International Journal of Enhanced Research in Science, Technology & Engineering
ISSN: 2319-7463, Vol. 6 Issue 5, May-2017

Optimized T-S Fuzzy Controller for Tracking the Maximum Power Point of Photovoltaic Systems

Mustapha. Kourchi[1], Mohamed. Ajaamoum[2], Azeddine. Rachdy[3]

[1,3]Electrical Engineering Department, EST Ibn Zohr University, BP 33/S, 80000, Agadir – Morocco
[2]Renewable Energy Department, EST Ibn Zohr University, BP 1317, 81000, Guelmim – Morocco

ABSTRACT

In this paper, we propose a zero order Takagi-Sugeno fuzzy controller with a simplified structure for maximum power point tracking of a photovoltaic system. The proposed fuzzy controller has a reduced rule base and a simplest membership functions. The particle swarm optimization algorithm is used to systematically determine the tuning parameters and to improve the dynamic performance of the studied photovoltaic system. The simulations results show that the proposed fuzzy controller allows a fast and stable maximum power point tracking. Compared to another Takagi-Sugeno controller, the proposed controller provides practically the same dynamic performance and has the advantage of having a simple and reduced structure, making it more suitable for real time applications.

Keywords: Takagi-Sugeno, fuzzy controller, MPPT, Particle Swarm Optimization, Photovoltaic system.

1. INTRODUCTION

The use of fuzzy controllers for controlling non-linear systems has grown significantly in recent years. This is due to the ability of fuzzy logic to formalize expert knowledge which allows with a minimum of information to control complex systems which are difficult to model.

However, there is no systematic general design method for determining the structure and parameters of these fuzzy controllers. In many cases, these parameters are determined empirically by choosing, through linguistic or relational reasoning, the number of membership functions for each variable and taking all the possible combinations to set up the rule base. The parameters of the fuzzy controllers are thus tuned via a "tests, errors" procedure which can prove to be long and tedious.

Various tuning and optimization techniques of fuzzy controllers are then developed. A very common technique, called metaheuristic, uses stochastic optimization methods that are often inspired by natural systems. In recent years, their use has attracted the attention of many researchers. Several algorithms have been proposed, including: genetic algorithms [1], particle swarm optimization algorithm (PSO) [2], Differential Evolution algorithm, Tabu search and the simulated annealing [3].

In this paper we are going to propose a zero-order Takagi-Sugeno (TS) type fuzzy controller with a reduced structure optimized by the PSO algorithm. This controller is used to track the maximum power point (MPPT) of a photovoltaic system [4 and 5]. For the choice of the overall structure of the fuzzy controller, we use the empirical method based on the expert know-how, which in many practical cases saves time for investigations and optimizes the operation of the system studied. The proposed zero-order TS controller has a base of five fuzzy rules and three membership functions associated with each input and output variable. Fuzzy sets of input variables are represented by symmetric triangular and trapezoidal membership functions. In comparison with another zero-order TS controller [6] with twenty-five fuzzy rules and five membership functions, the proposed structure is reduced, simple and thus is significantly alleviating the mechanism of the global calculation.

However, this structure generates unknown tuning parameters. These parameters are the scaling factors of the fuzzy controller inputs and the distances between the memberships functions used. We propose to use the PSO algorithm in order to allow a systematic determination of these parameters while improving the dynamic performance of the photovoltaic system. The PSO algorithm introduced by Kennedy & Eberhart [7] is a stochastic global optimization method. They have the advantage of being easy to be implemented and are a very efficient method for solving complex optimization problems [8].

The dynamic performance of our fuzzy controller optimized by the PSO algorithm is compared to the results obtained by the other TS controller [6]. The simulations and comparisons presented in this work are carried out using measurements from a weather forcast station in the city of Agadir.

This paper is organized as follows. After a brief introduction, we are going to introduce in section 2 the models and block diagrams under Matlab/Simulink associated with the various components of the photovoltaic system under study, that is to say the photovoltaic generator (GPV), the DC-DC converter and the TS controller. In section 3, we are presenting the optimization algorithm used for the optimal determination of the fuzzy controller tuning parameters. In section 4, we are going to evaluate the performance of TS controller studied. Finally, we are going to propose some perspectives to develop this work.

