REAL-TIME IMPLEMENTATION OF A PSO- OPTIMIZED FUZZY LOGIC CONTROLLER BASED ON A MPPT ALGORITHM USING DSPACE BOARD

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Abstract: *The aim of this work is to demonstrate the usefulness of Particle Swarm Optimization (PSO) for tracking Maximum Power Point (MPP) in stand-alone photovoltaic system. Maximum Power Point Tracking (MPPT) is one of approaches which boost efficiency of Photovoltaic (PV) cells by the load matching between the PV cells and the load. The idea is to optimize and implement a Fuzzy Logic Controller (FLC) based on a maximum power point tracking method for a PV system.. A hardware prototype of the maximum power point tracking controller was also implemented using a dSPACE DS1104 digital signal processor (DSP) based real-time data acquisition control (DAC) system. The digital experimental results confirm the accuracy of the adopted control strategy as well as the better tracking efficiency and rapid response under all weather conditions.*

Key words: *Real-time PV emulation, Maximum power point tracking (MPPT), Fuzzy logic controller (FLC), Particle Swarm Optimization (PSO), dSPACE DS1104.*

1. Introduction.

Photovoltaic (PV) cells are an attractive source of energy. Abundant and ubiquitous, this source is one of the important renewable energy sources that have been increasing worldwide year by year. The International Energy Agency (IEA) estimates that by 2050, photovoltaic will provide around 11% of global electricity production [1]. Generally, these systems are used today in several applications which can be classified into three main classes: the stand-alone PV systems [2], the grid connected PV systems [3, 4] and the hybrid systems [5]. In specialized applications and in remote areas, the stand-alone PV systems are used with an energy storage device which is typically implemented as battery bank, but other solutions exist including fuel cells. On the other hand, to answer the growing need for alternative energies, the grid connected PV systems are used. Hybrid power systems combine solar photovoltaic systems with another kind of generated energy (wind, tidal, thermal,...).

However, in order to extract maximum power from a PV panel and to make the PV generation efficient, a capable maximum power point tracking (MPPT) technique is required to predict and to track the Maximum Power Point (MPP) at all environmental circumstances and then force the photovoltaic system to run at that MPP point, which is a DC-DC converter associated with the control unit, is usually connected between the photovoltaic panel and the load [6-8]. Usually, the MPPT controller is associated with a DC–DC or DC–AC power converters. However, the energy delivered by the photovoltaic panels depends on a complex equation relating the solar radiation and the temperature which leads to a non-linear output power, which makes tracking of maximum power point sometimes, be a challenging task. Various MPPT techniques had been proposed by researches to improve the efficiency of PV systems in recent years such as distributed MPPT, such as hill climbing [9], perturb and observe (P and O) technique [10], incremental conductance technique [11] and ANFIS based algorithm [12].

The most used MPPT techniques in renewable energy systems is the fuzzy logic controller [13]. Due to their heuristic nature associated with simplicity and effectiveness, for both linear and non-linear systems, fuzzy logic controller (FLC) methods have showed their salient features in implementations for MPP seeking [14-18].For example, a survey of the most used MPPT methods is presented by [14], who have shown that the use of FLC is more suitable to track the MPP compared to conventional controllers because they produce a better performance under all weather conditions. These results have also revealed that a PV system based upon the proposed controller can reach a power efficiency of about 99%. However, in spite of the good results provided by all the aforementioned works, all have one common drawback in the design of the FLC employed, which was done according to the trial-and-error method rather than a guided approach. These difficulties encountered in the design of fuzzy controllers have guided researchers towards the use of Evolutionary Algorithms (EAs) techniques because of their overall exploration characteristic in a complex environment.

In this paper, the EA technique used is the Particle Swarm Optimization (PSO) To provide a way of surmounting this shortcoming, [19] choose the Particle Swarm Optimization algorithm tool to optimize the FLC of their MPP tracker. They applied PSOs to calculate accurately the base lengths and the peak locations of the membership functions in the FLC for which the rule-base have already been created. The proposed solution leads to a good performance improvement of the MPP tracker addressed. In similar approach, the authors in [20] have proposed to optimize and to design an FLC by PSO algorithm for obtaining maximum power from solar panel based on MPPT method. The proposed approach shows better results for the extreme environmental conditions.

In this article, the fuzzy logic controller based as MPPT optimized by PSO algorithm (fuzzy MPPT - PSO) is used in stand-alone PV system as a control algorithm. Afterwards, the practically proposed system is investigated with an Elgar 5500 programmable DC power supply is used to emulate the PV BP SX150S panel, and a DC-DC boost power converter. The procedure followed makes the design of this type of MPP tracker simpler and more efficient.

Additionally, a software implementation of the designed FLC on general purpose computer cannot be considered as a suitable design solution for this type of application, especially when it has to be used as MPPT controller for standalone PV systems installed in remote rural areas. To realize prototypes and to test the control strategies of energy conversion systems, the tendency of researches now is to employ digital implementation which provides more efficiency over their analogue equivalents. Traditionally, the FLC was usually implemented in microcontrollers [21, 22]. There are also other implementations in the field-programmable gate array (FPGA) chips [23-25]. For example, in [26] deal the digital implementation of a fuzzy logic controller on a Xilinx reconfigurable FPGA. The simulation results obtained with ModelSim Xilinx Edition-III show satisfactory results. However, the technological development of Digital Processing Boards (DSP) with fast computing capability and simplicity in programming makes it a solution for numerical implementation of more complex control algorithms. This paper gives the implementation details of a stand-alone PV system control algorithm based dSPACE platform.

