Integral backstepping improvement versus classical and multiscalar backstepping controllers for water IM-pump fed by backstepping MPPT PV source based on solar measurements in a tropical insular region

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Abstract

The work presented here deals with a comparison between integral, classical and multiscalar backstepping controllers applied for a PV water pumping system. The solar pumping system is controlled in its first part by a backstepping maximum power point tracking approach in order to extract a maximum power from solar panels. The second part, composed mainly by induction motor–pump is controlled by backstepping structures. The integral backstepping control structure gives interesting features in terms of stability using recursive Lyapunov design, increases robustness despite parameters variation, and provides good tracking and optimization performance. In order to validate the study with a real solar data, a measured irradiance profile is used to fed the PV system, based on solar measurements in tropical insular context. The measurements are collected at Sonapi site located in Haiti country. The fast variability of the tropical irradiance profile will allow to test the robustness of the used control algorithms and determine their limits. Simulation of the proposed solution is validated under Matlab/Simulink. Results demonstrate clearly that integral backstepping provides the best solution with a good tracking, and optimization performance: fast dynamic response and stable static power output, even when weather conditions (irradiation) are rapidly changing.

1 INTRODUCTION

The Republic of Haiti is located in the Caribbean region between 18° 02′ north latitude and 71° 41′ west longitude. Haiti has excellent renewable energy potential, including hydropower, wind, solar, and biomass, which is largely untapped.

The metropolitan region of Port-au-Prince benefits from some of the most efficient solar and wind resources [1]. Hydroelectric power constitutes the part of the most exploited renewable energies in Haiti and integrated into the electricity grid. It represents 15% of the electricity mix.

The solar energy potential in Haiti is extremely strong throughout the territory and remains so throughout the year, even in winter. It is estimated that 6 km² square of solar PV panels could produce as much electricity as Haiti currently produces [1]. The overall horizontal illuminance varies from 5 to 7 kWh/m²/day (equivalent of 210–292 W/m²) in most of the country. Compared with France where it is between 3.2 and 5 kWh/m²/day, Haiti has a very high potential for solar energy. Studies already carried out by the Belgian company (3TIER) have analysed six potential solar energy sites. Among them are the Plaine du Cul de Sac and the Sonapi Park (in the West department). The dataset for each of the sites is compiled over 15 years (January 1997 to March 2012) from visible satellite images at high resolution (about 1 km) every half hour. The observed irradiance is characterized by fast spatial and temporal variability.

In these tropical insular regions, food self-sufficiency is also very important as well as energy. These regions have a multiplicity of micro-climates. These allow it to own one of the most diverse cultures in the world on such a small territory. For that, photovoltaic water pumping systems are needed. They consist
of collecting solar energy via photovoltaic panels to produce electricity, which supplies an electric pump to ensure drainage of water.

The water extraction by photovoltaic solar energy has been the topic of many works these last years [2, 3]. The choice of an immersed group with DC motor driving a centrifugal pump responds well to constraints associated with this application, especially for the isolated zones: hostile sites and deep layers, difficult maintenance, impedance adaptation in real time is needed.

However, the use of an induction motors (IM) brings robustness, and a better efficiency. Moreover, it offers wide possibilities of adaptation to particular functioning, by the variety of magnetic structures achievable. It is known that mathematical induction motor model is:

- Non-linear
- Multivariable
- Electromagnetic and mechanical parts are strongly coupled

For that, the hard task when using induction motor is the choice of the control structure. The field oriented control (FOC) technique is the most used for IM drive, because it ensures decoupling between flux and torque as in the case of DC motor. The main drawback of this technique is deterioration of tracking desired performance under parameter variations and external load disturbances [4].

To overcome these drawbacks, many advanced control techniques were proposed such as:

- Direct torque control (DTC) [5]. Produces flux and torque with high ripples and operate with variable switching frequency due to hysteresis control.
- Fuzzy logic control [6]: adapted for non-linear control because no induction motor model is required in design. Otherwise, human experience is needed.
- Non-linear techniques:
  - Input–output feedback linearization [7]: Principal drawback is its sensitivity to parameter variations.
  - Sliding mode [8]: Major drawback is chattering problem with significant ripples.
  - Backstepping [9, 10]: provides static error in steady state in case of the classical version.

Backstepping design was proposed for the first time by Peter Kokotovic, Ioannis Kanellakopoulos and Miroslav Krstic in 1991 [11], which was mainly developed for non-triangular systems class. Its principle is based on a systematic design, which consists of dividing whole system into many interconnected single first-order subsystems through several steps. At the end of each step, an associated Lyapunov function is build based on Lyapunov stability theory. In the last step, a control law for the whole system can be calculated. In the field of induction control drives, backstepping technique became one of the most efficient and robust. This latter with integral action, and using Lyapunov theory, guarantee a good stability, and better robustness against external disturbances. In order to reduce complexity of induction motor model before applying the control technique, multiscale backstepping version was proposed [12]. It consists first of replacing classical IM model by multiscale one, followed by applying backstepping technique. The multiscale IM model is composed of two linear and fully decoupled Electromagnetic and mechanical subsystems.

The power characteristic of a photovoltaic panel is non-linear according to the voltage at its terminals. For that, in order to exact maximum power, we have to keep power at the maximum point of the power characteristic for any applied solar radiation value. In recent years, maximum power point tracking (MPPT) approaches have become the focus of a large number of researches in the literature. Different kind of algorithms were proposed. They can be classified as:

- Conventional: perturb and observe (P&O) [13], incremental conductance (IC) [14], and hill climbing (HC) [15]. Performance are not good during transient regime.
- Metaheuristic: particle swarm optimization (PSO) [16] and genetic algorithms (GA) [17]. Performance depends on initial conditions and design parameters.
- Artificial intelligence: fuzzy logic (FL) [18] and neural networks (NN) [19]. Performance mainly depends on human expertise.
- Non-linear: sliding mode [20] and backstepping [21]. Good performance in terms of robustness and stability. They are also more suitable to control and to optimize the non-linear PV generator system.
- Hybrid algorithms: association of two or more MPPT approaches cited above [22].