2. MODELING THE PHOTOVOLTAIC SYSTEM UNDER STUDY

In this section, we are going to present the conversion photovoltaic chain under study as well as the models of the photovoltaic generator, the buck converter and the TS controller developed and simulated under Matlab/Simulink.

A. Photovoltaic System

As shown through the photovoltaic conversion chain in figure 1, the pursuit of the maximum power point (MPP) is determined by the chain chopper controlled via (MPPT) TS controller. This latter adjusts the duty cycle so that it enables us to optimize the transfer of power from the photovoltaic generator to the load.

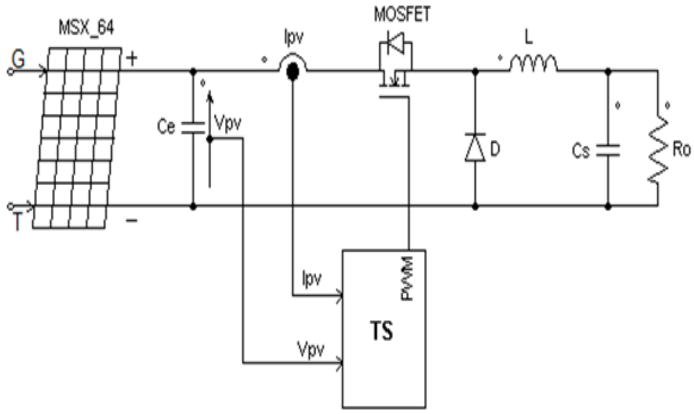

Fig. 1: photovoltaic Conversion chain under study

The panel studied in this article is a MSX-64. For its different electric characteristics under test standard conditions, see [9].

B. Model of the photovoltaic panel

The template is used to format your paper and style the text. All margins, column widths, line spaces, and text fonts are prescribed; please do not alter them. You may note peculiarities. For example, the head margin in this template measures proportionately more than is customary. This measurement and others are deliberate, using specifications that anticipate your paper as one part of the entire proceedings, and not as an independent document. Please do not revise any of the current designations.

The model used is based on the simplified equivalent diagram of a photovoltaic cell (Fig.2):

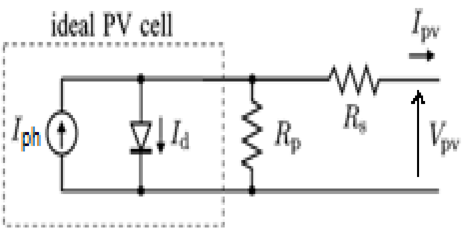

Fig. 2: Equivalent circuit diagram of a solar cell

This widely used model [6] is described by the following system of equations:

$$\begin{cases} I_{pv} = I_{ph} - I_0 \left[exp\left(\frac{V_{pv} + R_s\, I_{pv}}{A\, N_s V_t} \right) - 1 \right] - \frac{V_{pv} + R_s\, I_{pv}}{R_p} \\ I_{ph} = \left(I_{phn} + K_i\, \Delta T \right) \frac{G}{G_n} \\ I_0 = \frac{I_{scn} + K_i\, \Delta T}{exp\left(\frac{V_{ocn} + K_v\, \Delta T}{A\, N_s V_t} \right) - 1} \end{cases} \quad (1)$$

With:

I_{phn}: Photo-current (A) generated in the standard test conditions (STC).
V_{ocn}, I_{scn}: Open circuit voltage (V) and the short-circuit current (A) in STC.
$\Delta T = T - T_n$: Difference between the temperature T (°C) of the cell and standard T_n = 25°C.
G, G_n: Respectively, Measured and standard Irradiance (W/m^2).
I_0: Current of saturation Courant of diode (A).
N_s: Number of cells connected in series.
$V_t = N_s$ KT: Thermodynamic potential (K= 8.6173 10^{-5}).
K_v: Temperature coefficient of open circuit voltage (K_v = 80 ± 10 mV/°C).
K_i: Current temperature coefficient of short-circuit current (K_i = 0.065 ± 0.015) % A/°C.
R_s, R_p: Respectively, series resistors (= 0.2365 Ω) and shunt (= 415.405 Ω).
A: Ideality Factor of the Solar Cell (A = 1.3).