The remainder of the paper is organized as follows: In section 2, the PV system description is presented. The particle swarm optimization algorithm is detail in section 3. Experimental results are described in detail in section 4. Finally, a general conclusion is given in section 5.

2. System description

The structure of the studied stand-alone PV system is developed under Matlab/Simulink environment.

2.1. PV panel modeling

The PV panel is composed of 72 multi-crystalline silicon PV cells connected in series. For modeling purposes, the equivalent electrical circuit of a PV cell using a single diode model is presented in Fig. 1. The most commonly used expression of the output current I_{pv} and output voltage V_{pv} of a PV panel with N_s cells in series can be described by Eq. (1) which describes the current–voltage characteristics of a PV panel [28].

$$I_{pv} = I_{ph} - I_d - I_{R_p} \tag{1}$$

where, $I_d = I_0 \left(\exp\left(\frac{V_{pv}+R_s I_{pv}}{\alpha V_T}\right) - 1 \right)$

$$I_{R_p} = \frac{V_{pv}+R_s I_{pv}}{R_p}$$

$$V_T = \frac{kT}{q}$$

$$I_0 = I_{rs} \left(\frac{T}{T_r}\right)^3 \exp\left[q. E_g\left(\frac{1}{T_r} - \frac{1}{T}\right)\right]$$

where, I_{ph} is the light generated PV current,
I_0 is the reverse saturation current,
α is the diode ideality factor,
k is the Boltzmann constant,
T is the Kelvin temperature of the cell (K),
q is the electron's charge,
R_s and R_p are the series and parallel equivalent resistances,
N_s is the number of cells in series,
I_{rs} is the reverse saturation current at T,
E_g is the bandgap energy of semiconductor used in the solar cell,
T_r is the cell reference temperature.

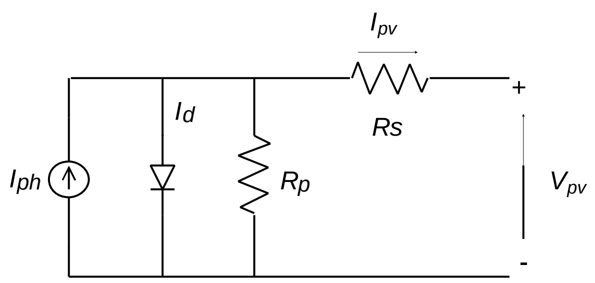


Fig. 1. Single diode model of solar cell.

The main electrical parameters of BP SX150S panel used are summarized in Table 1.

Table 1
Parameters of BP SX150S panel.

Electrical characteristics	BP SX150S
Maximum power (P_{MPP})	150 W
Voltage at P_{MPP} (V_{max})	34.5 V
Current at P_{MPP} (I_{max})	4.35 A
Short circuit current (I_{sc})	4.75 A
Open circuit voltage (V_{oc})	43.5 V
Temperature coefficient of I_{sc}	0.0065%/°C

2.2. Control of DC-DC Boost Converter

Fig. 2 presents the structure of the DC-DC boost converter used to increase the PV output voltage supplying the resistive load. The IGBT power switch modulates the power transfer from the input source to the load using the pulse width modulation (PWM) technique generated by the high frequency controlling device. A 8 kHz PWM signal generated by a controlling device is injected to the converter's switch S.

The duty cycle D of this PWM signal is adjusted in real time to perform a maximum power point tracking in order to extract the maximum power from the PV panel. In the case of a continuous conduction mode, the relationship between the average values of the input and output voltages is defined as follows [29]:

$$V_o = \frac{1}{1 - D} V_i \tag{2}$$

where, V_i and V_O are respectively the voltages at the input and the output of the PV panel.

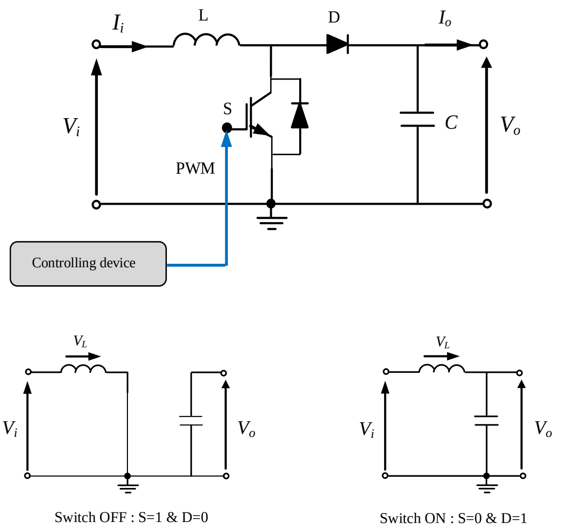


Fig. 2. Basic electrical circuit of a DC-DC boost converter and its operating mode.

