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Application of new modeling and control for grid connected photovoltaic systems based on artificial intelligence

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This review-paper focuses on the development the intelligent technology for modelling (Multi-Model Approach (MMA)) and control (Artificial Neural Networks Controller) of grid connected photovoltaic energy conversion system. This approach (MMA) is based on a black box modeling. A database consists of input variables (sunshine, temperature and voltage at the terminals of photovoltaic generator (PVG) and output (PVG current) is obtained by characterization of a photovoltaic module Sharp installed type at the "Polytechnic Higher School" (PHS) in Dakar in March 2012. Indeed 70% of this database is used to train the multi-model and 30% of the database is reserved for validation of the multi-model. The proposed model has a correlation of 89% and a Nash criterion (NS) average of 75.65%. Learning is performed with oil operating area. Each area of operation is made by a local affine model structure and function of validity sigmoid. These results show the good performance of the proposed model. Control design of a single phase grid-connected photovoltaic (PV) system including the PV array and the electronic power conditioning (PCS) system, based on Artificial Neural Networks Controller (ANNC) is presented. The developed controller is compared with a Proportional Integral (PI) controller through computer simulation. The obtained results show that the NNC have faster response and lower THD without overshoots.

Key words: Black box modelling, photovoltaic generator, inverter, maximum power point tracking (MPPT), neural network controller.

INTRODUCTION

Currently, the production of domestic energy and industry is based largely on a limited resource: fossil fuels. Primary oil resources are becoming increasingly scarce and expensive, while world energy demand is continuously increasing. It is therefore necessary to find an alternative. The constraint is to use an economical source of renewable energy with low emissions for the protection of the environment has become an important point. The search for alternative energy sources has become so crucial. Many scientific studies have been conducted not only in the field of electricity production from nuclear power stations, but also in the field of

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renewable energies such as electricity generation from wind or solar radiation.

The performance of a photovoltaic (PV) system is highly dependent on weather conditions, such as solar radiation and soil temperature: Intermittent production. The rational use of solar energy and its injection into the electrical networks imposes the determination of maximum operating photovoltaic generators and estimation of the produced energy, knowledge that passes through the modeling and optimization of photovoltaic systems.

In the literature, several researchers have proposed methods to model and simulate the photovoltaic generators based on the model to a diode. However, many of these methods are based on the adjustment of the visual mathematical curve I(V) at the points of the experimental curve, which requires the graphic extraction of curve slope at determined points or require an experimental analysis of photovoltaic device. These methods have drawbacks, for the experimental curves I(V), are not always available in manufacturers' data sheets, and devices for measurements of experimental data are not always available as well. Other researchers have proposed modelling methods based on the modification of the electronic characteristic of a diode model of a photovoltaic cell (Hongmei et al., 2012).

Some authors have proposed methods of modeling tools based on the adjustment of the curve P (V), but this latter is based only on the characteristic I (V) and the peak power of the resulting model is not always peak power of real device. Some researchers also use interpolation techniques (Koh et al., 1994). These methods are impractical and too complex for this type of application. In addition, many studies in the literature generally consider simplified models, where the series resistances (Rs) and parallel (Rsh) of the photovoltaic device are ignored (Zameer and Singh, 2013). Moreover, there are few studies in the literature on modeling PVGs, based on artificial neural networks (Ravinder et al., 2014). But there is almost in the literature a modeling study based on artificial intelligence such as multi-model approach.

The main difficulties in the control strategy of real dynamic systems are the non-linearity and uncertainties. The control of the system requires in general the development of a mathematical model making it possible to establish the transfer function of the system that links the inputs and the outputs. This requires good knowledge of the dynamic and properties of the system. In the non-linear system case, the conventional techniques have often shown their limits mainly when the system to be studied presents strong non-linearity. The lack of right knowledge necessary for the development of the mathematical models is somehow the origin of those limits (Mohammed et al., 2007).

Recourse to the control methods based on artificial intelligence has become a necessity. These control methods follow an extraction process of the knowledge of the system to be studied from collected empirical data, so as to be able to react in front of new situations; this strategy is known as intelligent control (Panos et al., 1993; Rival et al., 1995).

Artificial neural networks are used in intelligent control due to the fact that they are parsimonious universal approximators (Panos et al., 1993; Rival et al., 1995) and that they have the capacity to adapt to a dynamic evolving through time. Moreover, as multi-input and multi-output systems, they can be used in the frame of the control of the multivariable systems.

A feedforward ANN makes one or more algebraic functions of its inputs, by the composition of the functions made by each one of its neurons (Dreyfus, 2002). These are organized in layers and inter-connected by well-balanced synaptic connections. The supervised training of a neural network consists in modifying the weights to have a given behavior minimizing a cost function often represented by the quadratic error (Panos et al., 1993; Cybenko, 1989).