The model (1) of the photovoltaic panel is solved by the Newton-Raphson method. This method is a successive approximation procedure based on the use of Taylor's development. It has a fast convergence rate and is the most widely used method for solving nonlinear equations. Thus the current of the photovoltaic panel can be calculated iteratively according to equation (2).

$$I_{pv,k} = I_{pv,k-1} - \frac{I_{ph} - I_0 \left[exp\left(\frac{V + R_s\, I_{pv,k-1}}{A\, N_s V_t} \right) - 1 \right] - \frac{V + R_s\, I_{pv,k-1}}{R_p} - I_{pv,k-1}}{-I_0 \frac{R_s}{A\, N_s V_t} exp\left(\frac{V + R_s\, I_{pv,k-1}}{A\, N_s V_t} \right) - 1 - \frac{R_s}{R_p}} \quad (2)$$

The Newton-Raphson method for solving model (1) is implemented under Simulink by the block diagram of the following figure (3):

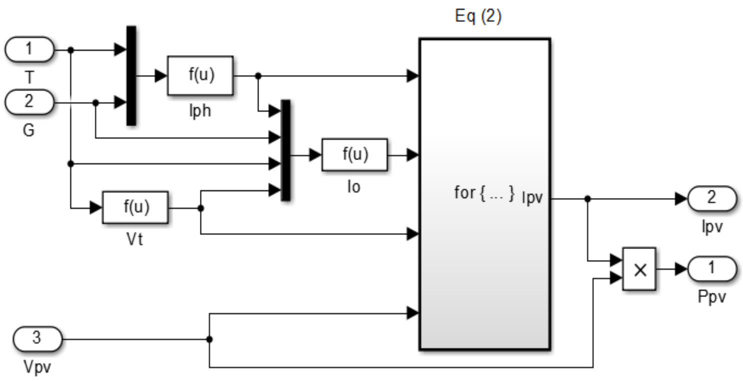

Fig. 3: Bloc Simulink of GPV

C. Buck converter

The power converter which is used in the photovoltaic conversion chain is buck converter (Fig.1). This converter is represented by its so called average model described by the following equations:

$$\begin{cases} C_s \frac{dV_s}{dt} = i_L - \frac{V_s}{R_s} \\ L \frac{di_L}{dt} = \alpha V_e - V_s \end{cases} \quad (3)$$

The values of the simulation parameters are the same as those used in Article [6, 10]. We use block diagrams to represent dynamic model (3) in Simulink environment (Fig 4):

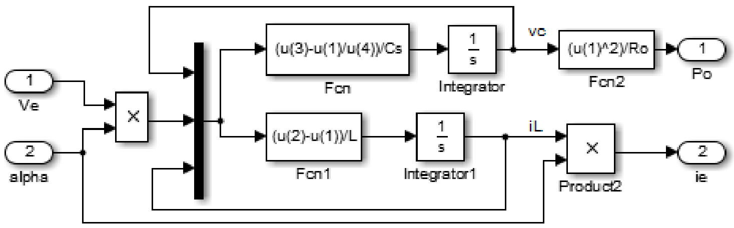

Fig. 4: Simulink block diagram of the buck converter average model

D. Takagi-Sugeno Fuzzy Controller

The proposed MPPT fuzzy controller is based on the Takagi-Sugeno model [11]. This model is considered to be an efficient technique to represent a non-linear system and to significantly reduce the fuzzy control calculation mechanism. In this paper, we have developed an incremental zero-order T.S fuzzy controller characterized by the following steps:

a) Calculation of input variables

The fuzzy controller receives as input the error E and the change of the error ΔE which are defined by:

$$E = \frac{\Delta P_{pv}}{\Delta V_{pv}} = \frac{P_{pv}(t)-P_{pv}(t-1)}{V_{pv}(t)-V_{pv}(t-1)} \quad (4)$$

$$\Delta E = E(t) - E(t-1) \quad (5)$$

With, $P_{pv}(t)$ as the instantaneous power delivered by the GPV and with $V_{pv}(t)$ representing the instantaneous voltage across the GPV.

b) Fuzzification

We choose a partition in 3 fuzzy classes (N, Z, P) of the discourse universe of the input and output variables. This partition is represented by triangular, trapezoidal and symmetric singletons membership functions according to Fig.5. The choice of the parameters (a, b, c) determines these membership functions completely and allows an easy real-time implementation of the fuzzification stage.