2.3. Fuzzy MPPT Control

Recently fuzzy logic controllers (FLCs) have been introduced in the tracking of the MPP in PV conversion systems. In this section it is not intended to give the theoretical background information about fuzzy logic; we will just give the necessary concepts that will allow the understanding of the analysis that follows. Unlike conventional control, which is based on mathematical model of a system, a FLC embeds the intuition and experience of a human operator. This is a great advantage since with the increasing complexity of systems; the ability to describe them mathematically becomes difficult. In this control approach, the control action is expressed with linguistic rules in the form of: IF a set of conditions are satisfied, THEN a set of consequences are inferred. Generally, as shows in Fig. 3, a conventional fuzzy logic controller contains four main components [30].

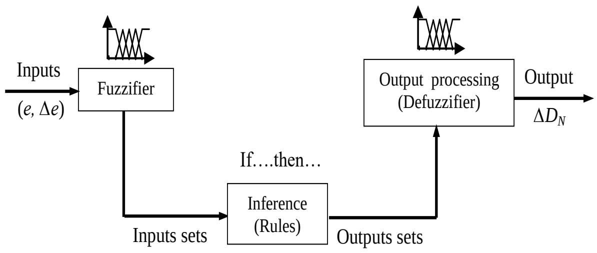


Fig. 3. Algorithm structure of fuzzy controller.

The fuzzification interface converts the numerical values of real variables into fuzzy variables. The two controller's inputs are an error *e(k)* and an change of error $\Delta e(k)$. These input variables are a set of membership functions such as Negative Big (NB), Negative Small (NS), Zero (ZE), Positive Small (PS) and Positive Big (PB). The shapes of membership functions associated to linguistic variables that we used are linear functions of trapezoidal and triangular type. At a sampling instant k, the controller's inputs are defined by the following equations:

$$e(k) = \frac{P(k) - P(k-1)}{V(k) - V(k-1)} \tag{3}$$

$$\Delta e(k) = e(k) - e(k-1) \tag{4}$$

where, $P(k)$ is the output power of PV panel and $V(k)$ is the terminal voltage of PV panel.

In this paper, we use five fuzzy sets for the input variables (e, Δe) nominated {NB, NS, ZE, PS, PB}. The forms of the membership functions associated to these input variables are trapezoidal and triangular linear functions. The partitioning of these membership functions of the fuzzy subsets is defined by 5 parameters, in example $\{e_1, e_2, e_3, e_4, e_5\}$ as shown in Fig. 4.

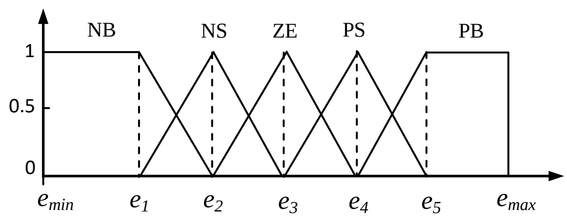


Fig. 4. Membership functions of FLC input.

Table 2 shows the rule table of a fuzzy logic controller with two inputs (e,Δe). This table can be seen as a 5x5 matrix. The matrix rows represent the five fuzzy sets of the error; the matrix columns depict the five fuzzy sets of the error's variation. Matrix cells represent the fuzzy sets outputs which are denoted as 1, 2, 3, 4 and 5 for NB, NS, ZE, PS and PB respectively. It is noted that the rules base defines the controller's behavior and it requires user knowledge to form the all fuzzy rules. For example, the rule given by the black cell of Table 2 is interpreted as follows:

If e is Positive Big (PB) and Δe is Zero (ZE) **then** ΔD_N is Negative Big (NB).

where, ΔD_N is the normalized incremental change of the duty cycle D.

Table 2.
Rule base table for computation ΔD_N.

e	Δe NB	NS	ZE	PS	PB
NB	3	3	5	5	5
NS	3	3	4	4	4
ZE	4	3	3	3	2
PS	2	2	2	3	3
PB	1	1	1	3	3

The defuzzification interface converts the resulting fuzzy output from the fuzzy inference mechanism into a numerical output ΔD_N. The shapes of membership functions associated to controller's output that we used are linear functions of singleton membership type. The controller's output will supply a signal to control the duty-cycle of power converter in order to track the MPP.

In this paper, we use five fuzzy sets for the output variable (ΔD_N) nominated {NB, NS, ZE, PS, PB}. The forms of the membership functions associated to this output variable are singleton functions. The partitioning of these membership functions of the fuzzy subsets is defined by 5 parameters {d_1, d_2, d_3, d_4, d_5} as shown in Fig. 5.

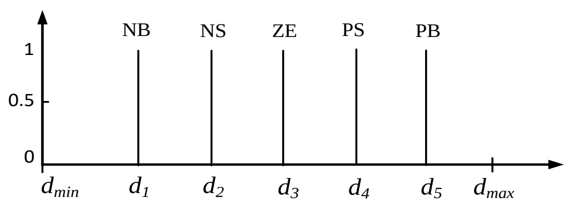


Fig. 5. Membership functions of output ΔD_N.

In this study, we consider a PI-type fuzzy controller for which the duty ratio D is obtained by:

$$D(k) = D(k-1) + G_D \times \Delta D_N(k) \tag{5}$$

where, G_D is the scaling output factor.