In the field of PV MPPT optimization, backstepping again became one of the most popular techniques [21, 23, 24]. It can track easily MPP with interesting features in terms of rapidity, accuracy, robustness, and stability even under critical weather conditions.

Thus, for our study context and from solar measurements, an irradiance profile was built. This profile is composed of 11 sampling values, spread over 1-year (2011) measured data from Sonapi site. It shows an important variability of sunshine all time. For that, backstepping MPPT technique was proposed for PV water pumping system using DC–DC boost converter in order to overcome this constraint. Incremental conductance algorithm is used to generate reference voltage for backstepping MPPT.

The main novelty of this article is the comparative study between different backstepping structures for induction motor–pump control application, fed by backstepping MPPT PV source. However, the most important challenge is still considered as tracking performances under rapid weather conditions.

For that, the proposed study was applied in a tropical insular context known by its high solar variability, using in situ real measured solar data. Integral backstepping improvement versus classical and multiscale backstepping controllers was validated and its performance was satisfactory. Efficiency, accuracy, and robustness were studied by simulations for a selected irradiance profile, representing fast variability of tropical climate over
1 year. Those results are advantageous to the design and component sizing of PV power plants, and to the design of induction motor drives.

This work is organized as follows. Section 2 describes global structure of the proposed PV system, and its different components: solar pv generator, DC–DC boost converter, DC–AC VSI converter, induction motor, and water pump. In Section 3, first part gives the description of Solar measurements and preprocessing of datasets. After a sampling processing, measured irradiance profile is given. Second part presents the MPPT backstepping optimization algorithm. Third part gives three versions of non-linear backstepping control structure: classical, integral, and multiscalar one. Section 4 gives a mathematical stability proof of the proposed backstepping control algorithms using Barbalat’s lemma and Hurwitz criterion. Section 5 shows simulation results obtained for the proposed solution. Finally, the different contributions given in this paper are summarized in Section 6.

2 PROPOSED SYSTEM CONFIGURATION

2.1 Global structure design

Figure 1 shows global structure diagram of the proposed PV water pumping system, which is composed of: 3 kW PV module generator (GPV), DC–DC boost converter, inverter, and induction motor–pump.

The description of the proposed structure is as follows:

Solar measurements data collected at Sonapi site on Haiti island for a year are used to feed our PV production system. For the configuration of our PV system, we propose the use of a DC–DC boost converter, controlled by an MPPT backstepping algorithm to extract the maximum power from the photovoltaic panels. The produced PV System power fed an induction motor–pump through an inverter controlled by backstepping structures and SVPWM modulation.

The following sections describe each part of the proposed structure illustrated in Figure 1.

2.2 Solar PV module generator

PV plant generator is composed of 10 PV modules in series. Each module can produce 300 Wp, and composed of 96 PV cells (module characteristics are given in Appendix). Circuit of PV cell using single diode is given in Figure 2.

PV cell represented by circuit in Figure 2, can be modelled by following equations:

\[ I = I_{ph} - I_D, \]
\[ I_{ph} = I_{ph}(T_1) \times [1 + K_0 \times (T - T_1)], \]
\[ I_{ph}(T_1) = I_{cc}(T_1) \times \left( \frac{G}{G_0} \right), \]
\[ K_0 = \frac{I_{cc}(T_2) - I_{cc}(T_1)}{T_2 - T_1}, \]
\[ I_D = I_s \left( e^{\frac{V_D}{T}} - 1 \right), \]
\[ V_T = \frac{nKT}{q}, \]
\[ V_D = V + R_s I, \]
\[ R_s = -\frac{dV}{dI_{V_{co}}} \cdot \frac{1}{I_{V_{co}}}, \quad (8) \]

\[ X_{V} = \frac{I_s(T_1)}{V_T(T_1)} \cdot \frac{e^\frac{V_T(T_1)}{kT}}{T_1}, \quad (9) \]

\[ I_s(T_1) = I_s \left( e^\left(\frac{V_T(T_1)}{kT}\right) \right)^\frac{3T_1}{\theta} \cdot \left( \frac{T}{T_1} \right)^\frac{1}{\eta} - 1, \quad (10) \]

\[ I_s(T_1) = \frac{I_{ac}(T_1)}{e^\left(\frac{V_T(T_1)}{V_T(T_1)}\right) - 1}. \quad (11) \]

Where \( I, I_{ph}, I_D, I_s, \) and \( I_t \) are, respectively, PV cell output current, photocurrent, diode current, short-circuit current, and saturation current in A. Reference temperature \((T_1 = 25^\circ C = 298^\circ K)\), \( T \) is absolute surface temperature, \( G_0 \) is reference irradiance \((G_0 = 1000 \text{ W/m}^2)\), \( K_0 \) is current variation coefficient, \( q \) is elementary electron charge, \( K \) is Boltzmann’s constant, \( n \) is diode ideality factor. \( V_T \) is thermodynamic potential, \( V_D \) is voltage across the diode, \( V \) is voltage at the cell terminals, \( R_s \) is resistance series, \( V_{co} \) is the open-circuit voltage.

Then, relationship between current and voltage for the solar cell is:

\[ I = I_{ph} - I_s \left( e^\left(\frac{V + R_s I}{nKT}\right) - 1 \right). \quad (12) \]

The PV generator represents a 3 kW PV module composed of 10 PV modules of 300 Wp (type SunPower SPR-300E-WHT-D) connected in series, and provide 547 V as the output voltage at the maximum power point.

Electrical characteristics of PV panel with respect of temperature and insolation variations are given in Figures 3 and 4.

A. Influence of insolation

2.3 DC–DC boost converter

In order to use less of PV panels, boost converter is chosen to increase the output voltage of a DC voltage. It ensures the impedance matching between the PV panels and the load. It is composed of the inductor \((L)\), input capacitor \((C_{in})\), output capacitor \((C_o)\), MOSFET transistor switch, and power diode \((D)\). Figure 5 shows the circuit diagram of the boost converter.

