

Performance Optimization of a Solar Photovoltaic Water Pumping System Based on FL-DTC Control of a Three-Phase Induction Motor

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Abstract—This paper presents a detailed investigation of a solar photovoltaic water pumping system (SPVWPS) driven by a three-phase induction motor (IM). The control scheme relies on three cooperating fuzzy regulators whose combined action aims to increase the energy efficiency and optimize the dynamic behavior of the installation. The first regulator, based on fuzzy logic and maximum power point tracking (FLC-MPPT), maintains the photovoltaic generator at its optimal operating point, thereby extracting the maximum available power irrespective of the prevailing weather. A second regulator implements a fuzzy direct torque control (FL-DTC), which enables precise and rapid regulation of the motor's torque and flux, while mitigating electromagnetic torque ripple and improving the quality of the electrical waveforms. A third fuzzy unit regulates the rotor speed, ensuring a faster dynamic response, better steady-state stability, and self-adaptation to load changes. The complete system was built and simulated in the MATLAB/Simulink environment in order to assess the proposed strategy. The obtained results demonstrate clear improvements in terms of settling time, stability and waveform quality as well as a higher flow rate that is a direct consequence of more precise motor speed regulation.

Keywords—SPVWPS, FLC-MPPT, FL-DTC, induction motor

I. INTRODUCTION

The exhaustion of fossil fuels and petroleum reserves has brought renewable resources to the forefront of energy planning. Among the clean solutions now available, solar energy stands out and is widely regarded as a strong replacement for conventional energy production. [1].

One of the drawbacks of photovoltaic conversion is its modest efficiency, since the power delivered by a PV array is strongly tied to both irradiance and cell temperature. The usual remedy is to add a maximum power point tracking (MPPT) stage, which lets the array yield its greatest output as the weather varies [2]. A wide range of MPPT schemes has consequently appeared. They fall into two broad families: conventional algorithms such as Perturb and Observe (P&O) [3]-[5], fractional open-circuit voltage [6] and incremental conductance (IC) [7]-[9]; and intelligent techniques including fuzzy logic (FL) [10], [11], neuro-fuzzy ANFIS [12]-[15], genetic algorithms (GA) [16], particle swarm optimization

(PSO) [10], [11], [15]-[17], neural networks (NN) [10], [11], [14] and sliding mode [18]. P&O remains popular because it is inexpensive and easy to code [19], yet it converges slowly, oscillates markedly about the maximum power point (MPP) and can drift when the irradiance changes rapidly [20]. To sidestep these shortcomings of the classical methods, intelligent MPPT strategies have been introduced [21]; a further advantage is that they neither demand accurate parameters nor rely on heavy mathematics [22]. The FLC-MPPT approach in particular is among the most capable controllers for PV plants thanks to its rapid convergence and small ripple around the MPP [22], [23].

Supplying water to remote or isolated communities is a recurring challenge. Connecting such sites to the utility grid in order to enable the operation of pumped-storage facilities, is costly, mainly because of the long distances that separate these areas from urban centres. Photovoltaic water pumping systems (PVWPS) offer an attractive way around this obstacle, being both affordable and effective [24]. Early pumping units were built around direct-current (DC)

machines, but these suffered from limited efficiency and frequent failures [25]. Induction motors (IM) have since displaced them, owing to their rugged construction, low cost, higher efficiency and superior reliability [26]. Maximising the efficiency of a solar pumping installation calls for attention to every stage, from the PV generator through to the motor-pump group that ultimately meets the crop water demand by way of the hydraulic circuit [27]. A poorly matched pumping profile can cause heavy pressure losses and faults that may even destroy the plant [28], so protective devices such as pressure limiters, filtration units and appropriate motor-control laws must be provided [29]. This is where that Direct Torque Control (DTC) proves valuable. DTC is comparatively easy to implement and requires fewer components and sensors than competing solutions, which eases maintenance and lengthens the service life of the system [30].

