

*This paper presents a method for neural network sliding mode control design to track the maximum power point (MPPT) for a photovoltaic pumping system. For the best use, the photovoltaic (PV) panel must operate at its maximum power point (MPP). Sliding mode control (SMC) can be used for non linear systems with small uncertainties. However, for complex nonlinear systems, the uncertainties are large and produce higher amplitude of chattering due to the higher switching gain. In this work, sliding mode control approach is combined with the neural network (NN) to adjust the duty cycle control law. NN is used for the prediction of model unknown parts. The proposed control law uses the full state of the system. However only the rotation speed variable is available for measurement. For this particular task, a robust differentiator via SMC is employed. Performance of the proposed controller is compared with the traditional SMC and investigated by simulation.*

Keywords: Sliding mode control, neural network, photovoltaic pumping system, maximum power point tracking, robust differentiator.

## 1. Introduction

Solar energy is one of the most important renewable energy sources in the world. The use of photovoltaic as the power source for pumping is considered as one of the most promising areas of PV application. Pumping photovoltaic systems are particularly suitable for water supply in remote areas where no electricity supply is available.

The efficiency of the PV pumping system depends on several climatic factors such as the solar radiation, the ambient temperature and the state of the solar panels [1]. Since the maximum power point varies with radiation and temperature, it is difficult to maintain optimum matching at all radiation levels. In order to improve the performance of a PV pumping system, a DC–DC boost converter known as a maximum power point tracker (MPPT) is used to match continuously the solar cell power to the environment changes. In the last decade, many algorithms and controllers have been developed for the MPPT [2], [3]. It should be noted that many of them cannot reduce the tracking error and accomplish the operation with accuracy process. Since the systems dynamics of photovoltaic pumping are highly nonlinear and usually contain uncertain elements, the system's control performance can be affected seriously [4]. Many methods to control the dynamics system have been made to get an appropriate solution to achieve the precise tracking control; these are namely fuzzy control [5], neural network [6], and sliding mode control (SMC) [7]. The SMC with boundary layer approach can be used to achieve robust tracking. However, in the presence of large uncertainties, the controller has a higher switching gain and produces

\* Corresponding author: J. Boumhidi, Department of computer science LIAN Laboratory, Faculty of Science, Sidi Mohamed Ben Abdellah University, Dhar Elmahrez, Fez, Morocco, E-mail: jaouad.boumhidi@usmba.ac.ma

<sup>1</sup> Department of Physics, LESSI Laboratory, Faculty of Science, Sidi Mohamed Ben Abdellah University, Dhar Elmahrez, Fez, Morocco

<sup>2</sup> Department of computer science, LIAN Laboratory, Faculty of Science, Sidi Mohamed Ben Abdellah University, Dhar Elmahrez, Fez, Morocco.

higher amplitude of chattering. In this paper, sliding mode control approach is combined with the neural network (NN) to adjust the duty cycle control law of the converter. NN is used for the prediction of model unknown part and hence enables a lower switching gain to be used. As a result, the SMC with boundary layer approach can be used to ensure the better tracking performance without any oscillatory behaviour. The network weights are adjusted during online implementation by using the gradient descent method (GD) [8]. The state observation is one of the most essential problems in modern control theory [9]. Many schemes for the estimation of states variables have been proposed in recent years. Some of these methods are based on nonlinear observer theory such as high gain observer, sliding mode observer and backstepping observer. In order to improve the performance of observers, another attractive method for the estimation is the differentiators via SMC. Differentiators are very useful tools to determine and estimate signals [10], [11].

The proposed control Motivated by using the robust differentiator (RDF) consists of the so called equivalent control with added robust control term. The neural network predicted unknown terms are incorporated in the equivalent control component. As a result, the responses will be fast without any chattering problems.

This study is organized as follows. The next section is PV pumping system description. In Section 3, the sliding mode controller with a robust differentiator via SM is presented. In section 4 the proposed neural network sliding mode controller is shown. Section 5 presents the simulation results. Finally, a conclusion is given.