The global model of the boost converter is given by:

\[ V_{pe} = \frac{I_{pe}}{C_{in}} - \frac{I_L}{C_{in}}. \quad (13) \]

\[ I_L = \frac{V_{pe}}{L} - \frac{V_D}{L} D, \quad (14) \]

\[ D = (1 - D). \quad (15) \]
Where: $I_o$ is the output current of the boost converter (A), $I_{pv}$ is the output current of the PV panels (A), $V_o$ is the output voltage of the boost converter (V), $V_{pv}$ is the output voltage of the PV panels, $I_l$ is the inductor current (A).

The switching state is controlled by a signal of duty cycle.

### 2.4 DC–AC VSI converter

The inverter used consists of transistors of the IGBT type controlled by the technique of space vector width modulation (SVPWM). Its diagram is given in Figure 6:

- $C_K$: arms K inverter signals control, with $K \in \{1, 2, 3\}$.
- $C_K = 1$: arm state: top switch is close and bottom switch is open.
- $C_K = 0$: arm state: top switch is open and bottom switch is close.

The inverter used consists of transistors of the IGBT type controlled by the technique of SVPWM whose principle consists in imposing voltages, chopped at a fixed frequency, at the terminals of the machine.

The vector of voltages in the inverter output is given by:

$$[V_{abc}] = \frac{1}{3} \cdot U_c \cdot \begin{bmatrix} 2 & -1 & -1 \\ -1 & 2 & -1 \\ -1 & -1 & 2 \end{bmatrix} \cdot [C_k]$$

$$[C_k] = [C_1, C_2, C_3]^T,$$

$$[V'_{abc}] = [V'_{ad}, V'_{db}, V'_{dc}]^T.$$  

In Figure 7, this reference vector is being constructed from the spatial switching vectors 4 and 6. The objective of the vector PWM technique is to approximate the reference voltage vector by a combination of eight switching combinations. The purpose of the approximations is to equalize the average of the inverter output voltage (in a short period of time $T_{PWM}$) and the average of the reference vector. For the position of the reference vector shown in Figure 7, the equation for the corresponding mean value is,

$$\frac{1}{T_{PWM}} \int_{nT_{PWM}}^{(n+1)T_{PWM}} \bar{v}_{ref} dt = \frac{1}{T_{PWM}} (T_4 \bar{v}_4 + T_6 \bar{v}_6),$$

for $n = 0, 1, 2, \ldots$, on $T_4 + T_6 \leq T_{PWM}$.

Assuming that the PWM period ($T_{PWM}$) is small and the variation of $v_{ref}$ is relatively slow compared to the PWM period. From Equation (17), we have

$$\int_{nT_{PWM}}^{(n+1)T_{PWM}} \bar{v}_{ref} dt = (T_4 \bar{v}_4 + T_6 \bar{v}_6),$$

for $n = 0, 1, 2, \ldots$, on $T_4 + T_6 \leq T_{PWM}$.

Because of $T_4 + T_6 \leq T_{PWM}$, the inverter needs to have a model $\bar{v}_0$ or $\bar{v}_7$ for the rest of the PWM period to create zero voltages for all phases. Therefore, one can write,

$$T_{PWM} \bar{v}_{ref} = (T_4 \bar{v}_4 + T_6 \bar{v}_6 + \bar{v}_0).$$

Where $T_0$ is the time interval for the spatial switching vectors $\bar{v}_0$ or $\bar{v}_7$, and $T_4 + T_6 + T_0 = T_{PWM}$.

### 2.5 Induction motor

In the stator rotating frame, the conventional model of the induction motor is given by [25]:

$$\frac{d\omega}{dt} = \frac{T_i}{J},$$

$$\frac{di_{dq}}{dt} = -\eta_1 i_{dq} - \beta n \alpha \omega i_{id} - n \beta \omega i_{id}$$

$$-R_i \left( \eta_1 i_{dq} + \alpha L_{m} \frac{i_{d}}{\Phi_{id}} \right) + \frac{1}{\sigma L_{m}} u_{dq}.$$
\[
\frac{d\phi_{rd}}{dt} = -\alpha R_l \phi_{sq} + \alpha I_{ms} R_r i_{rd}
\]
\[
\frac{di_{id}}{dt} = -\eta_1 i_{id} + n_r \omega i_{sq}
\]
\[
+ R_r \left( \eta_1 i_{id} + \alpha \beta \phi_{rd} + \alpha I_{ms} \frac{i_{sq}^2}{\phi_{rd}} \right) + \frac{1}{\sigma L_s} i_{nd}
\]
\[
\frac{d\theta_i}{dt} = n_r \omega + \alpha I_{ms} R_r i_{id}
\] (20)

Such as: \( \mu = \frac{3 m_L}{2i_L} \), \( \eta_1 = \frac{R_r}{\sigma L_c} \), \( \eta_2 = \frac{i_{sq}^2}{\sigma L_s} \), \( \alpha = \frac{1}{L_c} \), \( \beta = \frac{1}{L_s} \).

where: \( \sigma = 1 - \frac{L_c}{L_s} \).

The multiscalar model of induction motor is written with four multiscalar state variables [26]:
\[
x_{11} = \omega_m,
\]
(21)
\[
x_{12} = \phi_{r} \cdot i_{q} - \phi_{s} i_{d},
\]
(22)
\[
x_{21} = \phi_{s}^2 + \phi_{r}^2 \eta_1,
\]
(23)
\[
x_{22} = \phi_{r} \cdot i_{d} + \phi_{s} i_{q},
\]
(24)

The multiscalar state variables represent, respectively: rotor angular speed, scalar products of rotor current and stator flux vectors, vector products of rotor current and stator flux vectors, and square of the stator linkage flux.