Several authors have tried to exploit the advantages of neural networks to control a dynamic system (Mahmoud et al., 2012; Zameer and Singh, 2013) precisely, within the field of robotics (Rival et al., 1995; Yildirim, 1997) and for the control of asynchrony motors (Mohammed et al., 2007; Panos et al., 1993; Branštetter and Skotnica, 2000). More details on neural network controllers can be found in Panos et al. (1993), Wishart and Harley (1995), Ronco and Gawthrop (1997), Hagan and Demuth (1996), Wishart and Harley (1995), Ahmed et al. (2008), Tai et al. (1990), Hagan and Demuth (1996), Chen et al. (1997), Norgaard (1996) and Vandoorn et al. (2009) made a comparative study between PI controller, PID controller and a fuzzy logic based controller for an inverter control shows that the PI controller has better performances, though the fuzzy logic based controller is an intelligent one.

In the work presented in this article, the capacities of multi-layer perceptron (MLP) to learn the inverse model of non-linear systems are used to work out the control of a single-phase inverter used as an interface between a photovoltaic generator (PVG) and an electrical grid. The objective is to inject into the grid as much photovoltaic energy as available, with low Total Harmonic Distortion (THD) and good reference signal tracking a characteristic.

Intelligent modelling based multi-model approach for solar PV system

Presentation of photovoltaic test field

The photovoltaic platform shown in Figure 1 is used in this study. It is installed at the Higher Polytechnic School of Cheikh Anta DIOP University, Dakar, Senegal. Senegal is located on the extreme western Africa between 12.5° and 16.5° North latitude and 12° and 17° West longitude. It presents a dry tropical climate characterized

Figure 1. Bench characterization of PVG.

by two seasons: A dry season from November to June and a rainy season from July to October (ANAMS, 2012). Senegal has a significant solar potential with annual average radiation duration of about 3000 h and an exposure rate of 5.7 kWh/m^2/day. This radiation varies between the northern part more sunlit (5.8 kWh/m^2/day in Dakar) and the southern part richest in terms of precipitation (4.3 kWh/m^2/day in Ziguinchor) (PSA, 2011). The temperature varies from 16°C around Dakar (January) to 38 °C in the South (October). The rainfall increases from North to South with an annual average of 300 mm in the extreme North and 1500 mm in the extreme South (ANAMS, 2012). The relative humidity varies between 75 and 95% (Wofrance, 2012). The platform is installed in Dakar between 17.28° West longitude and 14.43° North latitude to 31 m altitude.

Pyranometer is used to measure sunshine of the site, as the module temperature it is measured by a thermocouple, voltmeter and ammeter we give the values respectively of the voltage and current of the PVG (Figure 1).

The characteristics of the photovoltaic system being modeled (Sharp module) are given in Table 1.

The phovoltaic generator to modeling is a system MISO (Multiple Inputs, Single Output), it is shown in Figure 2.

Multi-model approach

Mathematical formulation and application

Either a non-linear system represented by the general input-output model of Equation 1.

$$y_s(t) = f[\varphi(t)] \tag{1}$$

Where φ (t) is vector regression composed of input variables of the system.

Suppose that the decomposition of the system under study, we obtain a family of M local modelsf_i. Each local model describes the behavior of the system in its area of operation. To construct these models, we must have such a physical knowledge of the system behavior in these areas. Local validity of each sub-model is provided by a function of validity $\rho_i\left[\underline{\varphi}(t), \beta_i\right]$ parameters β_i. This function tends to 1 if the current point is close to the $\underline{\varphi}(t)$ "center" of the area and decreases more or less rapidly to 0 as soon as deviates from the "center". The normalization of a function of validity provides a degree of activation ω_i (activation function or interpolation) which determines the degree of activation of the local model associated.

Depending on the area where the system evolves, this function indicates the greater or lesser contribution of the local model. The global model sought F[φ(t)] is therefore the sum of these local models weighted by their activation function.

$$\omega_i\left(\underline{\varphi}, \beta_i\right) \in [0\ \ 1]$$

$$\sum_{i=1}^{M} \omega_i\left(\underline{\varphi}(t), \beta_i\right) = 1 \forall \varphi(t)$$

$$\omega_i\left(\underline{\varphi}(t), \beta\right) = \frac{\rho_i\left(\underline{\varphi}(t), \beta_i\right)}{\sum_{j=1}^{M} \rho_j\left(\underline{\varphi}(t), \beta_j\right)} \tag{2}$$

We obtained an expression of multi-architecture model (Komi, 2000):

Table 1. Model parameters PV Sharp.