## 2. Photovoltaic pumping system

### 2.1. System description

The Figure.1 shows the structure of the considered PV pumping system

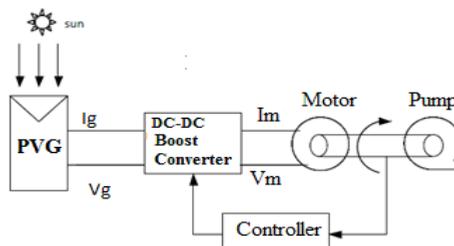


Figure1. Block diagram of photovoltaic pumping

### Photovoltaic generator model

The characteristic equation for the current and voltage of PV module is given as follows [5], [7], [12].

$$I_p = I_{ph} - I_0 \left( \exp \left( A \left( V_p + R_s I_p \right) \right) - 1 \right) - \frac{V_p + R_s I_p}{R_{sh}} \tag{1}$$

$$\text{With: } I_{ph} = \left[ I_{SCR} + K_I (T - T_r) \right] \frac{\lambda}{1000}, \quad A = \frac{q}{N \gamma K T},$$

$$I_0 = I_{or} \left[ \frac{T}{T_r} \right]^3 \exp \left[ \frac{qE_{G0}}{\gamma K} \left( \frac{1}{T} - \frac{1}{T_r} \right) \right]$$

where :

$I_{ph}$  – Photo current,  $I_0$  – cell reverse saturation current,  $I_{0r}$  – cell saturation current at  $T_r$ ,  $I_{SCR}$  – short circuit current at 298.15 K and 1 kW/m<sup>2</sup>,  $K_I$  – short circuit current temperature coefficient at  $I_{SCR}$ ,  $\lambda$  – solar irradiation in W/m<sup>2</sup>,  $E_{G0}$  – band gap for silicon,  $\gamma$  – ideality factor,  $T_r$  – reference temperature, T – cell temperature, K – Boltzmann’s constant and  $q$  – electron charge.

In this system we considered a DC motor of nominal tension 400V and nominal current 12.2A .We then need a PVG constituted by  $N_S = 20$  modules in series helps us to rise the required direct voltage value. And  $N_P = 5$  in parallel helps us to rise direct current value.

The optimum voltage of each panel is 17V and the optimum current is 3.14, then the power of PV generator is  $(17 \times 20)(3.14 \times 5)W$  is near to the motor’s power ( $P_m = 400 \times 12.2W$ ).

The current of PVG is [7]:

$$I_g = I_{phg} - I_{0g} \left( \exp \left( A_g (V_g + R_{sg} I_g) \right) - 1 \right) - \frac{V_g + R_{sg} I_g}{R_{shg}} \tag{2}$$

Where:

$V_g$  : The PVG output voltage,  $I_g$  : The PVG output current,  $A_g = \frac{A}{N_S}$  – the PVG constant,  $R_{sg} = \frac{N_S}{N_P} R_s$  : The PVG series resistance,  $R_{shg} = \frac{N_S}{N_P} R_{sh}$  : The PVG parallel resistance,  $I_{phg} = N_P I_{ph}$  : The photocurrent of the PVG,  $I_{0g} = N_P I_0$  : The saturation current of the PVG,  $N_S$  : The number of PV connected in series and  $N_P$  : the number of parallel paths.

**Boost converter**

The DC-DC boost converter presented in Figure 2 as voltage elevator takes an intermediate position between the generator and the motor in order to regulate its supply with a maximum power by regulating its gain. It is containing at least two semiconductor switches (a diode and the switch is typically MOSFET).