DTC technology enables fast and accurate command of the pump motor and can adjust the torque in real time to match demand, all without an elaborate outer control loop [31]. Used in solar-powered pumping, it significantly improves energy use while securing a reliable water supply for irrigation and a cornerstone of sustainable agriculture [32]. The conventional form of DTC presents several weaknesses: significant torque and flux ripple leading to vibration, acoustic noise and premature wear, reduced effectiveness at low speed and marked sensitivity to changes in the machine parameters, all of which are factors that compromise both precision and efficiency. Replacing the classical elements with fuzzy logic-direct torque control (FL-DTC) overcomes many of these

drawbacks by yielding better stability, lower ripple, finer control and improved efficiency, and so making the technique well suited to applications such as SPVWPS, among many others.

The present study seeks to improve the energy efficiency of solar pumping through a two-stage strategy. The first stage concentrates on drawing the greatest possible power from the PV source by means of fuzzy logic control (FLC), which continually retunes the operating point so that the array exploits the available sunlight to the full. The second stage applies fuzzy-logic direct torque control (FL-DTC) to the pump drive, regulating the motor torque promptly and precisely and thereby making the best use of the harvested solar energy. Combining photovoltaic optimisation with FL-DTC for the induction motor results in an integrated system designed to increase the overall efficiency of agricultural irrigation systems and, thereby fostering more sustainable energy management.

II. OPTIMIZATION STRATEGY FOR PHOTOVOLTAIC SOLAR WATER PUMPING SYSTEM

This section describes the two control levels used to optimise the pumping system. The first employs an FLC to extract maximum power from the PV field, whereas the second uses FL-DTC to drive the pump through its induction motor. The content is therefore divided into two parts. The overall configuration of the system under study is presented in Figure 1.

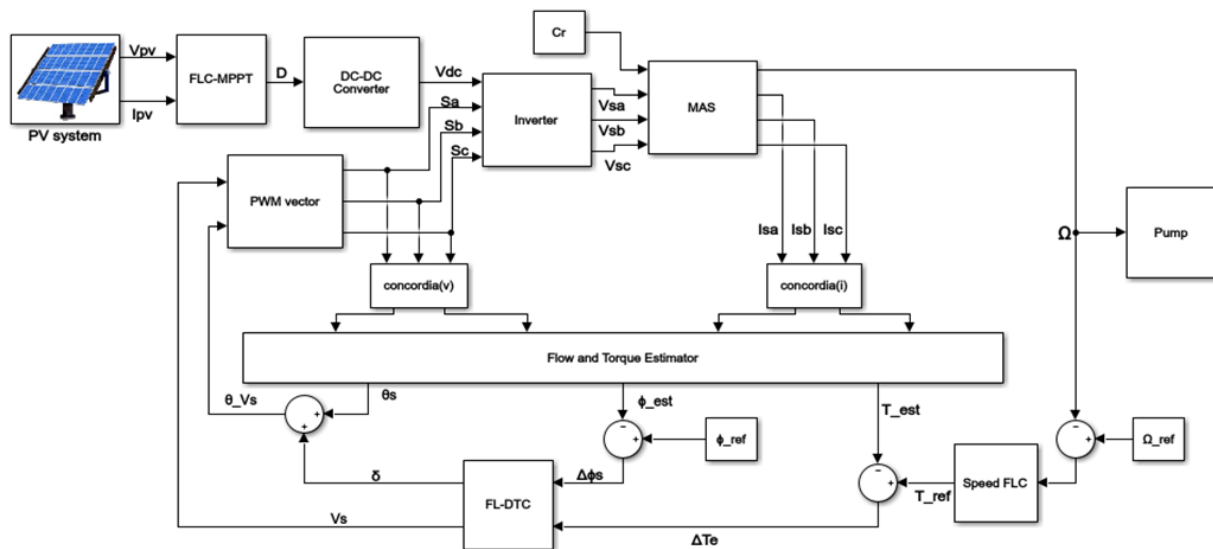


Fig. 1. Structure of the studied photovoltaic solar water pumping system (SPVWPS).

A. Fuzzy logic controller – maximum power point tracking (FLC-MPPT)

The conventional "Perturb and Observe" (P&O) tracking method converges slowly, oscillates around the Maximum Power Point (MPP) and mistracks when the irradiance changes abruptly. A fuzzy-logic approach is adopted to remove these drawbacks, since it responds faster and improves overall performance [2]. Fuzzy logic is today applied extensively in renewable energy, where it serves to optimise the power drawn from PV panels. Fuzzy controllers act quickly and help keep the system stable; moreover, they

require no analytical model, can process raw measurements directly and effectively handle non-linear behaviour [33].