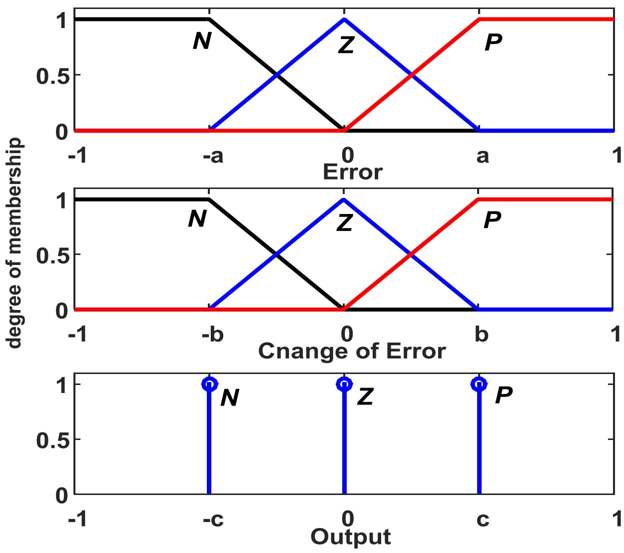

Fig. 5: Membership functions for the input and output variables.

c) Fuzzy Inference

We have opted for a reduced base with a five fuzzy rules represented in table 1:

Table 1: Fuzzy rules table

$\Delta\alpha$		E		
		N	***Z***	***P***
Δ*E*	***N***		c	
	Z	c	0	-c
	P		-c	

d) Calculation of the final output

Degree of activation w_i of the fuzzy rule is calculated with product operator (Fig.6). The final output representing the increment of the duty cycle Δα, is calculated as the average of the outputs of each rule weighted by the standardized activation degree according to equation (6):

$$\Delta\alpha = \frac{\sum_{i=1}^{n} c_i w_i}{\sum_{i=1}^{n} w_i} \tag{6}$$

The duty cycle α, is finally calculated by the equation:

$$\alpha(t) = \alpha(t-1) + \Delta\alpha \tag{7}$$

The fuzzy controller TS described by the above steps, is implemented and simulated using the following Simulink block diagram:

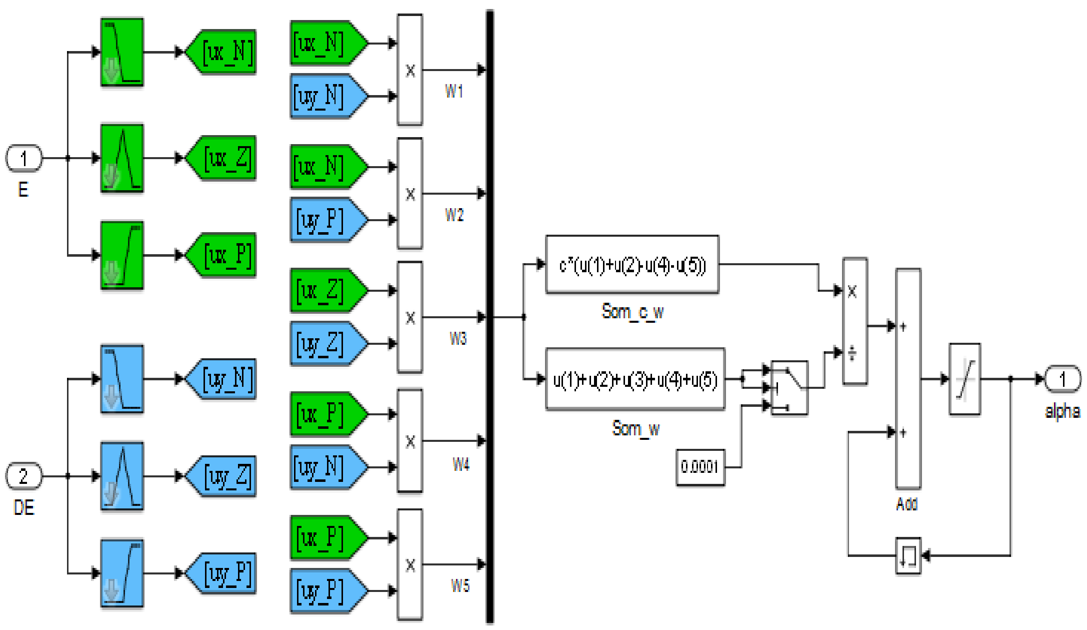

Fig. 6: Simulink block diagram of the proposed TS Fuzzy controller.