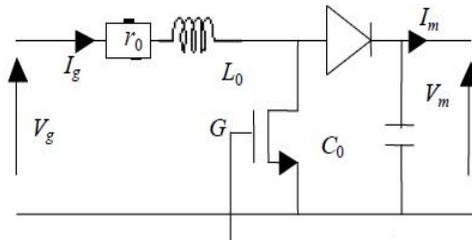


Figure2. Circuit of boost converter

The dynamics of this converter operating in continuous conduction mode is given as follows:

$$V_g = (1 - \alpha)V_m + L_0 \frac{\partial I_g}{\partial t} + r_0 I_g + \alpha R_{DS} I_g \tag{3}$$

$$I_m = (1 - \alpha)I_g - C_0 \frac{\partial V_m}{\partial t} \tag{4}$$

Where  $L_0$  – the inductor of the converter,  $C_0$  – the output capacitor of the converter,  $r_0$  – the inductor equivalent resistance and  $R_{DS}$  – the MOSFET resistance ON. The switch state is also governed by a control signal with a period  $T$  and a duty cycle  $\alpha$ .

**The group motor pump model**

The dynamics of a DC motor and centrifugal pump may be expressed as:

$$V_m = RI_m + L \frac{\partial I_m}{\partial t} + E_C \tag{5}$$

$$E_C = K_e \omega \tag{6}$$

The mechanical equation of the system is given by:

$$K_m I_m - K_r \omega^2 = J \frac{\partial \omega}{\partial t} \tag{7}$$

Where  $\omega$  and  $J$  are respectively the rotation speed and the moment of inertia of the group,  $K_m$  is the constant of the electric couple,  $L$  is the inductance of the rolling-up of the led,  $R$  is the resistance of motor,  $K_r$  Coefficient of proportionality and  $K_e$  is the strength’s constant against electrometrical. The useful power of the motor is given by:

$$P = K_r \omega^3 \tag{8}$$

Instead of maximizing the PVG power, we will maximize the pump power, i.e. his rotation speed, in order to maximise the water flow.

**2.2. Dynamic model of the system in the state space**

Let define:  $x_1 = \omega$ ,  $x_2 = \dot{\omega}$  and  $x_3 = \ddot{\omega}$ . By the combination of various equations we succeed in following model

$$\begin{cases} \dot{x}_1 = x_2 \\ \dot{x}_2 = x_3 \\ \dot{x}_3 = f_n(x_1, x_2, x_3) + \xi + g_n(I_g)u \end{cases} \tag{9}$$

Where  $u$  is the control law and  $\alpha$  is deduced from the following relation:

$$u = 1 - \alpha \tag{10}$$

$$f_n(x_1, x_2, x_3) = a_{02}x_2 + a_{03}x_3 + a_{12}x_1x_2 + a_{13}x_1x_3 + a_{11}x_1^2 + a_{22}x_2^2,$$

$$a_{02} = -\left(\frac{1}{LC_0} + \frac{K_e K_m}{LJ}\right), a_{03} = -\frac{R}{L}, a_{12} = -2\frac{RK_r}{LJ}, a_{13} = a_{22} = -2\frac{K_r}{J}, a_{11} = -\frac{K_r}{LJC_0},$$

$$g_n = \frac{K_m}{LJC_0} I_g, \text{ and } \xi \text{ is the uncertain model part.}$$

### 3. Traditional sliding mode control system using robust Differentiators

#### 3.1. Traditional sliding mode control

The fundamental theory of SMC may be found in [13-15]. The main objective is to design a control law to drive the system state presented in (9) to a properly designed sliding surface.

Let define some variables as:  $\underline{x} = [x_1 \quad x_2 \quad x_3]^T$

The tracking error is the derivative speed of the motor:

$$e(t) = x_2(t) \tag{11}$$

The relative degree  $r = 2$ , then the sliding variable can be defined as:

$$s = \beta e(t) + \dot{e}(t) \tag{12}$$

Where  $\beta$  is a positive constant.