3. Particle Swarm Optimization

The Particle swarm optimization (PSO) is new Evolutionary Algorithm (EA) technique developed by Kennedy and Eberhart in 1995 [31], and inspired by the social behavior of flocking birds and schooling fishes. In this algorithm, several cooperative agents are used to exchange information obtained in its respective search process. Each agent is referred to a particle following two simple rules, i.e., following the best performing particle, and moving towards the best position found by the particle itself. Through this way, each particle eventually approaches an optimal or close to optimal solution [19]. It can be obtained high quality solutions within shorter calculation time and stable convergence characteristics with PSO algorithm than other stochastic methods such as genetic. Particle swarm optimization uses particles which represent potential solutions of the problem. Each particles fly in search space at a certain velocity which can be adjusted in light of proceeding flight experiences. The projected position of *ith* particle of the swarm, and the velocity of this particle v_i at $(t+1)^{th}$ iteration are defined as the following two equations (6) et (7) in this study:

A basic PSO algorithm can be described as follows:

Step 1 (Initialization):
Initialize a population of particles with random positions and velocities on D-dimensions in the problem space,

Step 2 (Evaluation):
Evaluate desired optimization fitness function in D variables for each particle,

Step 3 (Update velocity and position of particles):
The velocity and position of each particle in the swarm are updated according to the following equation:

$$V_i(t+1) = CFa\Big(wV_i(t) + c_1r_1\big(pbest_i(t) - X_i(t)\big) + c_2r_2\big(gbest(t) - X_i(t)\big)\Big) \tag{6}$$

$$X_i(t+1) = X_i(t) + V_i(t+1) \tag{7}$$

where, $V_i(t)$ is current particle velocity, $V_i(t+1)$ is particle velocity update, $X_i(t)$ is current particle position, $X_i(t+1)$ is particle position update, $pbest_i(t)$ is best position found by the particle, $gbest(t)$ is best solution found by the swarm.

Step 4 (Stop criterion):
Loop to **step 2** until a criterion is met or end of iterations.

The general parameters of PSO are set as: w is the inertia coefficient, c_1 and c_2 are two positive constants, r_1 and r_2 are random numbers in the range [0, 1].

In [32] Clerc shows that the use of constriction factor (CFa) may be necessary to ensure convergence of

PSO algorithm. The coefficient ‘w’, corresponds to a kind of inertia, which is used to control the impact of the previous velocities on the current velocity of each particle and tries to explore new areas. It can be a positive constant or a positive linear or non linear function of time [33]. In this paper, we use an adaptive coefficient (w) proposed in [34]. The updating expression of w is given by:

$$w = \frac{t - t_{max}}{t_{max}} \tag{8}$$

where, t is current iteration number, t_{max} is maximum number of iterations.
The value of the constriction factor CFa used in this work is given by the following equation:

$$CFa = \frac{2}{\mathrm{abs}(2-C-\mathrm{sqrt}(C^2-4*C))} \tag{9}$$

with $C = c_1 + c_2$ and $C > 4$

In this paper, the parameters values c_1, c_2 and CFa are 2.04, 2.04 and 0.721, respectively.

At the end of the iterations, the best position of the swarm will be the solution of the problem. It is not possible to get an optimum result of the problem always, but the obtained solution will be an optimal one. It cannot be able to an optimum result of the problem, but certainly it will be an optimal one.

3.1. Optimization criterion

The design of a fuzzy MPPT can be formulated as an optimization problem where the objective is to find the best parameters of the fuzzy MPPT that minimize the power losses, mainly due to weather conditions, in the PV system. The power losses can be presented as a quadratic function as given in Eq. 10.

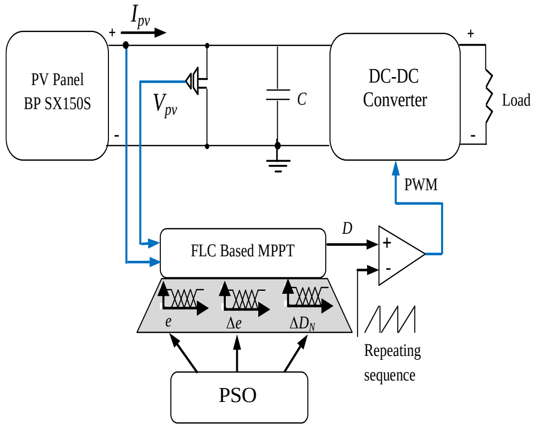
$$ISE = \int_0^{t_f} \left(e(t)\right)^2 dt \tag{10}$$

where, $e(t) = P_{max}(t) - P_{pv}(t)$

P_{max} is the maximum power of the PV panel, P_{pv} is the instant power provided by the PV panel and t_f is the simulation time.

ISE is the integral squared error criterion to be minimized using PSO. Fig. 6, illustrates this optimization approach by PSO and Fig. 7 shows the Matlab/Simulink model used to evaluate the ISE criterion.

In the subsequent sections, the detailed implementation strategy of PSO algorithm is described.



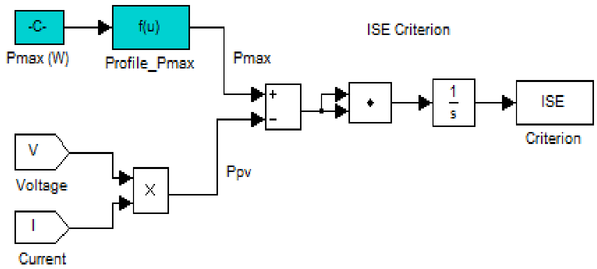


Fig. 7. Matlab/Simulink model used to evaluate the ISE criterion.

