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Adaptive Neural Network Sliding Mode Control for a Photovoltaic Pumping System

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Abstract—**This paper presents a method for neural network sliding mode control design (NNSMC) to track the maximum power point (MPP) 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. Performance of the proposed controller is compared with the traditional SMC and investigated by simulation.**

I. 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. All the uncertainties or time varying could affect the system's control performance 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 [7]. In this paper, sliding mode control approach is combined with the neural network (NN) to adjust the duty cycle control law of the converter. The network weights are adjusted during online implementation by using the gradient descent method (GD) [8]. The proposed control 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 oscillatory behavior.

This study is organized as follows. The next section is PV pumping system description. In Section 3, the proposed neural network sliding mode controller is shown. Section 4 presents the simulation results. Finally, a concluding remark is given in section 5.

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II. Photovoltaic pumping system model

A. System description

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

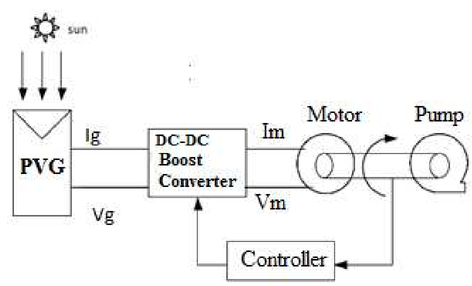

Figure 1. Block diagram of photovoltaic pumping

Photovoltaic generator model:

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

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

With:

$$I_{ph} = \left[I_{SCR} + K_I\left(T - T_r\right)\right]\frac{\lambda}{1000}$$

$$I_0 = I_{or}\left[\frac{T}{T_r}\right]^3 \exp\left[\frac{qE_{G0}}{\gamma K}\left(\frac{1}{T} - \frac{1}{T_r}\right)\right],\ A = \frac{q}{N\gamma KT} \text{ Where}$$

I_{ph} – photocurrent, I_0 – cell reverse saturation current, I_{or} – cell saturation current at T_r, I_{SCR} – short circuit current at 298.15 K and 1 kW/m2, K_I – short circuit current temperature coefficient at I_{SCR}, λ – solar irradiation in W/m2, E_{G0} – band gap for silicon, γ – 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 NS=20 modules in series helps us to rise the required direct voltage value. And NP = 5 in parallel helps us to rise direct current value.

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

where Vg : the PVG output voltage, Ig: the PVG output current, Ag = A/Ns – the PVG constant, Rsg = (Ns/Np) Rs: the PVG series resistance, Rshg = (Ns/Np)Rsh : the PVG parallel resistance, Iphg = Np Iph: the photocurrent of the PVG, I0g = Np I0 : the saturation current of the PVG, Ns: the number of PV connected in series and Np: the number of parallel paths.

Boost converter:

The DC-DC boost converter 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).

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

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

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

Where L0 – the inductor of the converter, C0 – the output capacitor of the converter, r0 – the inductor equivalent resistance and RDS – the MOSFET resistance ON. The switch state is also governed by a control signal with a period T and a duty cycle α.

The group motor pump model:

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

$$V_m = RI_m + L\frac{\partial I_m}{\partial t} + E_C \quad (5)$$

$$E_C = K_e\omega \quad (6)$$

The mechanical equation of the system given by:

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

Where ω 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's out is given by:

$$P = K_r\omega^3 \quad (8)$$

Equation (8) show power as a function of rotation speed, the power for a certain value is maximum at a certain value of rotational speed called optimum. In order to have maximum possible power, the rotational speed should always operate at it optimal values ω_n.

B. Dynamic model of the system in 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:

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

Where u is the control law and α is deducted from the following relation:

$$u = 1 - \alpha \quad (10)$$

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

$a_{02} = -\left(\frac{1}{LC_0} + \frac{K_eK_m}{LJ}\right)$, $a_{03} = -\frac{R}{L}$, $a_{12} = -2\frac{RK_r}{LJ}$,

$a_{13} = a_{22} = -2\frac{K_r}{J}$, $a_{11} = -\frac{K_r}{LJC_0}$, $g_n = \frac{K_m}{LJC_0}I_g$ and ξ is the uncertain model part.

I. Neural Network Sliding Mode Control System

The proposed method combines the neural network used for the prediction of model unknown part, with traditional sliding mode control to track the maximum power point (MPP) for the considered photovoltaic pumping system.

A. Traditional Sliding mode control

Define the fundamental theory of SMC may be found in [9–11]. 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:

$$e(t) = x_2(t) \quad (11)$$

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

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

Where β is a positive constant.