Here the fuzzy controller manages a buck-boost converter through the Mamdani method. Once inference is complete, the fuzzy quantities are returned to crisp values by defuzzification. The controller takes two inputs, namely the error and its variation [1]:

$$e(k) = \frac{P(k) - P(k-1)}{V(k) - V(k-1)} = \frac{\Delta P}{\Delta V} \quad (1)$$

$$\Delta e = e(k) - e(k-1) \quad (2)$$

The term $e(k)$ is the slope of the P-V characteristic and therefore locates the MPP on the module, while $\Delta e(k)$ signals whether the operating point is approaching that maximum. The controller output, the duty-cycle increment ΔD , may be

positive or negative according to where the operating point lies, and is passed to the DC-DC converter feeding the load. The Simulink realisation is given in Figure 2. Starting from ΔD , the duty cycle is recovered by accumulation [34]:

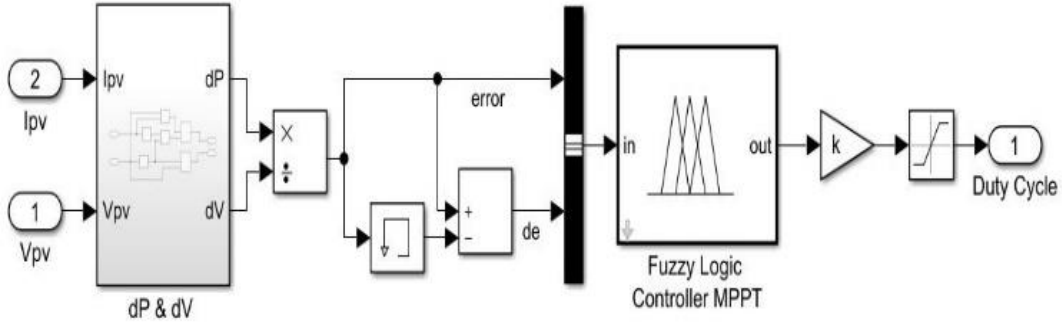


Fig. 2. Structure of the FLC-MPPT modelled in Simulink.

$$D(k) = D(k - 1) + \Delta D(k) \quad (3)$$

Triangular membership functions were used throughout the fuzzification. For the error e , its change Δe and the duty-cycle increment ΔD , five linguistic terms were defined: NB (Negative Big), NS (Negative Small), ZE (Zero), PS (Positive Small) and PB (Positive Big). The error and its change span $[-1, 1]$, while the duty-cycle increment spans $[0, 1]$. Figure 3 depicts the input and output membership functions.

The twenty-five inference rules are collected in Table I, with e and Δe forming the rows and columns and the cell entries giving the output ΔD .

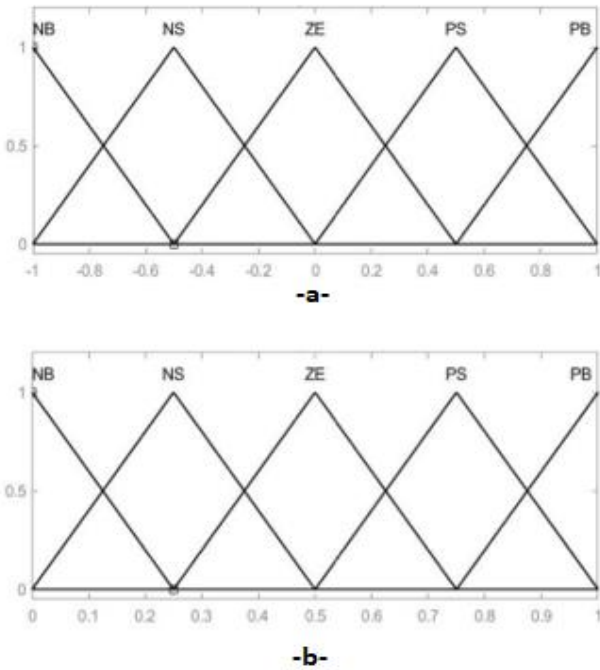


Fig. 3. Membership functions of the FLC: (a) error and change in error; (b) change in duty cycle.

TABLE I. TABLE I. FUZZY RULES TABLE.