E. Completed Photovoltaic System

The completed model of the photovoltaic system, which is driven by the proposed fuzzy controller, is represented by the Simulink block diagram figure (7). This model has five unknown tuning parameters. The parameters (a, b, c) which determine the memberships functions of the input-outputs and the scale factors (G_1, G_2). These latter are used to transform the physical quantities of the inputs to normalized values belonging to the discourse universe [-1,1]. The model in figure (7) will be used in the next section for optimal determination of the tuning parameters of the proposed TS fuzzy controller.

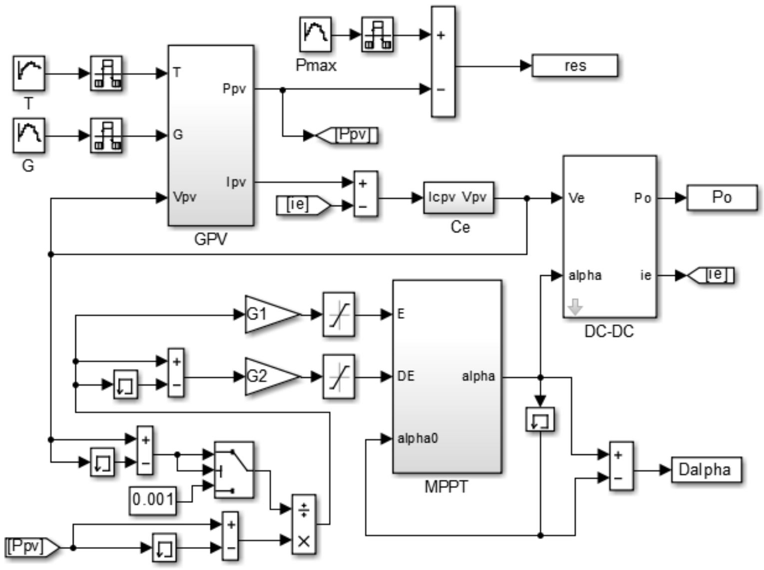

Fig. 7: diagram of the completed photovoltaic system

3. OPTIMIZATION METHODS

A. A Problem to Solve

The implementation of the fuzzy controller TS requires the determination of the parameters a, b, c, G_1 and G_2. The problem of the estimation of these parameters is formulated as constrained least squares problem [12]. The vector of the unknown parameters to be estimated is $\boldsymbol{x}$ = [a, b, c, G_1, G_2]. The objective function calculates for the same weather conditions the sum of squares of deviations between the maximum power point $\boldsymbol{P_{max}}$ and the power point $\boldsymbol{P_{pv}}$ that is supplied by the GPV (Fig.3). The aim is to determine the vector parameters minimizing the objective function $f(\boldsymbol{x})$:

$$\operatorname{Min}_{\substack{\boldsymbol{Lb} \leq \boldsymbol{x} \leq \boldsymbol{Ub} \\ |\Delta\alpha| \leq \Delta\boldsymbol{\alpha_{max}}}} \quad f(\boldsymbol{x}) = \left\| \boldsymbol{P}_{max}(\boldsymbol{G},\boldsymbol{T}) - \boldsymbol{P}_{pv}(\boldsymbol{G},\boldsymbol{T},\boldsymbol{x}) \right\|^2 \tag{8}$$

With $\boldsymbol{Lb}$ and $\boldsymbol{Ub}$ are the lower bound and the upper bound of the parameter vector $\boldsymbol{x}$. The variation $\Delta\alpha$ of the duty cycle is limited in order to ensure a continuous and smooth variation of the duty cycle α (Fig.7). To take into account the inequality constraint on the variation $\Delta\alpha$ of the duty cycle, we use the quadratic penalty method. The objective function to minimize then becomes:

$$\operatorname{Min}_{\boldsymbol{Lb} \leq \boldsymbol{x} \leq \boldsymbol{Ub}} \; f(\boldsymbol{x}) + \beta \sum max(\Delta\alpha(\boldsymbol{G},\boldsymbol{T}) - \Delta\boldsymbol{\alpha_{max}}, \boldsymbol{0})^2 \tag{9}$$

The penalty factor β is fixed in our case at 10^3.

B. Optimization Algorithm

In order to minimize the objective function $f(\boldsymbol{x})$, we use the particle swarm optimization algorithm (PSO). The PSO is a stochastic optimization method that is inspired by cooperative behavior in swarming animals such as bird flocking and fish schooling [2, 7].