The difference between the actual and nominal function is given as follows:

$$\xi = f - f_n \tag{13}$$

The sliding variable derivative is:

$$\begin{aligned} \dot{s}(t) &= \beta \dot{e}(t) + \ddot{e}(t) = \dot{x}_3(t) + \beta x_3(t) \\ &= f_n(x_1, x_2, x_3) + \beta x_3(t) + g_n(I_g)u \end{aligned} \tag{14}$$

To ensure that a sliding mode exists on a switching surface, one has to satisfy the condition given below:

$$s\dot{s} < 0 \tag{15}$$

The control law that satisfies (15) is given as:

$$u(t) = -\frac{f_n(x) + \beta x_3(t) + k \text{sat}(s)}{g_n} \tag{16}$$

Where sat is the saturation function, given by:

$$\text{sat}(s) = \begin{cases} s / \delta & \text{if } |s| < \delta \\ \text{sgn}(s) & \text{otherwise} \end{cases} \tag{17}$$

With  $\delta$  is the boundary layer thickness, sgn is the sign function and k is the positive switching gain to compensate the uncertainties.

#### 3.2. Robust differentiator via sliding mode

The control presented in (16) uses the full state of the system. However, only the rotation speed variable is available for measurement. In this study we propose to use the

robust differentiator (RDF) to estimate the full state. The differentiator considered features simple form and easy design. It was synthesized to be employed in real-time control systems.

Consider the successive first order differentiator with the following structure[19]:

$$\begin{cases} \dot{z}_0(t) = v_0(t) \\ v_0(t) = -\lambda_0 |e_1(t)|^{\frac{1}{2}} \text{sign}(e_1(t)) + \psi_1(t) \\ \dot{\psi}_1(t) = -\mu_1 \text{sign}(e_1(t)) \\ \dot{z}_1(t) = v_1(t) \\ v_1(t) = -\lambda_1 |e_2(t)|^{\frac{1}{2}} \text{sign}(e_2(t)) + \psi_2(t) \\ \dot{\psi}_2(t) = -\mu_2 \text{sign}(e_2(t)) \end{cases} \quad (18)$$

Here,  $v_0(t), v_1(t)$  are respectively the outputs of the first and second differentiator in equation (18).

The estimates given by the RDF can be written as:

$$\begin{cases} \hat{x}_1(t) = z_0(t) + \theta_1(t) \\ \hat{x}_2(t) = v_0(t) = x_2(t) + \theta_2(t) \\ \hat{x}_3(t) = v_1(t) = x_3(t) + \theta_3(t) \end{cases} \quad (19)$$

From (19) the states variables can be rewritten as:

$$\hat{\underline{x}} = [\hat{x}_1 \quad \hat{x}_2 \quad \hat{x}_3]^T = x + \theta \quad (20)$$

Where,  $\theta = [\theta_1 \quad \theta_2 \quad \theta_3]^T$  is the vector estimation error.

$\mu_i, \lambda_i > 0$ : determine the differentiation accuracy and must be chosen properly to ensure convergence [16], [19].

The control law in (16) can be rewritten as:

$$u(t) = -\frac{f_n(\hat{x}) + \beta \hat{x}_3(t) + k \text{sat}(\hat{s})}{g_n} \quad (21)$$

Where:

$$\hat{s} = \beta \hat{x}_2(t) + \hat{x}_3(t) \quad (22)$$

A system with large uncertainties needs to use higher switching gain which can produce higher amplitude of chattering.

In this paper a neural network sliding mode strategy is proposed, here, NN is used for the prediction of model unknown parts in (9), and hence enable a lower switching gain to be used.

#### 4. Neural network sliding mode strategy

The object of this work consists of a combination of the sliding mode strategy using the RDF and NN named, NNSMDF. The main objective is to track the maximum power point (MPP) for the considered photovoltaic pumping system.

In this study, we consider the NN with two layers of adjustable weights [17], [18] (Figure 3), where  $x$  is the state input variable and the output variable is:

$$y = \hat{\xi}(x, t)$$

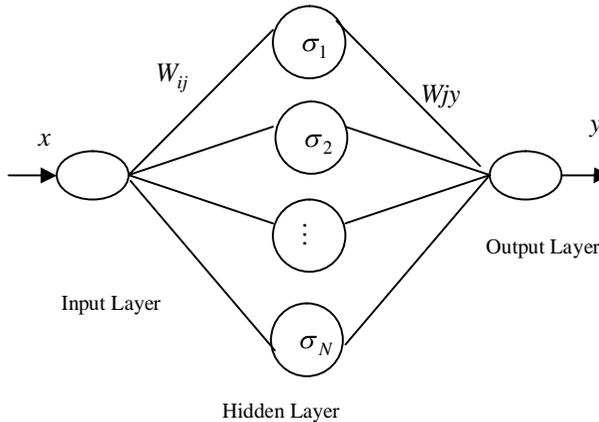


Figure3. The architecture of a multilayer neural network for the prediction of uncertain model part