3.2. Initial population

Particles of the initial population are initialized with random values. For each element $X_{i,j}$ of chromosome i, a random number $r_{i,j}$ between 0 and 1 is generated. Then the value of $X_{i,j}$ is defined by mapping [0, 1] into $[X_j^L, X_j^U]$, according the following equation:

$$X_{i,j} = X_j^L + r_{i,j} \times \left(X_j^U - X_j^L\right) \tag{11}$$

where, X_j^L and X_j^U denote the lower and upper bound of $X_{i,j}$, respectively.

3.3. Structure of particle

In this paper, we optimize the parameters of membership functions of the fuzzy MPPT including in PV system. For a FLC with 2 inputs variables and one output variable, we have 3×5 membership functions. Each 5 membership functions are defined by 5 parameters. Therefore the structure of PSO’s particle can be presented as vector of 15 real parameters as depicted in Fig. 8.

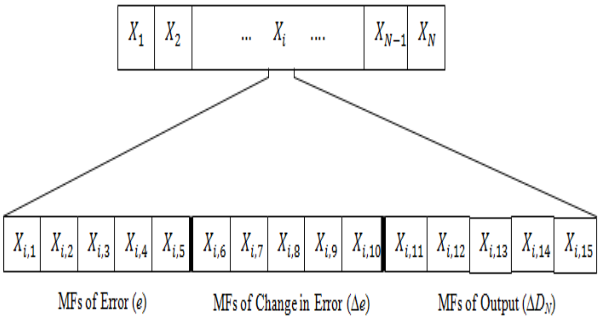


Fig. 8. Structure of the N particle using real coding.

4. Experimental results and discussion

This section describes the experiments in the implementation of the fuzzy MPP tracking method optimized by PSO algorithm of the PV conversion power system. The PSO parameters values are given in Section 3.

The bench test was based on the following equipment: an Elgar 5500 programmable DC power supply is used to emulate the BP SX150S PV panel [35], a DC–DC boost power converter operating with a switching frequency of 8 kHz and a resistive load. A hall effect current probe and a hall effect voltage probe were used to detect the PV output current and PV output voltage. A 2200 µF capacitor is used to filter the DC output voltage representing the PV panel output voltage and the PV output current is measurements are measured across the 0.6mH inductor.These measurements are both acquired by the dSPACE A/D converters and filtered once again with implemented digital filters. Fig. 9 shows the experimental setup representing the studied PV system. The experimental bench is carried out in the GREAH laboratory.

4.1. dSPACE implementation of the optimized FLC based PSO

The motivation behind the implementation of the fuzzy MPPT method presented in introduction, is the application in a dSPACE board. The FLC is designed and optimized with Matlab-Simulink. The controller is configured according to the previously structure detailed in subsection 2.3:

The input variables (e and Δe) and the output variable ΔD_N are characterized by five membership functions {NB, NS, ZE, PS, PB} and their respective domain intervals are [-35, 5] for e, [-49, 49] for Δe and [-1.5, 1] for ΔD_N output. These intervals are obtained by calculating the maximum values allowed for each used variable in the test environment of our PV system. Thus, the corresponding rule base includes 25 fuzzy rules (Table 2).