Parameter	Voc	Isc	Pc	Cell surface	Cells number
Value	22.50	2.24	30	49	36
Unit	Volts	Amperes	Watts	cm^2	-

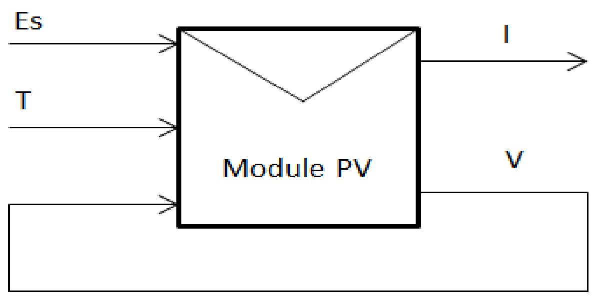

Figure 2. Block diagram of the PV generator. Es: vector of sunshine in terms of modules; T: Vector temperatures of the photovoltaic module; V: Vector of the voltages across the PVG; I: PVG current.

$$y(t) = \frac{\sum_{i=1}^{M} \rho_i(\varphi(t),\beta_i) f_i(\varphi(t))}{\sum_{j=1}^{M} \rho_j(\varphi(t),\beta_j)} \quad (3)$$

These functions of validity (ρi) and activation (ωi) of the area i must check the respective conditions:

$$\sum_{i=1}^{N} \rho_i(\varphi, \beta_i) > 0$$

Substituting Equation (5) in Equation (6), we obtain Equation (4) which is the output of a Multi-model.

$$y(t) = \sum_{i=1}^{M} \omega_i\left(\varphi(t), \beta\right) f_i(\varphi(t)) \quad (4)$$

The interpolation region is bounded by ω_i in the space of regression. The functions are based on β defined by: $\beta = [\beta_1^T \beta_2^T \ldots \beta_M^T]^T$; β_i parameters of activation functions; local models f_i are in turn parameterized by the vector $\theta = [\theta_1^T \theta_2^T \ldots \theta_M^T]^T$.

In reality, multi-model system is a decomposition of a system in several areas of operation. An area of operation is defined as an area of the space of operation where the system to model is represented by a given local model. Classic Auto, an area of operation of a system is referred to as a subspace of the state space "centered" on a point generally a fixed point (or equilibrium) system. The operating point assigned to this operating area is not necessarily an equilibrium point of the system. The zones of operation are limited in their function associated validity. A typical function of validity is a Gaussian function that the arrangement determines the extent of the area [Equation (4)]. For example, Figure 3 illustrates the functions of validity (left) and activation function (right) we apply the multi-model approach to identify a photovoltaic module types Sharp. For this we consider the function regression matrix consists of the concatenation of the input variables of the system, which expression is:

$$\varphi(t) = [E_s^T(t) T^T(t) \; V^T(t)]$$

These three variables are the input variables of the module of the PV generator. The grid partition has allowed subdividing the feature space in zones (subspace). Each subspace is associated with a local model.These local models have an affine structure. The validity of the model in its local area *i* of operation is ensured by the function of validity.

Training and validation of multi-model

Database used here includes the measurements of 2012. A part of the experimental data (70%) is used for learning (development of multi-model). The resulting model is validated by the remaining part of the data (30%).

Our non-linear system is to identify the PV generator. The operating area of the system is defined by three variables (Es, T, V). The decomposition of the zone of operation is based on these three variables. The grid has to partition the feature space subdivision into subspaces. Each subspace is associated with a local model. These local models have an affine structure. The validity of the model in its local area *i* operation is ensured by the function of validity. Data base learning is divided into eight zones. Identification of the multi-model is illustrated by the learning algorithm of Figure 4. A GPV modeled by the multi-model approach is used to power an inverter connected to the grid whose control by neural networks.

NEURAL NETWORK CONTROLLER FOR SINGLE PHASE INVERTER

Principles of artificial neural networks

The ANN network is based on models that try to explain human

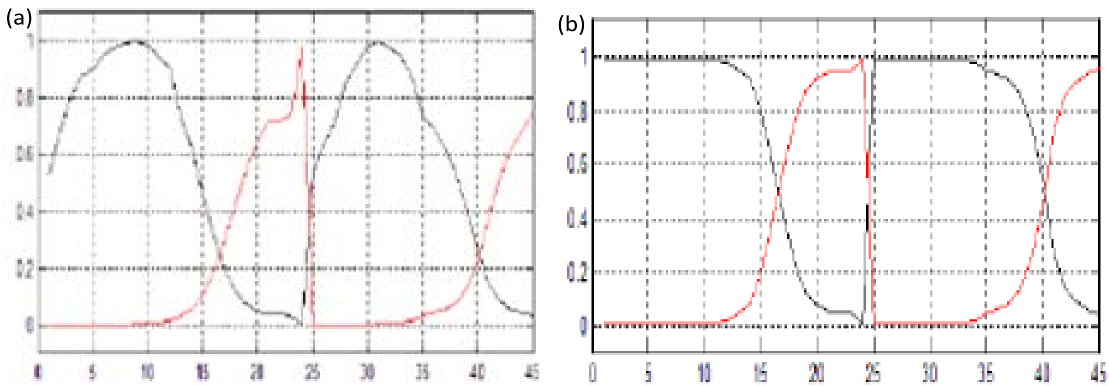

Figure 3. Example of validity (a) and activation (b) functions.