$\Delta P / \Delta V$	NB	NS	ZE	PS	PB
NB	PB	PS	NB	NS	NS
NS	PS	PS	NB	NS	NS
ZE	NS	NS	NS	PB	PB
PS	NS	PB	PS	NB	PB
PB	NB	NB	PB	PS	PB

B. Fuzzy logic direct torque control (FL-DTC)

In its standard form, DTC commands the torque and flux of the machine directly by picking the best voltage vector from a stored switching table [26]. The procedure is as follows: the torque and flux references are first compared with their estimates, and the resulting errors feed the corresponding hysteresis comparators. Combined with the sector in which the flux vector lies, the comparator outputs then designate the switching vector applied to the voltage-source inverter [35].

Classical DTC is widely used and offers outstanding dynamics, notably a fast and faithful torque response. It does, however, carry limitations such as sizeable torque and stator-flux excursions and a high current THD, both traceable to the switching table and hysteresis regulators [36], [37]. A fuzzy-logic version has been proposed to improve a conventional DTC: the two hysteresis blocks are replaced by two fuzzy regulators that generate, respectively, the angle and the amplitude of the voltage vector, so that the stator flux and the electromagnetic torque are steered smoothly toward their references. Estimating torque and flux first requires a few auxiliary quantities. Through the Concordia transformation, the stator voltage in the (α, β) frame is obtained from the bus voltage V_{dc} and the switch states (S_a, S_b, S_c) :

$$V_{s\alpha} = \sqrt{\frac{3}{2}} V_{dc} \left(S_a - \frac{1}{2}(S_b + S_c) \right) \quad (4)$$

$$V_{s\beta} = \sqrt{\frac{1}{2}} V_{dc} (S_b - S_c) \quad (5)$$

Applying the same transformation to the phase currents I_{sa} , I_{sb} and I_{sc} yields the stationary-frame current components ($I_{s\alpha}$, $I_{s\beta}$):

$$I_{s\alpha} = \sqrt{\frac{3}{2}} I_{sa} \quad (6)$$

$$I_{s\beta} = \sqrt{\frac{1}{2}} (I_{sb} - I_{sc}) \quad (7)$$

The flux magnitude is then defined by:

$$\phi_s = \sqrt{\phi_{s\alpha}^2 + \phi_{s\beta}^2} \quad (8)$$

Where the stator-flux components are obtained by:

$$\begin{cases} \phi_{s\alpha} = \int_0^t (V_{s\alpha} - R_s I_{s\alpha}) dt \\ \phi_{s\beta} = \int_0^t (V_{s\beta} - R_s I_{s\beta}) dt \end{cases} \quad (9)$$

And the flux angular position is given by:

$$\theta_s = \arctan(\phi_{s\beta} / \phi_{s\alpha}) \quad (10)$$

Finally, the electromagnetic torque is estimated from the measured stator currents and the computed flux components:

$$T_e = \frac{3}{2} p (\phi_{s\alpha} I_{s\beta} - \phi_{s\beta} I_{s\alpha}) \quad (11)$$

As in conventional DTC, the method rests on estimating the stator flux and torque and comparing them with their setpoints. The two resulting errors are supplied to two regulators: a Sugeno-type block that estimates the phase shift between the flux and voltage vectors, and a Mamdani-type block that sets the magnitude of the voltage vector. Their outputs drive a vector modulator (PWM vector) that commands the inverter.

Voltage vector position selection

The first fuzzy controller receives the torque error (ΔT_e) and the stator-flux error ($\Delta \phi_s$) and, after defuzzification, produces the angle δ that is added to the stator-flux angle, as sketched in Figure 4.

Fuzzification maps each input onto fuzzy variables using membership functions and suitable linguistic labels. The inputs ΔT_e and $\Delta \phi_s$ are each partitioned into three terms, "Negative" (N), "Zero" (Z) and "Positive" (P), consistent with a three-level hysteresis comparator. A triangular function models the "Zero" term, whereas trapezoidal functions model the "Negative" and "Positive" terms. Table II lists the rule used to select δ from these fuzzy inputs.