$$y(\underline{x}) = W_y^T \sigma(W_j^T \underline{x}) \tag{23}$$

Where  $\sigma(\cdot)$  represents the hidden-layer activation function considered as a sigmoid function given by:

$$\sigma(s) = \frac{1}{1 + e^{-s}} \tag{24}$$

$W_y = [w_{1y} \ w_{2y} \ \dots \ w_{Ny}]^T$  and  $W_j = [w_{1j} \ w_{2j} \ \dots \ w_{Nj}]^T$  are respectively the interconnection weights between the hidden and the output layers.

The actual output  $y_d(\underline{x})$  (desired output which is the difference between the actual and nominal functions) is:

$$y_d(\underline{x}) = y(\underline{x}) + \varepsilon(\underline{x}) \tag{25}$$

Where:  $\varepsilon(\underline{x})$  is the NN approximation error.

The network weights are adjusted during online implementation. The method used is based on the gradient descent method (GD), which is a simple and fast method for online adaptation.

The essence of GD consists of iteratively adjusting the weights in the direction opposite to the gradient of E, so as to reduce the discrepancy according to:

$$\frac{\partial w_{jy}}{\partial t} = -\eta \frac{\partial E}{\partial w_{jy}} \tag{26}$$

Where  $\eta > 0$  is the usual learning rate. And the gradient terms  $\frac{\partial E}{\partial w_{jy}}$  can be derived using the backpropagation algorithm [8]. And the cost function E is defined as the error index and the least square error criterion is chosen as follows:

$$E = \frac{1}{2} \varepsilon^2 \tag{27}$$

Let assume that the NN approximation error denoted,  $\varepsilon = \varepsilon(x)$  is bounded, and the upper bound of the network error prediction denoted,  $\varepsilon^*$  such that:  $\|\varepsilon(\underline{x}, t)\| < \varepsilon^*$

**Theorem:** Consider the pumping system described by (8) in the presence of large uncertainties. If the system control is designed as:

$$u = g_n^{-1}(\hat{x}) \left( -f_n(\hat{x}) - \hat{\xi}(\underline{x}, t) - \beta \hat{x}_3(t) - k \text{sat}(\hat{s}) \right)$$

With  $\hat{x}$  is the estimate state and  $\varepsilon^* < k$

The trajectory tracking errors will converge to zero.

**Proof:**

Consider the candidate Lyapunov function:  $V = \frac{1}{2} s^2$

$$\dot{V} = s\dot{s}$$

Replacing the expression of  $\dot{s}$  given in (13) we have:

$$\dot{V} = s(f(x_1, x_2, x_3) + \beta x_3(t) + g_n(I_g)u)$$

By replacing the expression of  $u$  given in the theorem we have:

$$\begin{aligned} \dot{V} &= s(\xi(\underline{x}, t) - \hat{\xi}(\underline{x}, t) - k \text{sat}(s)) \\ &= s\varepsilon(\underline{x}, t) - k \text{sat}(s) \leq |s| |\varepsilon| - k \text{sat}(s) \leq |s| \varepsilon^* - k \text{sat}(s) \end{aligned}$$

By choosing  $\varepsilon^* < k$ , with  $k$  is a small gain which is responsible only to compensate the network errors prediction, we have:

$$\text{For any } \delta > 0, \text{ if } |s| \geq \delta, \text{sat}(s) = \text{sign}(s), \text{ the function } \dot{V} = (\varepsilon^* - k)|s| < 0.$$

However, in a small  $\delta$ -vicinity of the origin (boundary layer),  $\text{sat}(s) = \frac{s}{\delta}$  is continuous, the system trajectories are confined to a boundary layer of sliding mode manifold  $s = 0$ .

