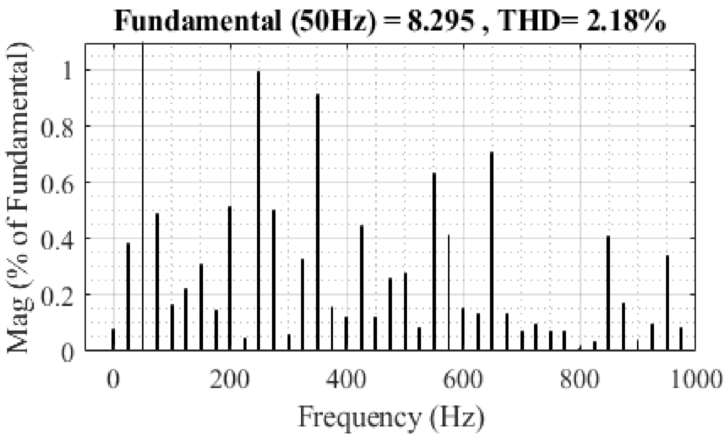

Figure 8. Currents THD using PID.

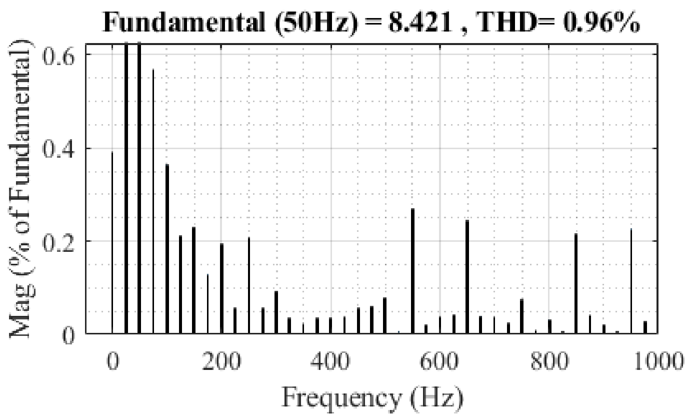

Figure 9. Currents THD using ANN-PID.

Operation at unit power factor can be justified by keeping the reactive current at zero but also by the zero dephasing between the corresponding injected currents and grid voltages. This last criterion is used and is shown in Fig. 10. This phenomenon explains the single injection of the active power to the grid.

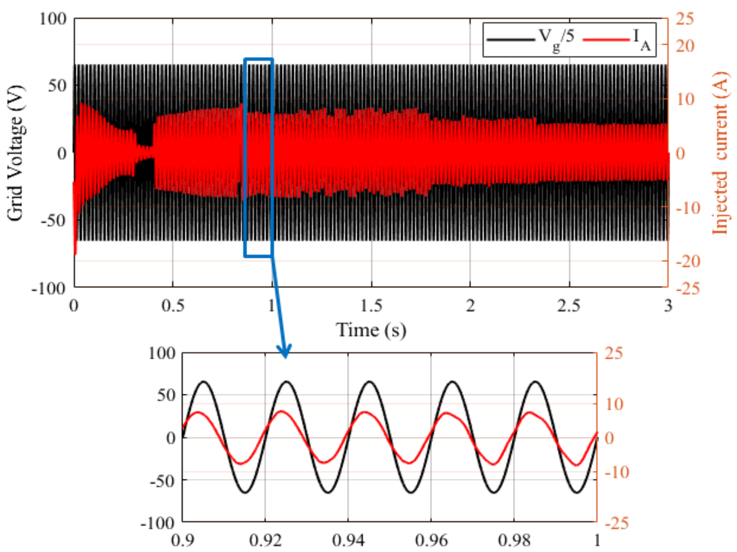

Figure 10. I_A phase current and grid voltage using ANN-PID.

4. CONCLUSION

This paper has been devoted to the design and implementation of a robust corrector to improve penetrations of the PV energy to the grid. For this, a PID controller based on ANN is proposed for the regulation of the BC output voltage and the output currents of the 3-PI in referential direct and quadratic (*dq*). The purpose of this regulation is to ensure a flexible injection of PV energy to the grid. System simulation results have proven the efficiency and robustness of the ANN-PID corrector in the regulation voltage. The proposed method ensures an overshoot of 3.16% against 74.86% of conventional PID. In addition, the injected currents have a sinusoidal form with a current THD of 0.96% with the ANN-PID corrector compared to the classic PID corrector which gives 2.18%.