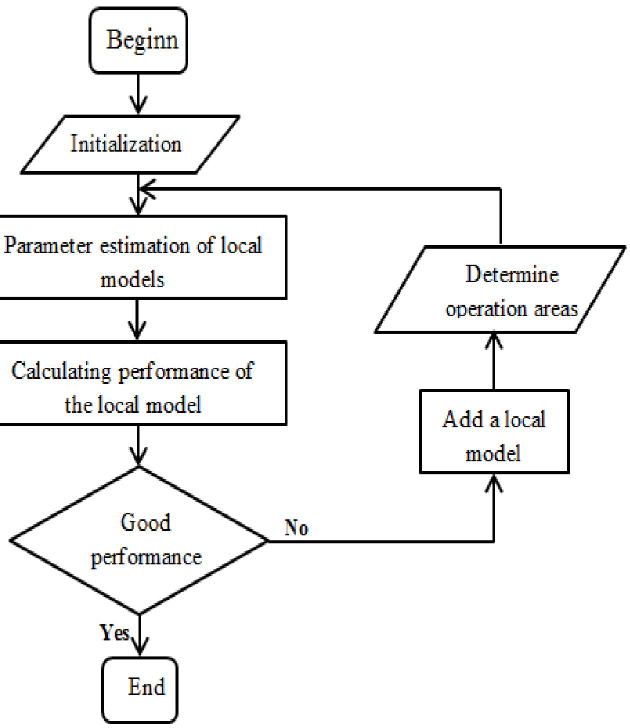

Figure 4. Identification of the photovoltaic system.

brain functioning. They are adapted to the treatment in parallel of complex problems such as speech and face recognition, or simulation of nonlinear functions. So they offer a new means of information treatment. In Figure 5, the main elements of an artificial neural are depicted: The input, processing unit and an output.
A formal neuron is characterized by Equations (10) and (11).

$$x_i = f(A_i) \tag{5}$$

$$A_i = \sum_{i=1}^{N_i} w_{ij} x_i + b_i \tag{6}$$

Where x_i is State of a neuron j connected to neuron i; A_i is activity of neuron *i*; w_{ij} is weight of the connection between the neurons *j* and *l*, and b_i is Bias.

The MLP network (Figure 6) is a feed forward network that is composed of several layers, each neuron of a layer being totally connected to the neurons of the next layer. The resulting network is able to approximate any nonlinear function.
The error $\delta_{p,k}$ made on the kth output neuron for a sample p is expressed by Equation (12).

$$\delta_{p,k} = O_{p,k} - x_{p,k} \tag{7}$$

Where, $O_{p,k}$ is desired output of the neuron k for the sample p;

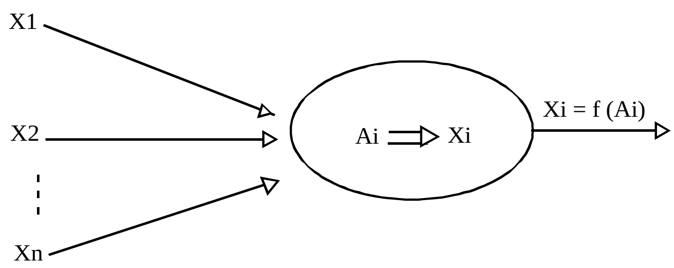

Figure 5. Representation of a formal neuron.

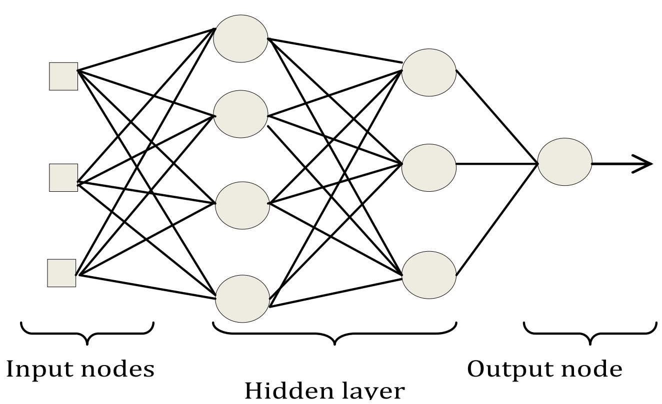

Figure 6. Architecture of an MLP network.

$x_{p,k}$ is output of the neuron k for the sample p.

As a result, the total error (for all output neurons) is estimated by:

$$e_p = \frac{1}{2}\sum_{i=1}^{N_i} \delta_{p,k}^2 = \frac{1}{2}\sum_{k=1}^{m} \left(O_{p,k} - x_{p,k}\right)^2$$

Where m is number of neurons on the output node.

The synaptic weights are then adjusted so as to reduce the output error for the whole samples of the data base:

$$e = \sum_{p=1}^{N} e_p \tag{8}$$

Where N designates the size of the database.

The process of the network parameters estimation is called training. The set of parameters that are to be estimated includes all the weights and biases. An algorithm called back propagation is mainly used for the network training (Ahmed et al., 2008) for more details on neural networks.

Proposed design method of the neural controller

Within the framework of this study, the system to control is a single-phase inverter serving as an interface between a photovoltaic generator and an electrical grid. The structure of the neural controller for photovoltaic energy injection into the grid is represented in Figure 7.

The inputs of the neural controller are the current injected into the grid, the grid voltage and the error between the actual and the reference values of the inverter output current.