After derivation, we obtain:
\[
\frac{dx_{11}}{dt} = \frac{p L_{ms}}{J L_r} x_{12} - \frac{p}{J} \Omega,
\]
(25)
\[
\frac{dx_{12}}{dt} = -\frac{1}{T} x_{12} + v_1,
\]
(26)
\[
\frac{dx_{21}}{dt} = -2 \frac{R_r}{L_r} x_{21} + 2 \frac{R_r L_{ms}}{L_r} x_{22},
\]
(27)
\[
\frac{dx_{22}}{dt} = -\frac{1}{T} x_{22} + \frac{R_r L_{ms} i_{sq}^2}{L_r} + v_2
\]
(28)

Where:
\[
\frac{1}{T} = \frac{R_r}{L_r} + \frac{1}{T_d},
\]
(29)
\[
v_1 = (\omega_r - \omega_m) x_{22} - \frac{1}{T_d} \phi_{r} i_{q}' \%
\]
(30)
\[
v_2 = (\omega_r - \omega_m) x_{12} + \frac{1}{T_d} \phi_{s} i_{d}'.
\]
(31)

\( \omega_r \) and \( I_s^* \) are calculated using inputs of the above system \( v_1 \) and \( v_2 \).

From the new multiscalar induction model, two fully linear decoupled subsystems are obtained:

**Mechanical subsystem:**
\[
\frac{dx_{11}}{dt} = \frac{p L_{ms}}{J L_r} x_{12} - \frac{p}{J} \Omega,
\]
(32)
\[
\frac{dx_{12}}{dt} = -\frac{1}{T} x_{12} + v_1.
\]
(33)

**Electromagnetic subsystem:**
\[
\frac{dx_{21}}{dt} = -2 \frac{R_r}{L_r} x_{21} + 2 \frac{R_r L_{ms}}{L_r} x_{22},
\]
(34)
\[
\frac{dx_{22}}{dt} = -\frac{1}{T} x_{22} + v_2.
\]
(35)

2.6 | Water pump

The general expression of the hydraulic power in Watt is [27]:
\[
P_{ht} = \rho \cdot g \cdot Q \cdot H.
\]
(36)

The centrifugal pump applies a load torque:
\[
T_c = k_r \omega^3 + C_r.
\]
(37)

Mechanical power \( P_{net} \) is expressed in kW and depends on the efficiency \( \eta_p \) of the pump:
\[
P_{net} = \frac{P_{ht}}{\eta_p}.
\]
(38)

The mechanical equation of the pump power is:
\[
P_{net} = k_p \omega^3.
\]
(39)

3 | CONTROL OF THE PROPOSED SYSTEM

3.1 | Solar measurements and pre-processing of datasets

Experimental measurements are collected in the Haiti republic, from Sonapi site every 1 h.

Parc Sonapi is located near the airport and the port of Port-au-Prince. It is considered as one of the most important industrial sites in Haiti. Parc Sonapi’s solar resource is characterized by a very strong solar potential. The long-term mean GHI (1997–2011) is 5.71 kWh/m²/day (237.8 W/m²) [1] (see Figure 8). It can be considered as one of the most important sites in Haiti and in Caribbean region with significantly high

insolation. The site’s DNI is 5.44 kWh/m²/day (226.5 W/m²), again strong globally. Parc Sonapi’s mean DIF is 1.95 kWh/m²/day (81.2 W/m²).

From Figure 8, we can notice that monthly mean GHI varies substantially throughout the year. This is because of the insular context located in tropical climate. This context is known by frequent formation of cloud and fast climatic parameters variation, especially irradiance. This makes solar profile very favourable for testing the efficiency and robustness of the proposed MPPT backstepping algorithm.

### 3.2 Backstepping MPPT algorithm

For MPPT optimization purpose, we applied backstepping technique [21].

**Step 1:**

The first error variable is chosen as:

\[ e_1 = V_{pe} - V_{ref} \]

\( V_{ref} \) is reference voltage generated by the incremental conductance MPPT.

The dynamic equation of the error can be written as:

\[ \dot{e}_1 = \dot{V}_{pe} - \dot{V}_{ref} = \left( \frac{I_{pe}}{C_{in}} - I_L \right) - \dot{V}_{ref}. \]  

(41)

Associated Lyapunov function is given by:

\[ V_1 = \frac{1}{2} e_1^2. \]

(42)

The derivative of \( V_1 \) is:

\[ \dot{V}_1 = e_1 \dot{e}_1 = e_1 \left( \frac{I_{pe}}{C_{in}} - I_L \right) - \dot{V}_{ref}, \]

(43)

\[ \dot{e}_1 = -k_1 e_1, \]

(44)

\( k_1 > 0 \) is a design parameter, it is chosen in order to obtain Lyapunov function with negative definite derivative. Then, we obtain:

\[ \dot{V}_1 = -k_1 e_1^2 < 0. \]

(45)

Therefore, global asymptotic is achieved. In Equation (41), \( I_L \) behaves as a virtual control input. Provided that:

\[ \left( \frac{I_{pe}}{C_{in}} - I_L \right) - V_{ref} = -k_1 e_1, \]

(46)

\[ I_L = I_{pe} + C_{in} \left( k_1 e_1 - \dot{V}_{ref} \right). \]

(47)

The Equation (47) shows that the desired value of the variable \( I_L \):

\[ I_L^{ref} = I_L = I_{pe} + C_{in} \left( k_1 e_1 - \dot{V}_{ref} \right). \]

(48)

**Step 2:**

Introducing a second error:

\[ e_2 = I_L - I_L^{ref} \rightarrow I_L = e_2 + I_L^{ref}. \]

(49)

The dynamic equation of the error can be written as:

\[ \dot{e}_2 = \dot{I}_L - \dot{I}_L^{ref} = \frac{1}{L} \left( V_{pe} - V_o \left( 1 - D \right) \right) - \dot{I}_L^{ref}. \]

(50)