The PSO is based on a set of simple agents, called particles. Each particle is characterized by position $\boldsymbol{x(t)}$ and velocity $\Delta\boldsymbol{x(t)}$ in search space. Each particle presents a potential solution to the problem of target function. At each iteration of the search procedure, the particle tends to move in its current direction toward its best position and toward its best neighbor. The next particle position is determined by combining linearly the three tendencies cited above. For simulations, we use the Matlab particle swarm solver [13].

4. RESULTS AND DISCUSSIONS

A. Parameters Estimation

For the calculations we use measurements of the irradiance G and the temperature T of a meteorological station in the city of Agadir [6]. The GPV model (3) is then used to determine the maximum power P_{max} that the panel can produce under the irradiance G and the temperature T.

Half of the data [G, T, P_{max}] (Fig.8.a) is used to determine the fuzzy controller parameters. The rest of the data is used for testing and validation of the proposed fuzzy controller. Figure 8 shows the evolution of the data [G, T] on a reduced scale (0.4 s).

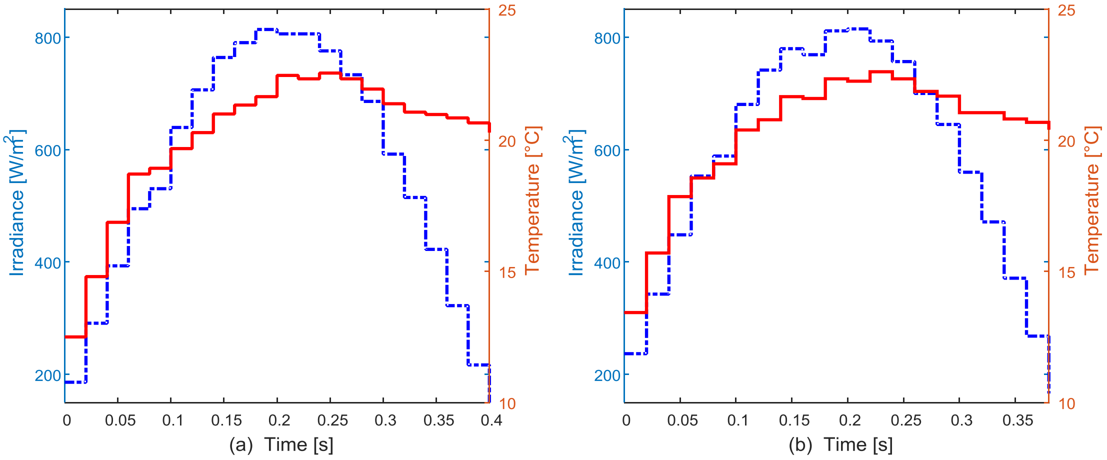

Fig. 8: [G, T] data. (a) used for parameter determination. (b) : used for testing and validation.

We have observed, after several tests, that the OEP optimization method converges to a stable value of the parameter vector $\boldsymbol{x}$ given in Table 2.

Table 2: Identified Parameters.

a	b	c	G_1	G_2
0.2256	0.1448	0.4137	0.0465	1.755

B. Evolution of Power Output for Variable Irradiance and Temperature

In this section we have compared the evolution of the power output obtained by the proposed TS controller (Fig.6) and the maximum power P_{max} that the GPV can produce under the same conditions of irradiance and temperature.
Figure (9) and (10) show the simulations results corresponding to a sample of the used data base (Fig.8.b). The temperature T and irradiance G obtained have a stair-step like shape of short duration.