Database for the neural controller training is obtainend from the system simulation with several PI controllers, each of witch being determined for a given system operating point, defined by the inverter input DC voltage.the parameters used for the simulation are given in Table 2.

RESULTS AND DISCUSSION

Photovoltaic generator modelling

The measured power of the PVG and multi-model are represented in Figure 8. In the initialization phase of the latter, the physical knowledge of the system was used to determine the parameters (scattering center) of activation functions. The only parameters that remain to be determined are those of local models. Since linear models are compared to the method of their parameters Ordinary Least Squares (OLS) is applied to determine these parameters. OLS is used because the overall criterion is chosen to estimate the parameters of the local models. The model obtained with optimized parameters is tested for loyalty. If the developed model gives satisfactory results, the procedure is stopped: the model is ready for use. On contrary, if the model has poor performance we add a local model, then set a new vector values (identification of areas of operation). The procedure continues until a successful model. The parameters giving the performance model corresponds to the minimum of the criterion function. Figures 9 and 10 show a good correlation (89%) between the output of the system and the multi-model.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(I_{measured} - I_{model}\right)^2} \tag{9}$$

$$R = \frac{\mathrm{cov}\left(I_{measured}, I_{model}\right)}{\delta I_{measured}\,\delta I_{model}} \tag{10}$$

$$NS = 1 - \frac{\sum_{i=1}^{n}\left(I_{measured} - I_{model}\right)^2}{\sum_{i=1}^{n}\left(I_{measured} - \bar{I}_{model}\right)^2} \tag{11}$$

The Nash criterion measures, the proportion of variance explained by the model.

In general, a value greater than 0.7 is considered satisfactory, and the optimal value being 1 [9]. The criterion is used in particular to estimate the quality of the multi-model developed.

It should be noted that as the number of zones increases less the difference between the measured current and the output of multi-model decreases (Table 3). Therefore the model is better when we have

Table 2. Inverter and photovoltaic generator parameters.

Parameter	Value
DC bus voltage (Vdc = Vopt at 1 kW/m² and 25°C)	800 V
Opened circuit voltage of the PV generator	1000 V
Short circuit current of the PV generator	6.8 A
Filter inductor value (L)	5 mH
ESR value of the inductor	0.2 Ω
Maximum power of the PV generator	4 kW
Grid RMS voltage value (Vgeff)	220 V
Grid frequency (f_o)	50 Hz
Inverter switching frequency (*fs*)	20 kHz

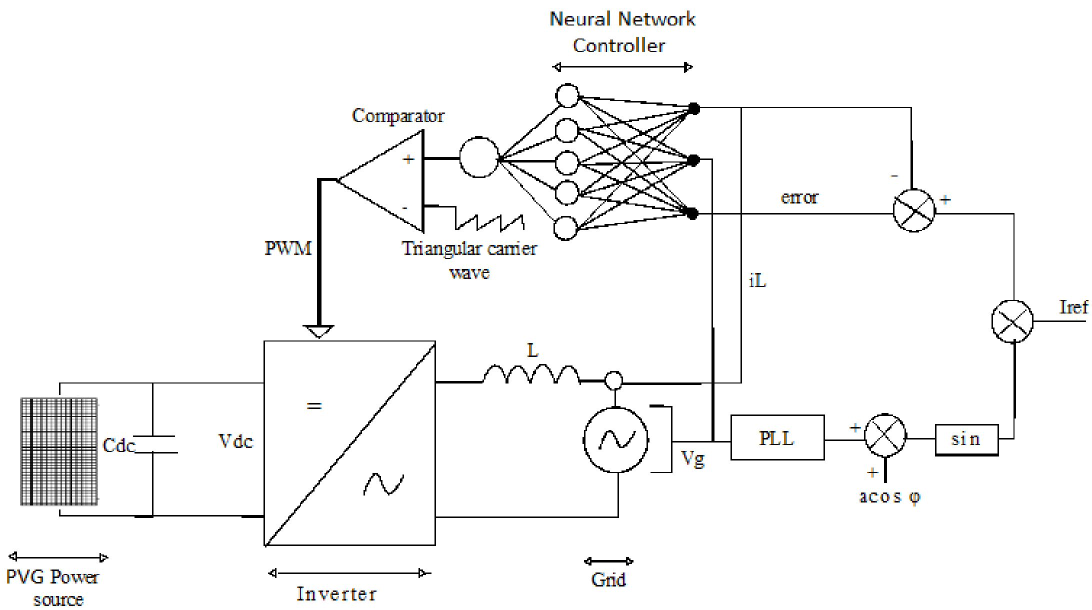

Figure 7. Grid connected photovoltaic system with single phase inverter and neural controller.