**Remark:** Before incorporating the neural network into the proposed control strategy, the network was trained off-line so that to let the network learn the functional nonlinearities to

a certain degree of accuracy before its implementation into the controller, and thus can give faster online adaptation as needed.

## 5. Simulation results

The simulations are performed with Matlab. The considered uncertainty affecting the solar irradiation is a random noise and the conditions specific to the simulations are

$$\lambda = 1000W/m^2 \text{ and } T = 29815K .$$

The system is controlled by both; the traditional sliding mode controller using the RDF and the proposed NNSMDF.

For comparison we have considered in the control law, for both NNSMDF and traditional SMDF controllers, the same gain.

The Figure 4 shows the state estimation errors given by the used robust differentiator. The compared performances are shown on Figure 6 and Figure 7. The rotation speed and power trajectory converges quickly toward the theoretical nominal value when the NNSMDF is applied.

The PV generator is then better forced to operate at its maximum power point by using the proposed NNSMDF controller. Figure 5 shows the adjusted duty cycles control.

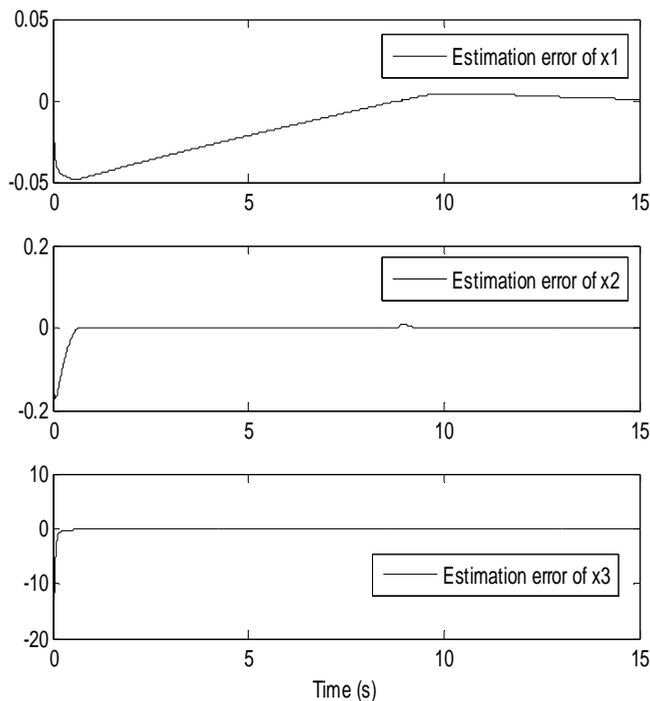


Figure 4. Response of state estimation errors given by the RDF

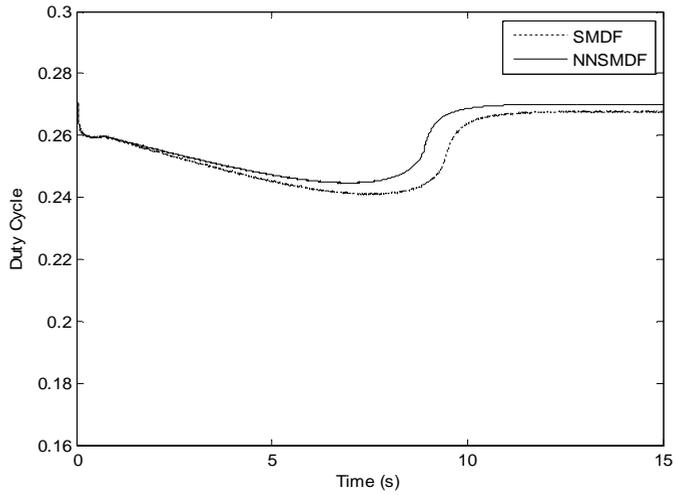


Figure 5. Duty cycle control

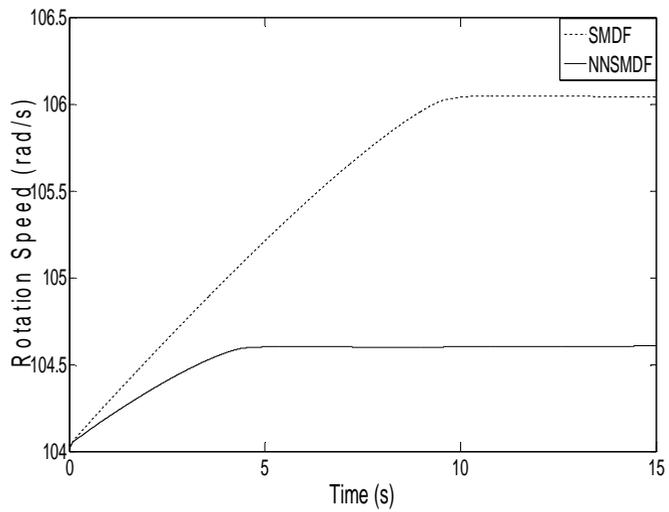


Figure 6. Response of rotation speed of the motor

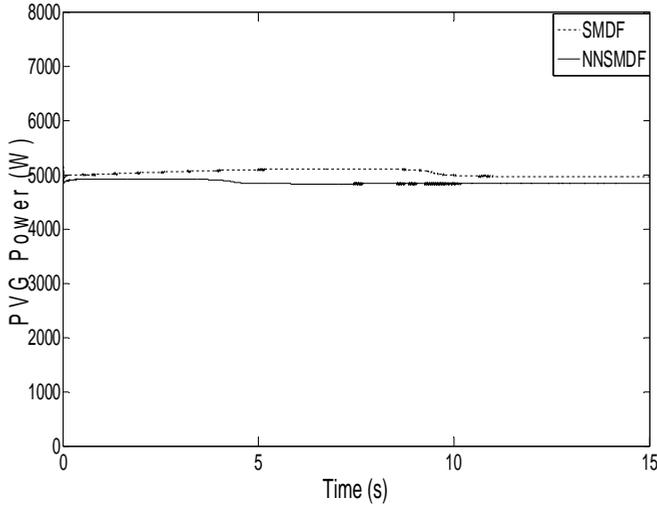


Figure7. Response of the PVG Power