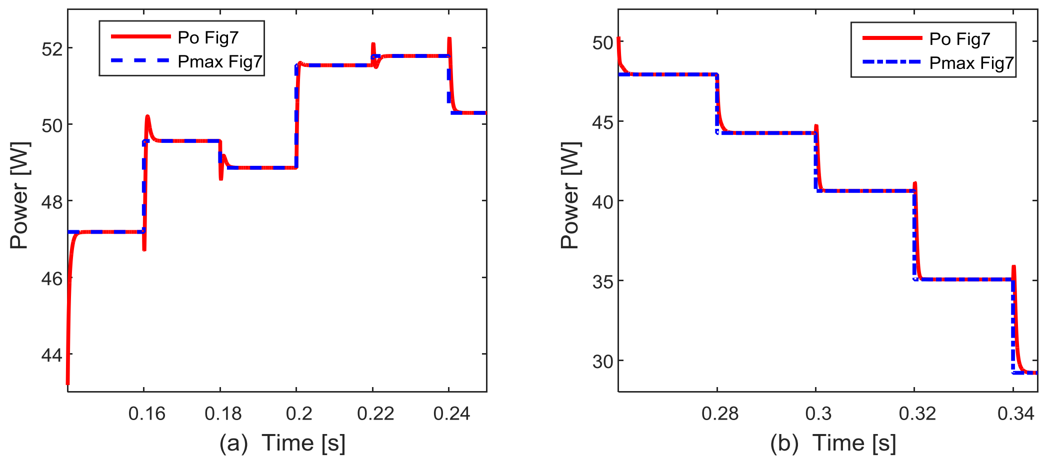

Fig. 9: Output power and maximum power under the same conditions of irradiance and temperature.

Under these conditions of temperature and irradiance of the city of Agadir, it is found that the proposed fuzzy controller ensures a smooth and rapid convergence towards the point of maximum power. The output power curve (Fig 9) shows maximum overshoot of about 30% and an average response time of the order of 1 ms.

In order To confirm the efficiency of the proposed fuzzy control, we compare the power at the buck converter output and the static characteristics of photovoltaic panel (Fig.10). The results of the simulations are obtained for the test data (Fig.8.b). The curve analysis in figure 10 shows again that the fuzzy controller allows a fast and stable convergence towards the PPM of the P(V) static characteristics.

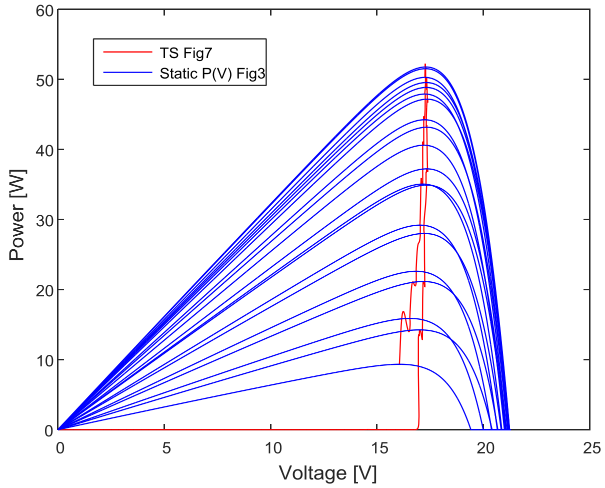

Fig. 10: Convergence to the PPM of the static characteristics

C. Performance of MPPT Controller

In this section we are going to compare the performance of the proposed TS controller and the results obtained by another TS controller with twenty-five fuzzy rules and five symmetric membership functions [6].

In order to evaluate the performance of the two fuzzy controllers, we have calculated the MPPT efficiency η_{MPPT} and the Integral of squared error (*ISE*) criterion defined respectively by:

$$\eta_{MPPT} = \frac{\int_0^t P_{pv}(t)\,dt}{\int_0^t P_{max}(t)\,dt} \tag{10}$$

$$ISE = \int_0^t \left[P_{max}(t) - P_{pv}(t)\right]^2 dt \tag{11}$$

We have noticed that the bigger is $\eta_{MPPT,}$ the weaker is *ISE* and the more efficient and quicker will MPPT be. Table 3 below presents an example of a calculation result for the η_{MPPT} efficiency and the steady-state *ISE* criterion of the two MPPT controllers for a temperature of 25 °C, an irradiance of 1000 W/m^2 and a simulation time of 0.5s.

Table 3: Performance Criteria for MPPT Controllers

Criteria	T.S. Fig.7	T.S. [6]
μ_{MPPT} (%)	99.59	99.58
ISE.10^4	13.32	13.33

The comparing results in Table 3 shows that the proposed TS controller has the same η_{MPPT} and ISE criteria as those obtained by the TS controller studied in [6]. The proposed TS controller has, in addition, the advantage of having a simple and reduced structure, which makes it more suitable for real-time applications, for which computing time is of paramount importance.