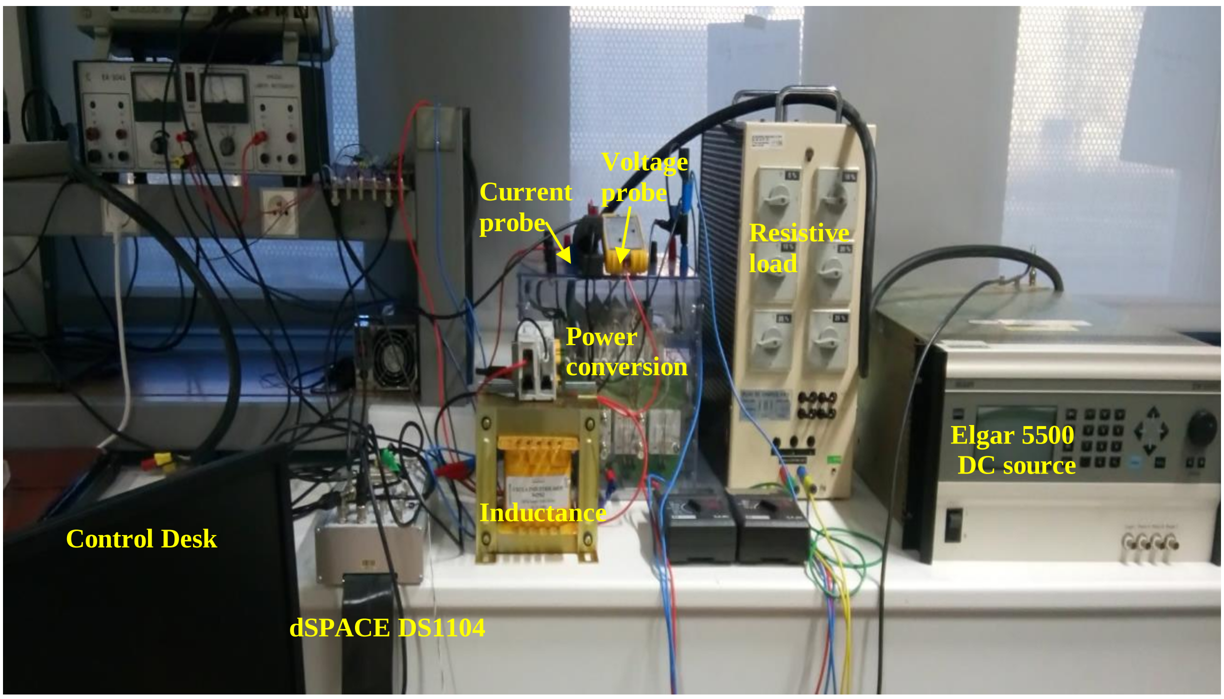


Fig. 9. Experimental setup of the emulated PV system.

The fuzzy MPPT -PSO was digitally implemented on a dSPACE DS1104 DSP controller board platform with a sample time of Ts = 50 µs. Fig. 10 shows the overall PV system diagram of the experimental set-up. Real-time control of continuous systems is done using a PC connected to the dSPACE DS1104 board.

The programming is done using the SIMULINK modeling tool, which helps to pose the problem in a graphical way using the interconnected blocks. In fact, many DSP-based real-time development systems now come with an interface to Simulink by which they can convert Simulink blocks into machine code that can be run on a DSP-based system. These controllers make use of the real time interfacing toolbox available in MATLAB to interface the SIMULINK model with the real hardware models.

We can easily modify the controller's parameters, control the output load or change the emulated weather conditions in the PV panel's model. In addition, acquired currents and voltages can be saved or plotted.

4.2. PSO learning algorithm

.To take more realistic operating conditions in account, three levels of irradiance (500 W/m^2, 1000 W/m^2 and 800 W/m^2) were adopted in this study, as shown in Fig. 11.

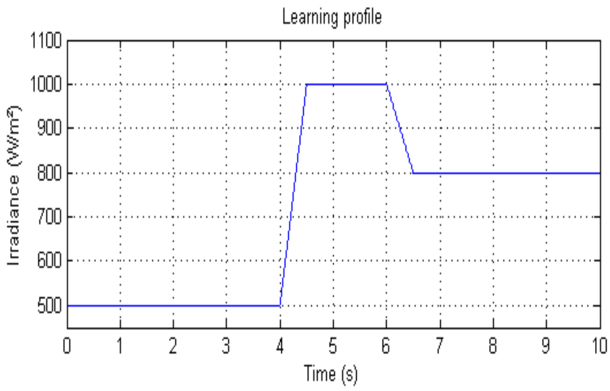


Fig. 11. Learning profile.

The convergence profile of the PSO algorithm is given to a population of 20 particles in the Fig. 12. It can be seen in this figure that the PSO algorithm converges towards the best fitness with few generations. Thus, the PSO evolves efficiently in search of better parameters to design an optimal FLC and increase the system robustness with respect to the weather conditions.

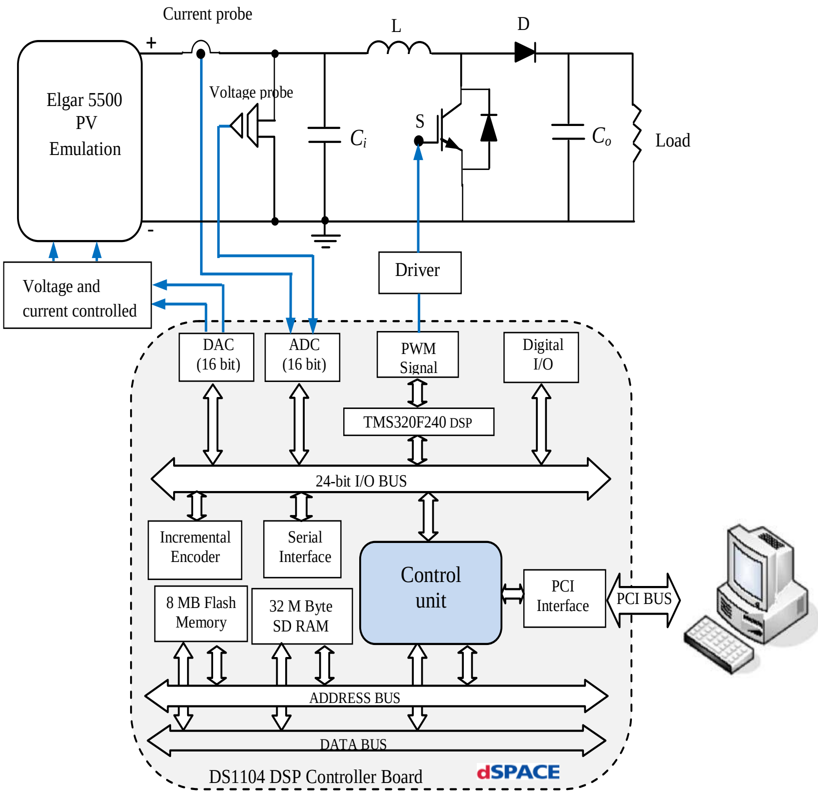


Fig. 10. Overall PV system diagram of the experimental set-up.