Using (49) in (41):

\[ \dot{e}_1 = \dot{V}_{pe} - \dot{V}_{ref} = \left( \frac{I_{pe}}{C_{in}} - \frac{e_2 + I_L^{ref}}{C_{in}} \right) - \dot{V}_{ref}. \]

(51)

The dynamic equation of the error and \( V_1 \) becomes:

\[ \dot{V}_1 = e_1 \dot{e}_1 = e_1 \left( \frac{I_{pe}}{C_{in}} - \frac{e_2 + I_L^{ref}}{C_{in}} \right) - \dot{V}_{ref}. \]

(52)

\[ \dot{V}_1 = -k_1 e_1^2 - \frac{e_1 e_2}{C_{in}}. \]

(53)

The extended Lyapunov function is given by:

\[ V_2 = V_1 + \frac{1}{2} e_2^2. \]

(54)

The dynamic equation of the error is:

\[ \dot{V}_2 = \dot{V}_1 + e_1 \dot{e}_2. \]

(55)

Using (50) and (53), duty cycle is given by:

\[ D = 1 - \frac{L}{V_o} \left( \frac{V_{pe}}{L} - \frac{e_1}{C_{in}} + k_2 e_2 - I_L^{ref} \right). \]

(56)
3.3 Classical and integral backstepping control

Now, for induction motor–pump control purpose, again we applied backstepping technique [9]. The proposed control is based on dividing the MIMO system in first-order subsystems, and to calculate recursively step by step the control laws using Lyapunov functions and virtual inputs concept [28].

Step 1

For the tracking objectives: rotor speed and rotor flux amplitude, we define errors:

\[ e_1 = \omega_{ref} - \omega, \quad e_3 = \varphi_{ref} - \varphi_{ref}. \]  

(57)

After derivation we get:

\[ \dot{e}_1 = \dot{\omega}_{ref} - \mu \varphi_{ref} \omega_{ref} + \frac{T_L}{J}, \quad \dot{e}_3 = \dot{\varphi}_{ref} + \alpha R \varphi_{ref} - \alpha L_i R_i \omega_{ref}. \]

(58)

We choose \( i_{eq} \) and \( i_{id} \) as “virtual control” to control \( e_1, e_3 \).

Lyapunov function is:

\[ V_e = \frac{1}{2} e_1^2 + \frac{1}{2} e_3^2. \]

(59)

After derivation we get:

\[ \dot{V}_e = e_1 \dot{e}_1 + e_3 \dot{e}_3 = e_1 \left[ \dot{\omega}_{ref} - \mu \varphi_{ref} \omega_{ref} + \frac{T_L}{J} \right] + e_3 \left[ \dot{\varphi}_{ref} + \alpha R \varphi_{ref} - \alpha L_i R_i \omega_{ref} \right], \]

\[ = -k_1 e_1^2 - k_3 e_3^2 + \left[ k_1 \dot{\omega}_{ref} + \omega_{ref} - \mu \varphi_{ref} \omega_{ref} + \frac{T_L}{J} \right] \]

\[ + \left[ k_3 \dot{\varphi}_{ref} + \alpha R \varphi_{ref} - \alpha L_i R_i \omega_{ref} \right]. \]

(60)

Where \( k_1, k_3 \) are positive constants.

The stabilizing virtual controls are chosen as:

\[ (i_{eq})_{ref} = \frac{1}{\mu \varphi_{ref}} \left[ k_1 \dot{\omega}_{ref} + \omega_{ref} + \frac{T_L}{J} \right], \]

\[ (i_{id})_{ref} = \frac{1}{\alpha L_i R_i} \left[ k_3 \dot{\varphi}_{ref} + \alpha R \varphi_{ref} \right]. \]

(61)

We obtain:

\[ \dot{V}_e = -k_1 e_1^2 - k_3 e_3^2 \leq 0. \]

(62)

Then, the virtual controls in Equation (61) will be considered as references for second step of the backstepping approach.

Step 2

The new tracking variables for this step are the currents: \( i_{eq} \) and \( i_{id} \).

Then, new errors are defined as:

\[ e_2 = (i_{eq})_{ref} - i_{eq} = \frac{1}{\mu \varphi_{ref}} \left[ k_1 \dot{\omega}_{ref} + \omega_{ref} + \frac{T_L}{J} \right] - i_{eq}, \]

\[ e_4 = (i_{id})_{ref} - i_{id} = \frac{1}{\alpha L_i R_i} \left[ k_3 \dot{\varphi}_{ref} + \alpha R \varphi_{ref} \right] - i_{id}. \]

(63)

Then first derivatives could be rewritten as:

\[ \dot{e}_2 = -k_1 e_1 + \mu \varphi_{ref} \omega_{ref}, \quad \dot{e}_3 = -k_3 e_3 + \alpha L_i R_i \omega_{ref}. \]

(64)

Derivatives for new errors could be expressed by:

\[ \dot{e}_2 = \psi_1 - \frac{1}{\sigma L_s} \psi_2, \quad \dot{e}_4 = \psi_2 - \frac{1}{\sigma L_s} \psi_2. \]

(65)

Where \( \psi_i' (i = 1, 2) \) are known, defined as:

\[ \psi_1 = \frac{k_1}{\mu \varphi_{ref}} (-k_1 e_1 + \mu \varphi_{ref} \omega_{ref}), \]

\[ -\frac{\alpha R}{\mu \varphi_{ref}^2} (L_i R_i \dot{\varphi}_{ref} - \varphi_{ref}) \left( k_1 \dot{\omega}_{ref} + \frac{T_L}{J} \right) \]

\[ + \frac{1}{\mu \varphi_{ref}} \omega_{ref} \dot{\varphi}_{ref} + \eta_1 i_{eq} + \beta \eta_2 \varphi_{ref} + \eta_3 \omega_{ref} i_{eq} \]

\[ + R_L \left( \eta_2 i_{eq} + \alpha L_i R_i \frac{i_{eq}}{\varphi_{ref}} \right). \]

(66)

Extended Lyapunov function is given by:

\[ V_e = \frac{1}{2} \left[ e_2^2 + e_4^2 + e_3^2 + e_4^2 \right]. \]