CONCLUSION

In this paper, we have developed a simple Takagi-Sugeno type fuzzy controller. This reduced structure consists mainly of five fuzzy rules and three symmetric membership functions. The proposed fuzzy controller must drive a buck converter to optimize power transfer between a GPV and its load. We have, therefore, used a PSO algorithm to systematically determine the parameters of the fuzzy controller along with improving the dynamic performance of the photovoltaic system studied. The photovoltaic system is studied and simulated under Matlab/Simulink using the temperature and irradiance measurements of the city of Agadir.

The simulation results confirm that the proposed fuzzy controller significantly improves the dynamics performances of the photovoltaic system. It allows a smooth and rapid convergence towards the point of maximum power with an average response time of the order of 1ms.

Finally, we have found that the developed TS controller has the same η_{MPPT} and *ISE* performances as those obtained by another TS controller with twenty-five fuzzy rules and five symmetric input-output variables [6]. The proposed TS controller has, in addition, the advantage of having a simple and reduced structure, which makes it more suitable for real-time applications, for which computing time is of paramount importance. This facilitates, in a future work, its implementation on a microcontroller driving an MPPT control on a real site.

REFERENCES

[1]. Belarbi, K., F. Titela, W. Bourebiaa et K. Benmahammed (2005). Engineering applications of artificial intelligence. Design of mamdani fuzzy logic controllers with rule base minimisation using genetic algorithm 18, 875–880.

[2]. A. Chatterjee, K. Pulasinghe, K. Watanabe, and K. Izumi, “A particleswarm-optimized fuzzy-neural network for voice-controlled robot systems,” IEEE Trans. Ind. Electron., vol. 52, no. 6, 2005, pp. 1478–1489.

[3]. [Boussaïd et al., 2013c] I. Boussaïd, J. Lepagnot, & P. Siarry. "A survey on optimization metaheuristics". Information Sciences, 237: 8–117, 2013. ISSN 0020-0255. doi : 10.1016/j.ins.2013.02.041.

[4]. M. Ajaamoum, M. Kourchi, R. Alaoui, L. Bouhouch, "Fuzzy Controller to Extract the Maximum Power of a Photovoltaic System", IEEE, International Renewable and Sustainable Energy Conference (IRSEC), Ouarzazate 7-9 March 2013, pp. 141-146.

[5]. Victor-Hugo Grisales Palacio, "Modélisation et commande floue de type Takagi-Sugeno Appliquées à un bioprocédé de traitement des eaux usées", Thèse de Doctorat de l’Université Paul Sabatier - Toulouse III, France, en cotutelle avec l’Université de los Andes, Colombie, 2007.

[6]. M. Ajaamoum1, M. Kourchi, B. Bouachrine, A. Ihlal, and L. Bouhouch, "Comparison of Takagi-Sugeno fuzzy controller and the command "P & O" for extracting the maximum power from a photovoltaic system". International Journal of Innovation and Applied Studies ISSN 2028-9324 Vol. 10 No. 1 Jan. 2015, pp. 192-206 © 2015 Innovative Space of Scientific Research Journals

[7]. J. Kennedy & R. Eberhart. Particle swarm optimization. IEEE International Conference on Neural Networks, 4: 1942–1948, 1995.

[8]. ENGELBRECHT A. (2010). Heterogeneous Particle Swarm Optimization. In Swarm Intelligence, volume 6234 of Lecture Notes in Computer Science, p. 191–202. Springer.

[9]. MSX-64 PDF Spec sheet, MSX-60 and MSX-64 Photovoltaic Modules, http://www.solarelectricsupply.com/solarex-msx-64-w-junction-box-548.

[10]. M. Ajaamoum, M. Kourchi, B. Bouachrine, A. Ihlal, L. Bouhouch, “Modelling an Emulator of Photovoltaic Panels”, International Journal of Enhanced Research in Science Technology & Engineering, ISSN: 2319-7463, Vol. 3 Issue 10, October-2014, pp: (163-171),

[11]. T. Takagi, M. Sugeno, "Fuzzy identification of systems and its application to modeling and control", IEEE Transactions on Systems, Man, and Cybernetics, Vol. SMC-15, No 1, January/February 1985, pp. 116-132.

[12]. G.R., Liu, X. Han, Computational Inverse Technique in Nondestructive Evaluation, New York: CRC Press LLC, 2003.

[13]. Global Optimization Toolbox, Global Optimization Toolbox User's Guide, Version 3.3.1 (Release 2015a). The MathWorks, Inc.