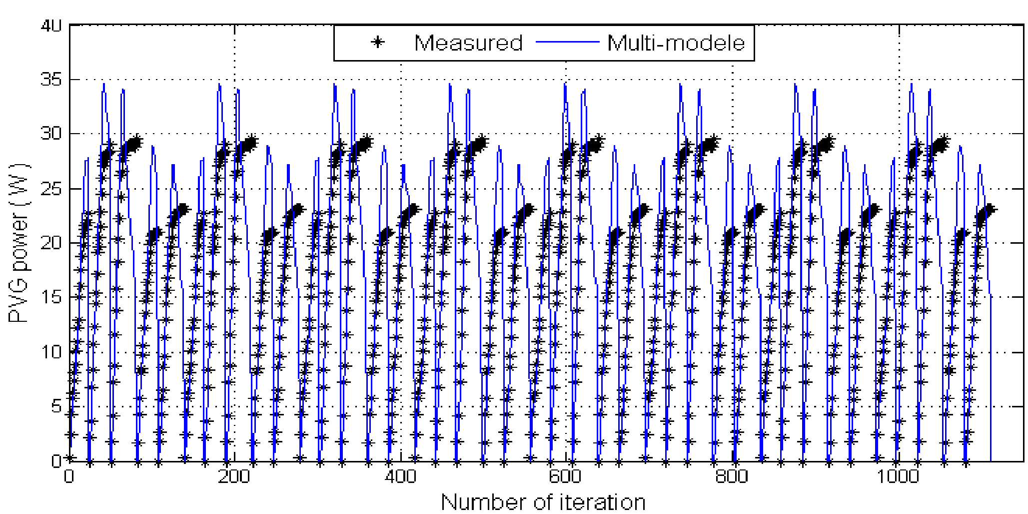

Figure 8. Results of learning.

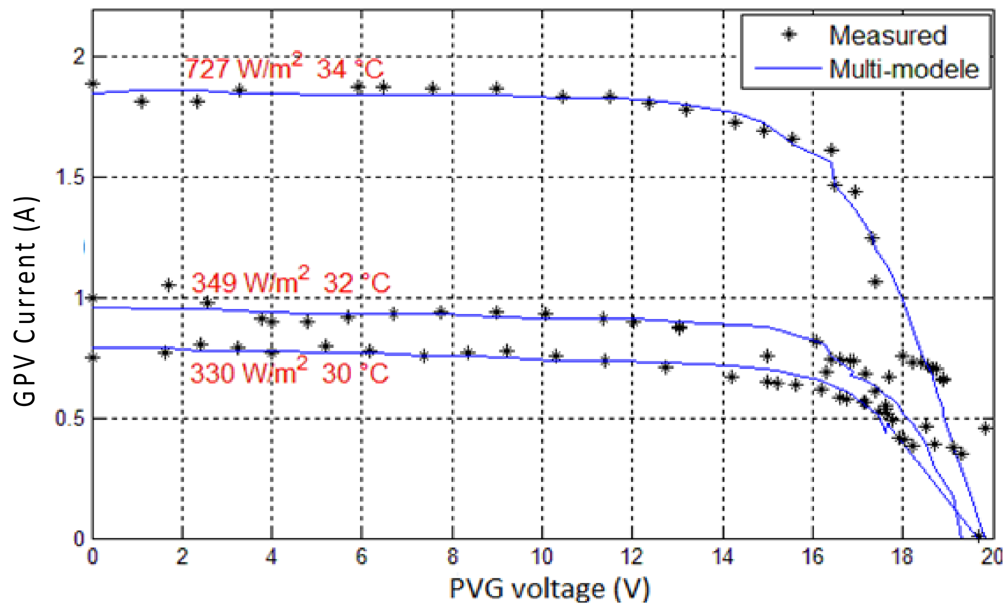

Figure 9. Characteristic I = f (V) for validating the multi-model.

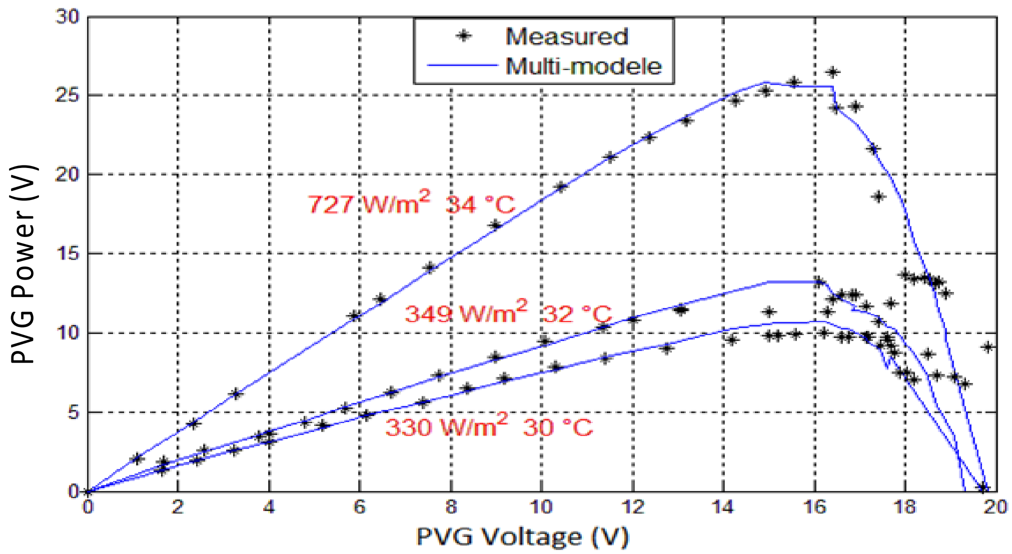

Figure 10. Characteristic P = f (V) for validating the multi-model.