(67)

To obtain the control laws, we again calculate the derivate of \( V_e \):

\[ \dot{V}_e = e_1 \dot{e}_1 + e_3 \dot{e}_3 + e_2 \dot{e}_2 + e_4 \dot{e}_4 \]

\[ = e_1 (-k_1 e_1 + \mu \varphi_{ref} \omega_{ref}) + e_2 \left( \psi_1 - \frac{1}{\sigma L_s} \psi_2 \right) \]

\[ + e_3 (-k_3 e_3 + \alpha L_i R_i \omega_{ref}) + e_4 \left( \psi_2 - \frac{1}{\sigma L_s} \psi_2 \right), \]

\[ = -k_1 e_1^2 - k_2 e_2^2 - k_3 e_3^2 - k_4 e_4^2 \]

\[ + e_2 \left[ \mu \varphi_{ref} e_1 + k_1 e_2 + \psi_1 - \frac{1}{\sigma L_s} \psi_2 \right] \]

\[ + e_4 \left[ \alpha L_i R_i e_3 + k_3 e_4 + \psi_2 - \frac{1}{\sigma L_s} \psi_2 \right]. \]

(68)

Where \( k_2, k_4 \) are positive constants, which will be tuned to improve system performance.
Then, the control laws can be obtained under the form:

\[ u_q = \sigma I_a \left[ \alpha I_{qw} R_c e_1 + k_2 e_2 + \psi_1 \right], \]
\[ u_d = \sigma I_a \left[ \alpha I_{qw} R_c e_1 + k_4 e_4 + \psi_2 \right]. \]  \hspace{1cm} (69)

Which gives:

\[ V_r = -k_1 e_1^2 - k_2 e_2^2 - k_3 e_3^2 - k_4 e_4^2 \leq 0. \]  \hspace{1cm} (70)

Now, integral backstepping version design is mainly based on the adding of integral action. The latter will be introduced in current references for the second step by [9]:

\( (i_{qf})_{ref} = \frac{1}{\mu \phi_{ref}} [k_1 e_1 + \omega_{ref} + \frac{T_f}{f}] + e \int_0^t e_1(\tau)d\tau, \) \hspace{1cm} (71)

\( (i_{df})_{ref} = \frac{1}{\alpha I_{qw} R_c} [k_3 e_3 + \dot{\phi}_{ref} + \alpha R_c \dot{\phi}_{ref}]. \)

The constant \( \epsilon \) is integral action parameter.

Following same development as before we will obtain the new derivative of Lyapunov function:

\[ V_r = -k_1 e_1^2 - k_2 e_2^2 - k_3 e_3^2 - k_4 e_4^2 \leq 0. \]  \hspace{1cm} (72)

Introduction of integral action in backstepping design is to remove completely speed error at steady state, and to reject external disturbances and parameters uncertainties. This implies improvement of tracking performance and provide new references for the PI currents loop in IFOC design.

### 3.4 Multiscalar backstepping control

Backstepping approach is again applied as in the previous subsection [10]. The conventional mathematical model of IM is replaced by the multiscalar one, defined by Equations (25)–(28).

The backstepping approach consists of two steps. In step 1, tracking objectives are:

\[ x_{11} = \omega_m \text{ and } x_{21} = \phi_m^2. \]  \hspace{1cm} (73)

After that, tracking errors (\( e_1, e_3 \)) can be calculated and Lyapunov function constructed. The stabilizing virtual controls are given as:

\[ \left\{ \begin{array}{l}
\dot{x}_{12} = \frac{f I_{aq}}{p L_{aq}} \left[ k_1 e_1 + x_{11}^{*} + \frac{\mu}{f} H \right], \\
x_{22}^{*} = \frac{I_{aq}}{2 R_c} \left[ k_3 e_3 + 2 R_c \frac{L_q}{L_r} x_{21} \right].
\end{array} \right. \]  \hspace{1cm} (74)

Virtual controls given in (74) are considered as references for the next step.

In step 2, a new sub-system is considered taking in account \( x_{12} \) and \( x_{22} \) as tracking objectives.

After tracking errors calculation (\( e_2, e_4 \)), and construction of the extended Lyapunov function, and in order to ensure global Lyapunov stability for the whole system.

The final control variables are chosen as:

\[ \left\{ \begin{array}{l}
v_1 = \frac{p L_{aq}}{f L_r} e_1 + k_2 e_2 + \phi_1, \\
v_2 = 2 R_c \frac{L_q}{L_r} e_3 + k_4 e_4 + \phi_2.
\end{array} \right. \]  \hspace{1cm} (75)

To satisfy:

\[ V_r = -k_1 e_1^2 - k_2 e_2^2 - k_3 e_3^2 - k_4 e_4^2 \leq 0. \]  \hspace{1cm} (76)

The inverter output voltages can be calculated as [26]:

\[ u_{sq} = \left( k_p + k_i \frac{1}{L} \right) \left( i_{sq} \right)_{ref} - i_{sq}, \]
\[ u_{sd} = -\omega L_c \sigma (i_{sq})_{ref} + L_c \sigma \frac{d(i_{sq})_{ref}}{dt}, \]
\[ u_{i2} = \left( k_p + k_i \frac{1}{L} \right) \left( i_{i2} \right)_{ref} - i_{sq}, \]
\[ + \omega L_c \sigma (i_{i2})_{ref} + \omega L_c \frac{d\dot{\phi}_{ref}}{dt}. \]  \hspace{1cm} (77)

\( k_p \) and \( k_i \) are PI controller parameters.