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

$$\xi = f - f_n \quad (13)$$

The sliding variable derivative is:

$$\dot{s}(t) = \beta \dot{e}(t) + \ddot{e}(t) = \dot{x}_3(t) + \beta x_3(t)$$
$$= f(x_1, x_2, x_3) + \beta x_3(t) + g_n(I_g)u \quad (14)$$

To ensure that a sliding mode exists on a switching surface, and this switching surface can be reached in finite time, one has to satisfy the condition given below:

$$s\dot{s} < 0 \quad (15)$$

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

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

Where sat is the saturation function, given by:

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

With δ is the boundary layer thickness, sgn is the sign function and k is the positive switching gain to compensate the uncertainties. In the presence of large uncertainties, k increase, and we will need a height thicker boundary layer to eliminate chattering. Thus only guarantees that the state be driven to the boundary layer, but with no sliding mode.

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

B. *Neural Network Design*

In this paper, we consider A NN with two layers of adjustable weights [12] (Fig. 2).

x is the state input variable and the output variable is:

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

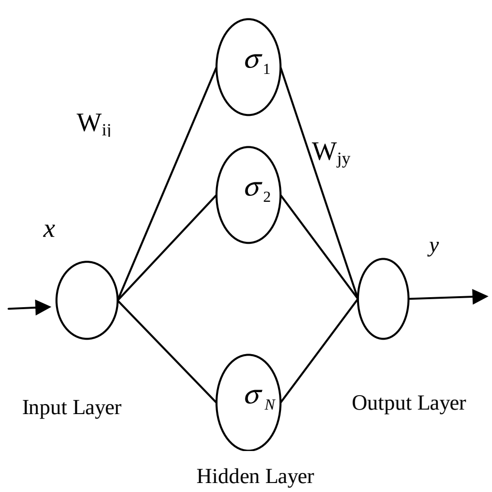

Figure 2. The architecture of a multilayer neural network for the prediction of uncertain model part

$$y(\underline{x}) = W_y^T \sigma(W_j^T \underline{x}) \quad (18)$$

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

$$\sigma(s) = \frac{1}{1+e^{-s}} \quad (19)$$

$W_y = \left[w_{1y} \quad w_{2y} \quad .. \quad w_{Ny}\right]^T$ and $W_j = \left[w_{1j} \quad w_{2j} \quad .. \quad w_{Nj}\right]^T$ 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:

$$y_d(\underline{x}) = y(\underline{x}) + \varepsilon(\underline{x}) \quad (20)$$

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:

$$\frac{\partial w_{jy}}{\partial t} = -\eta \frac{\partial E}{\partial w_{jy}} \quad (21)$$

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:

$$E = \frac{1}{2}\varepsilon^2 \quad (22)$$

C. *Sliding mode neural network strategy*

Let denote and assume that the NN approximation error $\varepsilon = \varepsilon(X)$ is bounded.

Let denote the upper bound of the network error prediction by ε^*, as: $\|\varepsilon(\underline{x},t)\| < \varepsilon^*$.

Theorem: Consider the pumping system modeled by (9) in the presence of large uncertainties. If the system control is designed as:

$$u = g_n^{-1}(\underline{x})\left(-f_n(\underline{x}) - \hat{\xi}(\underline{x},t) - \beta x_3(t) - k\, sat(s)\right)$$

with $\varepsilon^* < k$ 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 (14) we have:
$\dot{V} = s\left(f(x_1, x_2, x_3) + \beta x_3(t) + g_n(I_g)u\right)$

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

$$\dot{V} = s(\xi(\underline{x},t) - \hat{\xi}(\underline{x},t) - ksat(s))$$
$$= s\varepsilon(\underline{x},t) - ksat(s) \le |s||\varepsilon| - kssat(s)$$
$$\le |s|\varepsilon^* - kssat(s)$$

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

For any $\delta > 0$, if $|s| \ge \delta$, $sat(s) = sign(s)$, the function $\dot{V} = (\varepsilon^* - k)|s| < 0$. However, in a small δ-vicinty of the origin (boundary layer), $sat(s) = \frac{s}{\delta}$ is continuous, the system trajectories are confined to a boundary layer of sliding mode manifold $s = 0$.

II. SIMULATION RESULTS

The simulations are performed with Matlab. The considered uncertainty affecting the solar irradiation is a random noise. The system is controlled by both, the sliding mode controller and the proposed NNSM. The compared performances are shown on Figure 3 and Figure 4. The rotation and power trajectory converges quickly toward the theoretical nominal value when the SMNNC is applied. The PV generator is then better forced to operate at its maximum power point by using the proposed NNSM controller. The duty cycle control is judiciously adjusted to its optimal value (Figure 5). The Figure 6 shows the neural network approximation error.