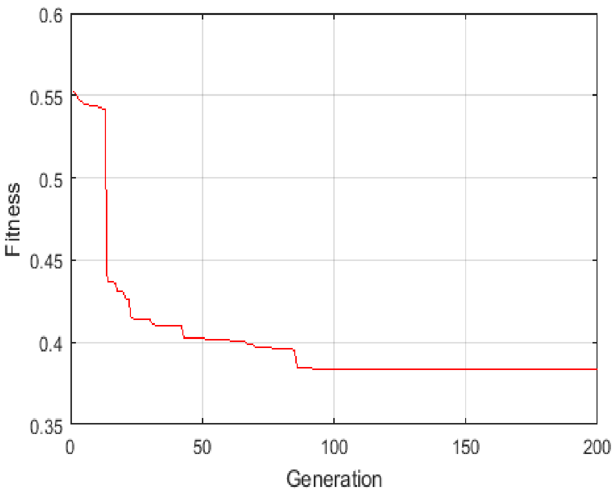


Fig. 12. PSO convergence profile.

4.3. Tests

4.3.1. Test under standard tests conditions

In this section, the test is carried out under standard test conditions (STC: E=1000W/m², T=273 K).

To evaluate the MPPT performance, a transient load step change from R=20Ω to R=14Ω is applied at time 0.5s.

Figs. 13 show respectively the fuzzy logic controller optimized by PSO algorithm in order to generate an optimal duty cycle for the maximum power point tracking. As it can be seen also on Fig. 13 the generated PV power is always maintained at its 150W maximum power. During each acquisition period, the controller generates the corresponding new duty ratio *D* which sets the new position of the tracked MPP and vice versa.

The current and voltage curves are given respectively in Figs. 13.

The results presented here have shown that the advantages of the system developed are the adaptation of the PSO- FLC parameters for fast response, good transient performance, and robustness to variations in external disturbances.

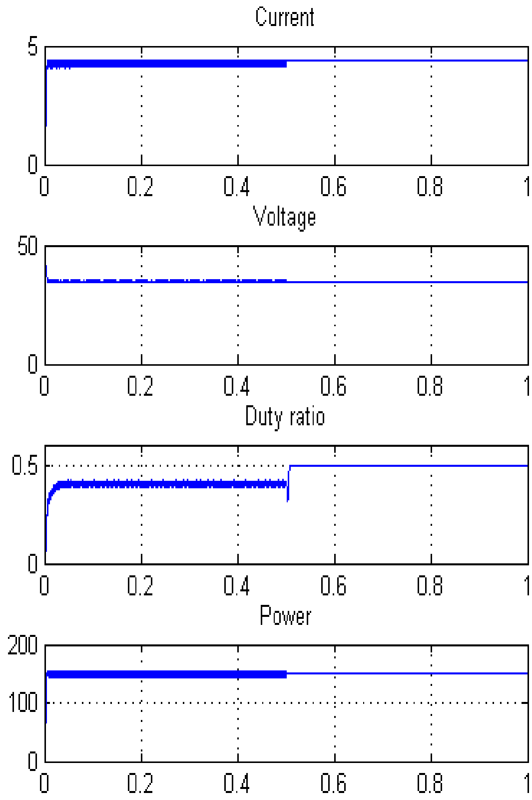


Fig. 13. PV output power under STC.

4.3.2. Test under different weather conditions

Fig. 14 shows the effects of variations in irradiance level by imposing some increment and decrement. Thus, the irradiance level starts from 800W/m² then decreases to 1000W/m² after that increases to 900 W/m² and each variation occurs after 0.5 s and the temperature is kept constant during the simulation at 273 K.

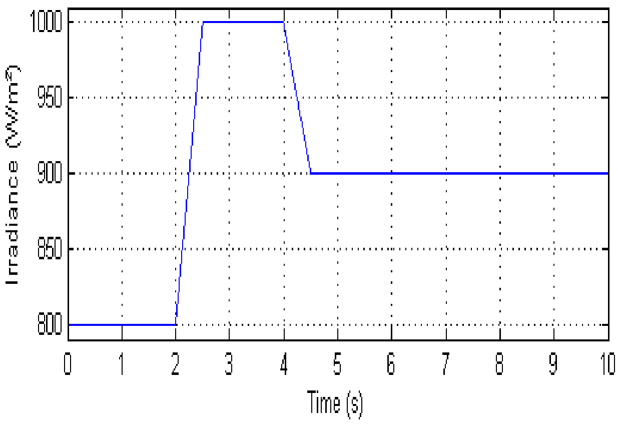


Fig. 14. Irradiance profile.

Although the temperature of a photovoltaic cell does not vary quickly during a day, a rapid change of temperature is tested to evaluate the performance of the optimized fuzzy controller. In the Fig. 15, a rapid increase in temperature from 288 K to 308 K and a rapid decrease also from 308 K to 298 K were simulated. The solar irradiation is keeps constant during the simulation at 1000W/m².