Table 3. Evolution of the performance of multi-model for the identification of a PVG.

Total operating zones	RMSE	NS	R
7	0.3668	0.7179	0.8475
8	0.3663	0.7187	0.8479
10	0.3604	0.7277	0.8531
15	0.3161	0.7906	0.8895
17	0.3141	0.7931	0.8908
20	0.3155	0.7913	0.8898

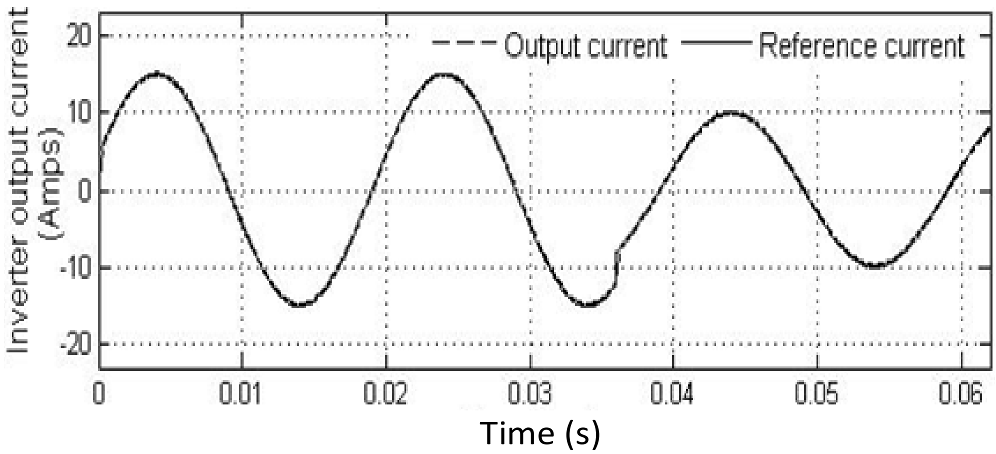

Figure 11. Inverter output current and its reference value when a neural controller is used.

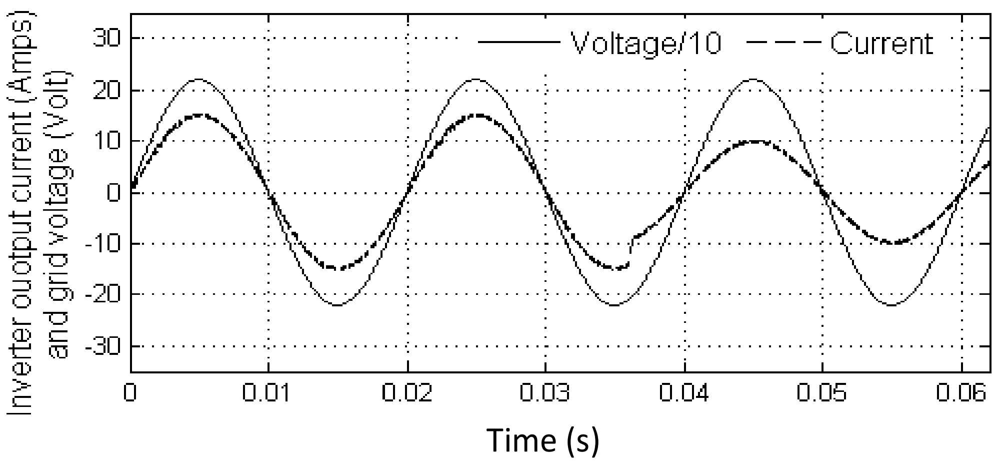

Figure 12. Grid voltage and inverter output current when a neural controller is used.

a large number of zones of operation. The data of this Table are obtained by numerical application of the Equations (14) to (16).

Artificial neural networks controller of inverter

The inverter is designed so that its switches will be able to support the maximum current i_{gmax} and the maximum open circuit voltage (V_{co}) of the photovoltaic generator. Table 2 gives the inverter parameters and those of the photovoltaic generator.

The design of the neural network controller consists of designing several PI controllers for various meteorological conditions. The following values are used for the solar irradiation and the temperature:(0.25 kW/m², 25°C), (0.25 kW/m², 40°C), (0.6 kW/m², 25°C), (0.6 kW/m², 40°C), (1 kW/m², 25°C) and (1 kW/m², 40°C).

Control signals from the PI (Proportional Integral) controllers, grid voltage, inverter output current and its reference value are gathered to form a large database used for the neural controller training.