However, to make the THD almost perfect, the future works is the use of ANN based on genetic algorithm technics of controlling currents of the 3-PI. An experimental validation of the obtained results is also envisaged on dSPACE.

Acknowledgment

The authors thank the Efficiency and Energy System (EES) team of Alioune Diop University of Bambey (Senegal) and the Laboratory of Renewable Energies of Higher School in Cheikh Anta Diop University of Dakar (Senegal).

REFERENCES

[1] Kebe A. Contribution to the pre-sizing and control of electrical energy production units on isolated sites from renewable energies: Application to the case of Senegal. PhD, University of Paris-South, Faculty of Sciences of Orsay, France 2013.
[2] Ba, A. Universal and sustainable access to electricity in Senegal: The success conditions. PhD, University of Paris Dauphine, PSL, Research University, France, 2018.
[3] Traore, M, Ndiaye, A, Mbodji, S, Faye, M, Gueye, D, Tankari, M, Lefebvre, G, Thiaw, L. Supervision of a PV system with storage connected to the power line and design of a battery protection system. *Wireless Networks* 2018. DOI: 10.1007/s11276-018-1886-x
[4] Ndiaye, A, Thiaw, L, Sow, G. Application of new modelling and control for grid connected photovoltaic systems based on artificial intelligence. *Journal of Electrical and Electronics Engineering Research* 2015; *7*: 1-7, DOI: 10.5897 / JEEER2013.0523
[5] Mlilo, N, Brown, J, Ahfock, T. Impact of intermittent renewable energy generation penetration on the power system networks - A review. *Technology and Economics of Smart Grids and Sustainable Energy* 2021; 1–19, DOI: 10.1007/s40866-021-00123-w
[6] Hellier, P, Ladommatos, N. The influence of biodiesel composition on compression ignition combustion and emissions. *Journal of POWER AND ENERGY* 2015; *229*, 714–726, DOI: 10.1177/0957650915598424
[7] Ozcan, M, Enhancing the renewable energy auctions in Turkey. *Journal of Polytechnic* 2021*; 24*: 1379-1390, DOI: 10.2339/politeknik.721850
[8] Nureddin, A, Rahebi, J, Ab-BelKhair, A. Power Management Controller for Microgrid Integration of Hybrid PV/Fuel Cell System Based on Artificial Deep Neural Network. *International Journal of Photoenergy* 2020; 8896412: 21. doi.org/10.1155/2020/8896412
[9] Madougou, S. Study of the wind potential of the nocturnal jet in the Sahelian zone from observations of wind profiler radars. PhD, University of Toulouse 3, Paul Sabatier, France, 2010.
[10] Ab-BelKhair, A, Rahebi, J, Abdulhamed, A. A Study of Deep Neural Network Controller-Based Power Quality Improvement of Hybrid PV/Wind Systems by Using Smart Inverter. *International Journal of Photoenergy* 2020; *8891469*: 22. doi.org/10.1155/2020/8891469