### 4 STABILITY ANALYSIS

Stability of the proposed backstepping techniques is analysing by proving that all tracking errors are bounded and converge asymptotically to zero using Barbalat’s lemma [28].

a. Boundedness

In order to demonstrate boundedness of the errors \( e_1, e_2, e_3 \) and \( e_4 \), we can reorganize the dynamical equation from tracking errors derivatives equations as:

\[ \dot{E} = A E, \]  \hspace{1cm} (78)

where

\[ E = \begin{bmatrix} e_1 \\ e_2 \\ e_3 \\ e_4 \end{bmatrix}, \text{ tracking errors vector.} \]

The matrix \( A \) in case of classical and integral backstepping is given as:

\[ A = \begin{bmatrix}
-k_1 & 0 & \frac{\mu}{f} & 0 \\
0 & -k_2 & 0 & \alpha L_{aq} \\
-k_3 & 0 & -k_4 & 0 \\
0 & -\alpha L_{aq} & 0 & -k_4
\end{bmatrix}. \]
For multiscalar backstepping, the matrix $A$ is:

$$
A = \begin{bmatrix}
-k_1 & 0 & \frac{pL_m}{JL_r} & 0 \\
0 & -k_2 & 0 & \frac{2R_r}{L_r} \\
-\frac{pL_m}{JL_r} & 0 & -k_3 & 0 \\
0 & -\frac{2R_r}{L_r} & 0 & -k_4
\end{bmatrix}.
$$

$\emptyset_{rd}$: constant (transient regime is neglected).

All errors $e_1, e_2, e_3$ and $e_4$ are bounded if the matrix $A$ is Hurwitz (roots have a negative real parts). This can be obtained by a good tuning of gains $k_1, k_2, k_3, k_4$

b. Convergence

From Barbalat’s lemma:

The closed loop system is stable and all errors converge to zero if we can demonstrate that:

$$e_1, e_2, e_3, e_4 \in L_\infty \cap L_2, \dot{e}_1, \dot{e}_2, \dot{e}_3, \dot{e}_4 \in L_\infty.$$

It means that we have to demonstrate that all errors and its derivatives are bounded and also $e_1, e_2, e_3, e_4 \in L_2$. For that, we will use the Lyapunov candidate function.

$V_e$ is positive definite, and $\dot{V}_e$ is semi-negative definite. It implies that all errors are bounded.

From equations given before of errors derivatives we can notice that $\dot{e}_1, \dot{e}_2, \dot{e}_3$ and $\dot{e}_4$ are also bounded. We can also get:

$$V \dot{V}_e \leq 0 \text{ and } V_e \dot{V}_e \leq 0. \quad (79)$$

Finally, we can conclude for the boundedness of all errors and its convergence asymptotically to zero.

5 | RESULTS AND DISCUSSION

5.1 | Datasets used for the simulation

From measured data collected during the year 2011 at Sonapi site in Haiti, a representative irradiance profile of 11 values over 12 months were built. Two or three successive points were chosen every 3 months. These points were selected according to the fast variability in irradiance amplitude values. The eleven values are given in Figure 9 with their associated index points of time.

Table 1 gives correspondence between index points time and dates.

| Index point time ($t$) | Date         |
|------------------------|--------------|
| 547                    | 23/01/2011   |
| 548                    |              |
| 549                    |              |
| 2011                   | 25/03/2011   |
| 2012                   |              |
| 4095                   | 20/06/2011   |
| 4096                   |              |
| 6380                   | 23/09/2011   |
| 6381                   |              |
| 8462                   | 19/12/2011   |
| 8463                   |              |
| 8464                   |              |

Simulation results are given in order to check the PV MPPT backstepping performance. The comparison in terms of robustness, rapidity, accuracy, and stability of the proposed controller with the conventional P&O and fuzzy logic ones is tested for a real measured data irradiance profile given in Figure 11, including sudden changes, which is presented in solar forecasting section. The temperature is taken constant and equal to 25°C.

The simulation curves are represented under two time scales:

- The first from 0 to 11 s to show the static performance;
- The second from 0 to 0.1 s to show dynamic performance.

5.2.1 | Comparison with perturb and observe algorithm

Figure 12a,b shows us static and dynamic performance of the voltage of the GPV for the P&O and backstepping techniques under a variable irradiance profile.

Figure 12a shows us the static voltage performance for the P&O and backstepping techniques. We can notice that the voltage is regulated for the two techniques, but it also presents
Figure 10: Structure of the photovoltaic system under Matlab–Simulink.

Figure 11: Measured irradiance profile.

Errors in case of P&O technique for certain segments (e.g., between 8th and 9th second). Figure 12b shows us a pseudo-oscillatory temporal response with an overshoot equal to 4.35% in case of P&O technique.

Figure 13a,b shows us the static and dynamic performances of the current intensity of the GPV for the P&O and backstepping techniques under a variable irradiance profile. Figure 13a shows us the static performance of current intensity for P&O and backstepping techniques. We can notice that the intensity of the current follows the profile of the irradiance with noticing again static errors for certain segments (e.g., between 8th and 9th second) in case of P&O technique. As for the voltage, Figure 13b shows us a pseudo-oscillatory temporal response with an undershoot equal to 9.15% in case of P&O technique.

Figure 14a,b shows us static and dynamic performance of GPV power for P&O and backstepping techniques under a variable irradiance profile. The Figure 14a shows us static performance of the power for P&O and backstepping techniques. We can notice that the power follows the profile of the irradiance. We can see that despite the multiple changes in tropical sunshine data, both techniques are able to follow these changes in sunshine in order to reach the PPM.

5.2.2 Comparison with fuzzy logic algorithm

Figure 15a,b shows us static and dynamic performance of the voltage of the GPV for the fuzzy logic and backstepping techniques under a variable irradiance profile.
Figure 13 shows us the static voltage performance for the fuzzy logic and backstepping techniques. We can notice that the voltage is regulated for the two techniques. Figure 15 shows us a pseudo-oscillatory temporal response with an overshoot more important with ripples in case of fuzzy logic technique.

Figure 16a shows us the static performance of current intensity for fuzzy logic and backstepping techniques. We can notice that the two curves are very close, but with a larger bandwidth in case of fuzzy logic technique. As for the voltage, Figure 16b shows us a pseudo-oscillatory temporal response with an undershoot more important with ripples in case of fuzzy logic technique.