Figure 11 shows inverter output current and its reference value when neural controller is used for the following meteorological conditions: A solar irradiation of 1 kW/m² and a temperature of 25°C. A disturbance consisting of a 67% reduction of reference current magnitude is introduced at t = 36 ms. The obtained results prove fast tracking capability of the neural controller without overshoots. Grid voltage and injected current for unity power factor are shown in Figure 12.

Conclusion

The application of multi-model approach to the PVG was presented in detail in the first part of this chapter. The goal is to represent a PV generator composed of Sharp module with a set of simple models with limited validity in well-defined areas. The identification of the PV generator multi-model is made in two steps:

1. The structural identification (determining the number of local models and structure);
2. The parametric estimation of local models and those of validity functions known in advance.

The final model obtained is of a good performance with a correlation of 89%. The multi-model is able to describe the behavior of the photovoltaic generator. GPV modelled is used to power an inverter connected to the grid whose control by neural networks.

Development of a MLP based neural controller is presented. The training and validation data of the used neural controller were obtained by simulation of the whole system with several PI controllers calculated for various meteorological conditions. The simulation results show that the neural controller gives good results.

The advantage of neural network based controller is that it adapts to the changing of meteorological conditions.

Conflict of Interest

The authors have not declared any conflict of interest.

REFERENCES

Ahmed T, Hamza A, Abdel GA (2008). La commande neuronale de la machine à réluctance variable, Rev. Roum. Sci. Techn.–Électrotechn. Énerg. 53(4):473-482. Bucarest.

ANAMS: National Agency for Meteorology of Senegal (2012). http://WWW.meteo-senegal.net.

Branštetter P, Skotnica M (2000). Application of artificial neural network for speed control of asynchronous motor with vector control, Proceedings of International Conference of Košice, EPE-PEMC, pp. 6-157-6-159.

Chen CT, Chang WD, J Hwu (1997). Direct control of nonlinear dynamical systems using an adaptive single neuron, IEEE Trans. Neural Netw. 2(10):33-40.

Cybenko G (1989). Approximation by superposition of a sigmoidal function'', Math. In: Control Signals System 2nd ed, pp.303-314.

Dreyfus G (2002). Réseaux de neurones: Méthodologies et applications, editions Eyrolles.

Hongmei T, Mancilla-Davida F, Kevin E, Eduard M, Peter J (2012). A cell-to-module-to-acell detailed model for photovoltaic panels. Solar Energy 86(9):2695-2706.

Hagan MT, Demuth HB (1996). Neural network design, Thomson Asia Pte Ltd, 2nd ed.

Koh C, Khouzam K, hoon C Ly, Poo Yong Ng (1994). Simulation and real-time modelling of space photovoltaic systems. In Conference Record of the 24th IEEE Photovoltaic Specialists Conference, 2:2038-2041.

Komi GASSO (2000). Identification des systèmes non-linéaires : approche multi-modèle. PhD these Doctorat soutenue en.

Mohammed S, Djamel EC, Fayçal KM (2007). Commande neuronale inverse des systèmes nonlinéaires, In 4th International Conference on Computer Integrated Manufacturing CIP, 2007 03-04 November.

Norgaard M (1996). System identification and control with neural networks'', Thesis, Institute of automation, Technical University of Denmark.

Panos J, Antsaklis K, Passino M (1993). Introduction to Intelligent and Autonomous Control, Kluwer Academic Publishers, ISBN: 0-7923-9267-1.

PSA: Senegalese-German program (2011). DASTPVPS\SOLARIRR.INS.

Ravinder KK, Shimib SL, Chatterjib S, Fahim A (2014).Modeling of solar pv module and maximum power point tracking using anfis. Renew. Sustain. Energy Rev. 33:602-612.

Rival I, Personnaz L, Dreyfus G (1995). Modélisation, classification et commande, Par réseaux de neurones: principes fondamentaux, Méthodologie de conception et illustrations industrielles, Mécanique Industrielle et Matériaux, no 51 (Septembre 1998).

Ronco E, Gawthrop PJ (1997). Neural networks for modelling and control, Techncal Report CSC-97008, Center for Systems and Control, Glasgow.

Tai P, Ryaciotakiboussalis HA, Tai K (1990). The application of neural networks to control systems: A survey, Signals, systems and Computers, Record Twenty-Fourth Asilomar Conference on Vol. 1.

Vandoorn T, Bert R, Frederik De B, Bart M, Lieven V (2009). A Voltage-Source Inverter for Microgrid Applications with an Inner Current Control Loop and an Outer Voltage Control Loop, International Conference on Renewable Energies, and Power Quality (ICREPQ09) Valencia (Spain), 15th to 17th April.

Wofrance (2012). http://www.wofrance.fr/weather/maps/city.

Wishart MT, Harley RG (1995). Identification and Control of Induction Machines Using Artificial Neural Networks. IEEE Trans. Ind. Applic. 31:3.

Yildirim S (1997). New neural networks for adaptive control of robot manipulators, Neural Networks, International Conference, 3:1727-1731.

Zameer A, Singh SN (2013). Modeling and control of grid connected photovoltaic system: A review. Int. J. Emerg. Technol. Adv. Eng. 3:2250-2459.