[11] Ayadi, F, Colak, I, Garip, I, Bulbul, I. Impacts of Renewable Energy Resources in Smart Grid. In: icSmartGrid 2020 8. IEEE International Conference on Smart Grid; 17-19 June 2020: Paris-FRANCE, pp. 183-188.
[12] Kacejko, P, Pijarski, P. Optimal Voltage Control in MV Network with Distributed Generation. *Energies* 2021; *469*: 1-19, DOI: 10.3390/en14020469
[13] Chandra, S, Agrawal, S, Chauhan, S. Impact of Photovoltaic Module Temperature on Size and Voltage Stability, a Case Study in Indian Climate. *Appl. Sol. Energy* 2020; *56*: 324–333. DOI: 10.3103/S0003701X20050059
[14] Boukezata, B, Choui, A, Gaubert, J, Hachemi, M. Photovoltaic solar system connected to the grid and assocoated a parallel active filter. In: SGE 2014 Symposium of Electrical Engineering; 8-10 July 2014: Cachan-France, pp. 1-9.
[15] Latha, R, Bharatiraja, C, Palanisamy, C, Subhransu, D. Hysteresis Current Controller based Transformer-less Split Inductor NPC MLI for Grid Connected PV- System. *Procedia Engineering* 2013; 224-233. DOI: 10.1016/j.proeng.2013.09.094
[16] Boukezata, B, Gaubert, J, Chaoui, A, Hachemi, M. Photovoltaic generator with direct power control and connected with the addition of services to the grid. In: SGE 2016 Symposium of Electrical Engineering; 7-9 June 2016: Grenoble-France, pp. 1-7.
[17] Lakshmi, M, Hemamalini, S. Coordinated control of MPPT and voltage regulation using single stage high gain DC/ DC converter in a grid connected PV system. *Electric Power Systems Research* 2018; 65-73. DOI: 10.1016/j.epsr.2018.12.011
[18] Gueye, D, Ndiaye, A, Tankari, M, Faye, M, Thiam, A, Thiaw, L, Lefebvre, G. Design Methodology of Novel PID for Efficient Integration of PV Power to Electrical Distributed Network. *International Journal of Smart Grid* 2018; *2*: 77-86.
[19] Hamrouni, N, Jraidi, M, Dhouib, A, Cherif, A. Design of a command scheme for grid connected PV systems using classical controllers. *Electric Power Systems Research* 2017; 503-512, DOI: 10.1016/j.epsr.2016.10.064
[20] Malakondareddy, B, Krumar, S, Gounden, N, Anand, I. An adaptive PI control scheme to balance the neutral-point voltage in a solar PV fed grid connected neutral point clamped inverter. *Electrical Power and Energy Systems* 2019; 318-331, DOI: 10.1016/j.ijepes.2019.03.012
[21] Xie, B, Mao, M, Zhou, L, Wan, Y, Hao, G. Systematic design of linear quadratic regulator for digitally controlled grid-connected inverters. *IET Power Electronic* 2020; *13*: 557-567 DOI: 10.1049/iet-pel.2019.0514
[22] Deepamangai, P, Manoharan, P. Robust controller for grid-connected quasi-admittance source inverter for photovoltaic system. *Electric Power Systems Research* 2019; DOI: 10.1016/j.epsr.2019.105879
[23] Altin, N, Sefa, I. dSPACE based adaptive neuro-fuzzy controller of grid interactive inverter. *Energy Conversion and Management 2012*; 130-139, DOI: 10.1016/j.enconman.2011.11.017
[24] Aouchiche, N. Meta-heuristic optimization algorithms based direct current and DC link voltage controllers for three-phase grid connected photovoltaic inverter. *Solar Energy* 2020; 683-692, DOI: 10.1016/j.solener.2020.06.086
[25] Sujatha, B, Anitha, G. Enhancement of PQ in grid connected PV system using hybrid technique. *Ain Shams Engineering Journal* 2016, DOI: 10.1016/j.asej.2016.04.007
[26] Sathiya, S, Punitha, K. Artificial Neural Network for Control and Grid Integration of Floating Solar Photovoltaic System. *International Journal of Advanced Research in Electrical Electronics and Instrumentation Engineering* 2018; *7*: 3974-3984, DOI: 10.15662/IJAREEIE.2018.0711009
[27] Meddour, S, Rahem, D, Yahia, A, Hachelfi, W, Hichem, L. A novel novel approach for PV system based on metaheuristic algorithm connected to grid using FS-MPC controller. *Energy Procedia* 2019; 57-66, DOI: 10.1016/j.egypro.04.007
[28] Mohamed, A, Metwally, H, El-sayed, A, Selem, S. Predictive neural network based adaptive controller for grid-connected PV systems supplying pulse-load. *Solar Energy* 2019; 139-147, DOI: 10.1016/j.solener.2019.09.018
[29] Garcia, L, Mendoza, A, Navarro, J. Artificial Intelligence artificial neural networks in microgrids: A review. *Engineering Applications of Artificial Intelligence* 2020; DOI: 10.1016/j.engappai.2020.103894