Figure 17a shows us static performance of the power for fuzzy logic and backstepping techniques. We can notice that the power follows the profile of the irradiance. We can see that both techniques are very close.

5.2.3 Comparison between proposed techniques

The comparison of the proposed MPPT techniques can be made for their performance in transient and permanent regimes. The dynamic response of the P&O technique presents unwanted ripples which are dangerous drawbacks in the case of PV systems.

The performance indicators are presented in Table 2. The table is constructed by comparing output voltage response of the proposed techniques based on rise time (RT), settling time (ST), steady state error (SSE), overshoot (Oversh), and ripples in V measured peak to peak.
In terms of response time, both backstepping and fuzzy logic (FL in Table 2) are very close, and they exhibit the lowest RT. However, backstepping technique reaches steady state with a very small error compared with the others techniques (almost two and three times less). We notice the same superiority of backstepping with the same proportions concerning ripples magnitude. The biggest overshoot and the largest ripples were observed in the case of P&O. Robustness of backstepping comparing to the remaining techniques is again demonstrates regarding overshoot indicator. We notice an insignificant overshoot in case of backstepping, and a significant overshoot for the others techniques, especially in case of P&O. Hence, results presented in Table 2 confirm advance in terms of performance of backstepping technique against the others.

5.3 Motor–pump control performance

Simulation results are given in order to check the PV system performances. The comparison in performance, robustness, stability, and limits of the three backstepping control approaches is tested for the irradiance profile given above, based on real measured data.

The speed reference is chosen as a smooth step function equal to 400 rpm.

Between instances $t = 3$ s and $t = 5$ s, we apply a constant load torque of 14 N m, as presented in Figure 18.

Now concerning tracking performance, Figures 19a, 20a, and 21a show simulation results. The speed tracks its reference during all time simulation. When comparing Figures 19a, 20a, and 21a, we can see that in the case of classical backstepping the presence of a significant speed static error, slight peaks at the instances of applying the load torque, and a significant speed bandwidth. This demonstrates the weakness of the classical backstepping controllers face to external perturbations. In case of multiscalar backstepping speed response, we can see significant peaks at the instances of applying the load torque, and a slight speed bandwidth. The multiscalar backstepping
controllers can better bear external perturbations. Unlike that, the integral backstepping controllers tracking performances are satisfactory: speed response static error is completely removed, external disturbance is completely rejected, and speed response more stable.

We can verify this observation more clearly for the absolute values of speed error in Figures 19b, 20b, and 21b.

Simulation results show the lack of robustness and weakness of efficiency of the classical backstepping technique. Introduction of integral action improve tracking performance in terms of accuracy, robustness and speed of response.

6 | CONCLUSION

Here, PV water pumping system control has been treated under tropical meteorological conditions. The proposed solution is designed in order to face two challenges: maximum power extraction from PV generator, and robust induction motor–pump control.

In the first part, we have dealt with a problem of finding the maximum power point (MPPT) of a SPV based on a conventional technique, artificial intelligence technique, and a non-linear technique. The backstepping technique has been separately described, as well as the PV system components. The model chosen consists of a GPV with a power of 3 kW. A comparative study was carried out with MPPT techniques using the highly variable sun profile of the Sonapi Industrial Park (Port-au-Prince metropolitan region) and a constant temperature of 25°C. This variable irradiance profile is used in order to test the robustness and the efficiency of the proposed techniques. The simulation results showed that backstepping MPPT technique versus P&O and fuzzy logic ones: reaches steady state very quickly, ensures better stability almost without ripples and overshoots, more precise with a little static error in steady state, and presents better robustness against fast dynamic varying of irradiance profile.
In the second part, we have again used backstepping technique, but this time it was used for induction motor control and not for PV MPPT optimization. Comparative study was conducted between three backstepping control versions: classical, multiscalar, and integral. The integral backstepping gives better results compared to the classical and multiscalar ones. The introduction of the integral action overcomes the drawbacks of classical backstepping by disturbances rejection and static error removing. For that, from simulation results, the PV integral backstepping induction motor–pump speed control gives the best tracking performances: faster with instantaneous reference tracking, presents superior accuracy without static error in transient and steady state, guarantee a better stability without ripples and overshoots, and it is more robust by an instantaneous rejection of the applied load torque.

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**APPENDIX A**

We chose model SunPower SPR-300E-WHT-D, this generator statement is composed of 96 cells series-connected ($n_j = 96$).

- These data given in Table 3 represent the typical performance of the panel SPR-300E which measured with output, and not additional equipment effect is included like the diodes and the cables. The data are based on the measures under the standards conditions SRC (Standard Reporting Conditions, knowledge also: STC or Standard Test Conditions) which are:

  - An illumination of 1 kW/m² (1 sun) to a spectrum AM 1.5
  - A cell temperature of 25°C

Most important parameters of the used induction motor are given in Table 4.

**TABLE 3** Photovoltaic panel parameters

| Parameter                        | Value   |
|----------------------------------|---------|
| Maximal power $P_m$              | 300 W   |
| Voltage for maximal power $V_{pm}$| 54.7 V  |
| Current for maximal power $I_{pm}$| 5.49 A  |
| Current of short circuit $I_s$   | 5.87 A  |
| Voltage of open circuit $V_{oc}$ | 64 V    |
| Temperature coefficient of $I_s$ $T_s$ | (0.061738) %/°C |
| Temperature coefficient of $V_{oc}$ $T_{oc}$ | (−0.2727) %/°C |

**TABLE 4** Induction motor parameters

| Parameter | Value |
|-----------|-------|
| $R_s$ (Ω) | 1.34  |
| $R_r$ (Ω) | 1.24  |
| $L_s$ (H) | 0.17  |
| $L_r$ (H) | 0.18  |
| $M_s$ (H) | 0.18  |
| $\rho$    | 2     |
| $f$ (kg/m²) | 0.0153 |
| $P$ (kW)  | 1     |