### Parameters used in simulation

For the simulation we consider the parameters of the system as follows [7]:

The photovoltaic panel *SM55* :

$$R_s = 0.1124 \Omega, R_{sh} = 6500 \Omega, \gamma = 1.7404, I_{SCR} = 3.45 A, N_s = 20, N_p = 5$$

$$I_{or} = 4.842 \mu A, K_I = 4.10^{-4} A/K, T_r = 298.15 K \text{ and } P_n = 4.88 kW.$$

DC motor: *ABB DMI 180B*.

$$V_{mn} = 400V, I_{mn} = 12.2 A, \Omega_n = 104.7 rad/s,$$

$$R = 9.84 \Omega, L = 0.12 H, J = 0.06 \text{ Kg m}^2.$$

Chopper parameters:

$$L_o = 3.5 mH, C_o = 4.7 mF, r_o = 60 m\Omega, R_{DS} = 85 m\Omega.$$

Centrifugal pump parameters:

$$K_r = 28.10^{-4} w(s/rad)^3, \Omega_n = 104.7 rad/s.$$

### Conclusion

This paper proposes a sliding mode controller using neural network for pumping photovoltaic system, the aim of the proposed NNSMDF strategy is to control the DC-DC boost converter for maximizing the power's PVG. So, we compare the proposed controller with classic SMDF, both of two are motivated by using the robust differentiator RDF, which is used to estimate the first and the second derivative of the input signal. The simulation results prove that the proposed controller is robust and it is very well suited for systems with large uncertainty or unknown variations in plant parameters.

The application of the practical chosen sliding mode neural network controller motivated by using the robust differentiator, with cheap available electronic instruments rests an objective for generalizing and spreading the use of photovoltaic.

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