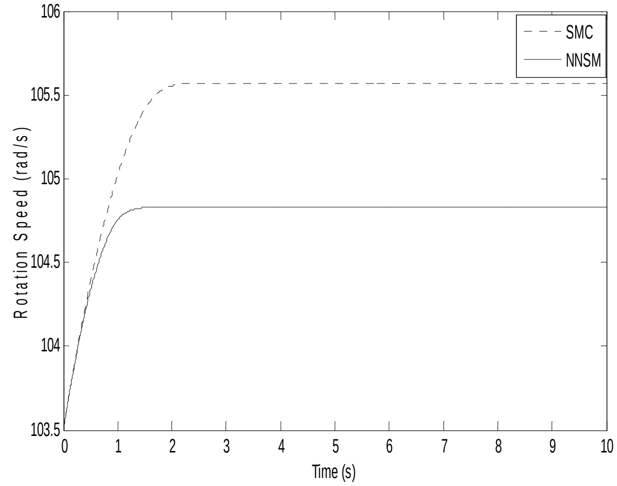

Figure 3. Rotation speed of the motor

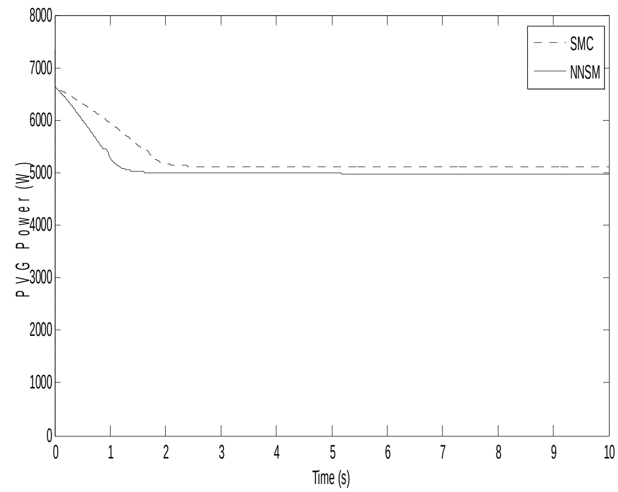

Figure 4. PVG Power

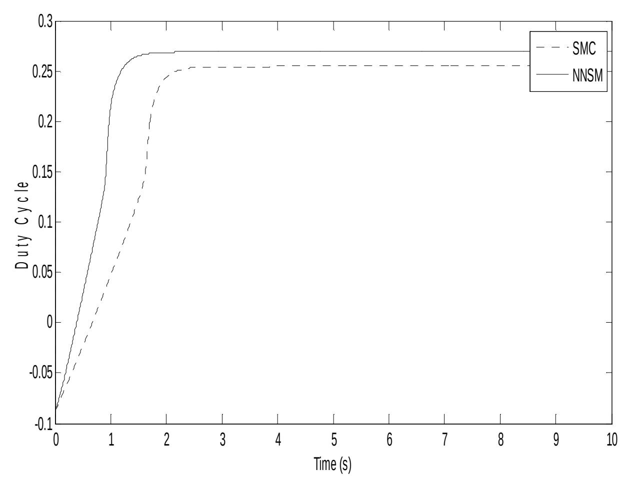

Figure 5. Duty cycle

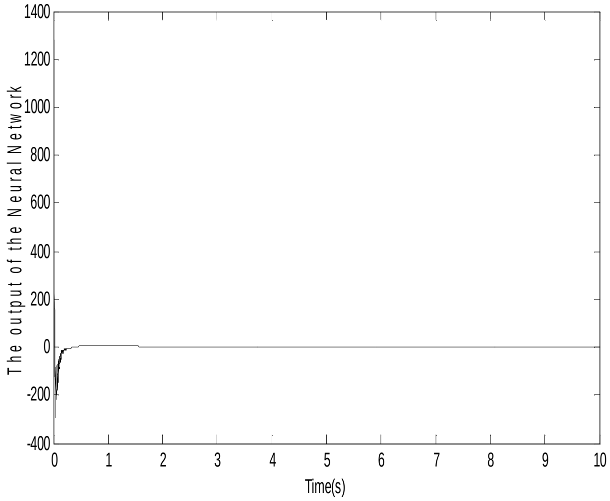

Figure 6. The NN approximation error.

Parameters used in the simulation:

$L = 0.12H$, $J = 0.06 kgm^2$, $\omega_n = 104.7 rad/s$, $P_n = 4.88kW$, $R_s = 0.112\Omega$, $R_{sh} = 6500\Omega$, $\gamma = 1.7404$, $I_{SCR} = 3.45A$, $I_{or} = 4.482A$, $K_I = 4.10^{-4} A/K$, $N_s = 20$, $N_P = 5$, $V_{mn} = 400V$, $I_{mn} = 12.2A$, $R = 9.84\Omega$, $L_0 = 3mH$, $C_0 = 4.7mF$, $r_0 = 60m\Omega$, $R_{DS} = 85m\Omega$, $T_r = 298.15K$.

III. CONCLUSION

In this paper, we proposed the sliding mode controller using neural network for pumping photovoltaic system, the SMNN strategy has been proposed to control the DC-DC boost converter for maximizing the power's PVG. So, we compare the proposed controller with classic SMC, The simulation results proved that the proposed controller is a robust and insensitive controller and it is very well suited for systems with uncertain or unknown variations in plant parameters.

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

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