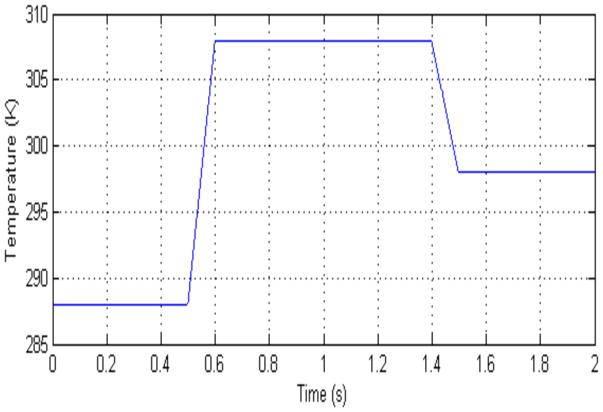


Fig. 15. Temperature profile.

Fig. 15 and Fig. 16 shows the behavior of the PV system under rapid changes in irradiance and temperature are presented, respectively. As it is clearly shown in Fig.15(c), the corresponding generated power of the fuzzy MPPT -PSO track the MPP after each irradiance variation step (Similar for the temperature case as Fig.16). The response of controller presents little oscillations around the operating point even at steady state as we can see in Fig.15(c) and Fig.16.

The MPP of a PV panel varies according to irradiance variation and temperature variation. The corresponding fuzzy MPPT -PSO can drive quickly the system to the new MPP when an abrupt change of the MPP occurs.

The current and voltage curves are given respectively in Figs. 15 (a) and (b).

The results presented here have shown that the advantages of the system developed are the adaptation of the fuzzy MPPT -PSO parameters for fast response, good transient performance, and robustness in face of changing weather conditions.

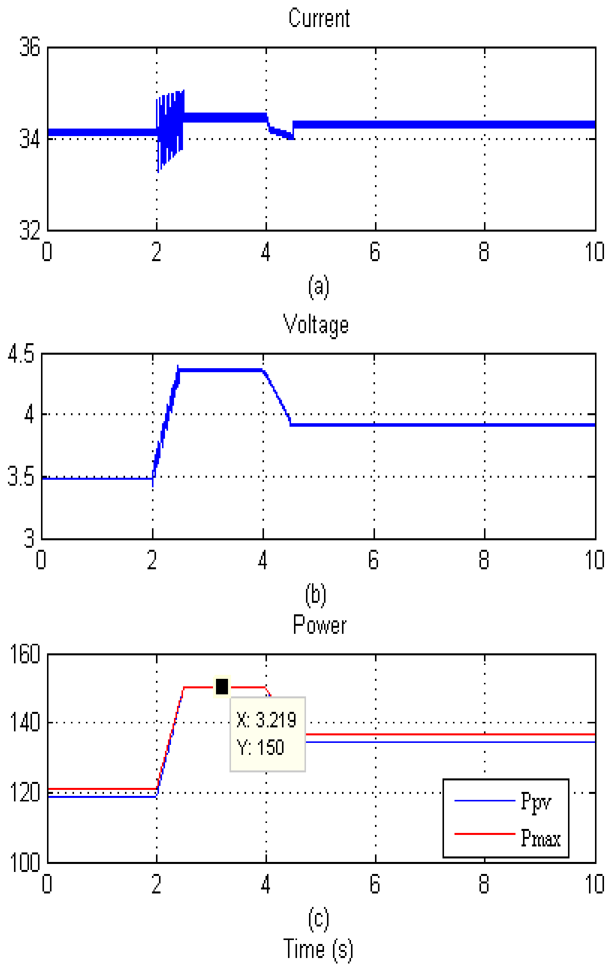


Fig. 15. Experimental results under variations irradiance.

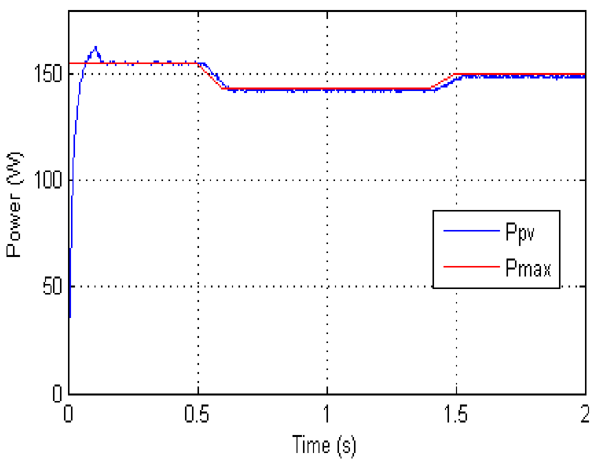


Fig. 16. Experimental results under variations temperature.

5. Conclusion

In this study, an improved maximum power point tracking (MPPT) method based Fuzzy- Particle swarm optimization algorithm for solar panel is proposed. As it is shown, they were successfully used in this work, to improve the performance of a fuzzy logic-based MPPT controller by optimizing the membership functions of this controller. The main advantage of the method is the reduction of the oscillation (to practically zero) once the maximum power point (MPP) is located. Furthermore, the proposed method has the ability to track the MPP for the extreme environmental condition, e.g., large fluctuations of irradiation condition. In addition to the software simulations, an dSPACE 1104 was also used to implement the hardware prototype of the whole MPP tracker including the designed fuzzy MPPT -PSO.

This work is the first step before a final field installation to experimentally validate the effectiveness of the proposed fuzzy MPPT -PSO in a stand-alone photovoltaic system.

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