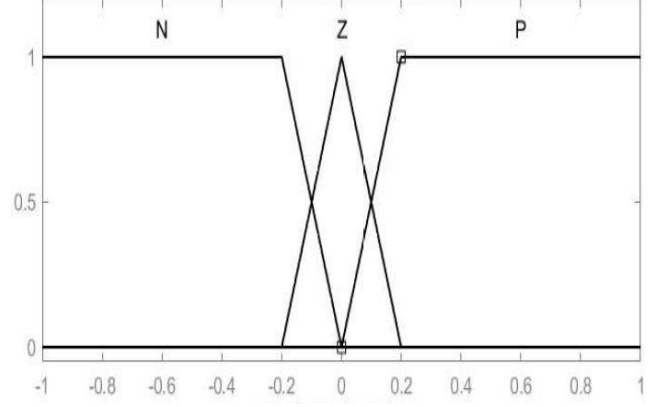


Fig. 4. Membership functions for the torque error (ΔT_e) and the stator-flux error ($\Delta \phi_s$).

TABLE II. RULES FOR SELECTING THE ANGLE Δ .

$\Delta \phi_s$	P			Z			N		
	P	Z	N	P	Z	N	P	Z	N
δ	$+\pi/4$	0	$-\pi/4$	$+\pi/2$	$+\pi/2$	$-\pi/2$	$+3\pi/4$	$+\pi$	$-3\pi/4$

Selection of the voltage vector modulus

The amplitude of the voltage vector is chosen so as to reduce the torque error and the stator-flux error at the same time. A dedicated fuzzy controller was therefore developed to produce the optimal value of the voltage-vector modulus dynamically.

The controller returns a normalised value that is multiplied by a reference maximum to give the actual amplitude of the voltage vector V_s . In this work the reference maximum was fixed at the value reached by a space-vector PWM (PWM vector) operating at a modulation index of unity; the peak amplitude is thus set by the converter under optimal modulation. That is:

$$V_s = \sqrt{\frac{3}{2}} \frac{E}{2} du_{V_s} \quad (12)$$

The membership functions of the inputs and output of this fuzzy controller are shown in Figure 5 and Figure 6. Trapezoidal and triangular shapes were selected. The universes of discourse are fixed to $[-1, 1]$ for the normalised torque and flux errors and to $[0, 1]$ for the fuzzy output that represents the voltage modulus. Table III presents the proposed table for choosing the voltage-vector modulus.

Where NL: Negative Large, NM: Negative Medium, NS: Negative Small, NZ: Near Zero, PS: Positive Small, PM: Positive Medium and PL: Positive Large.

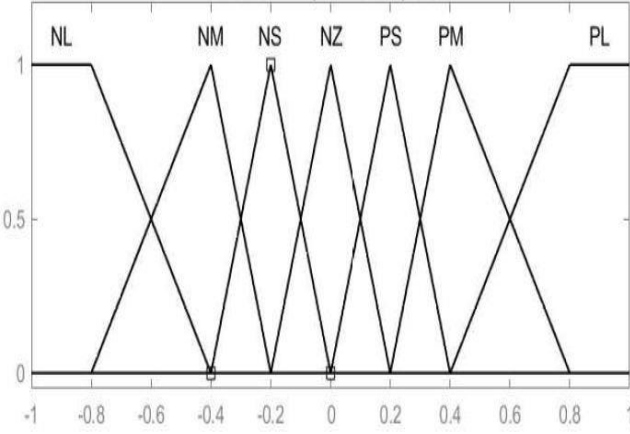
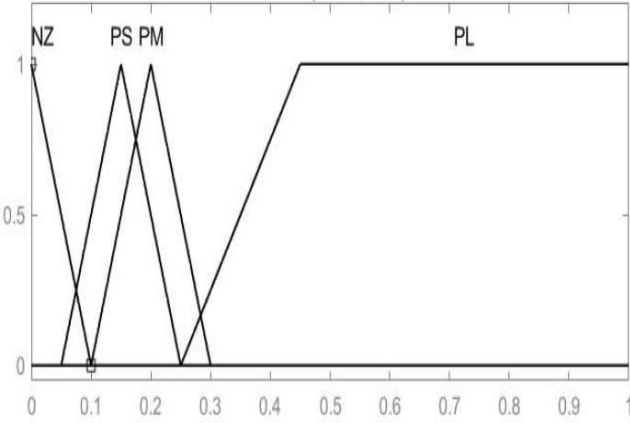

 Fig. 5. Membership functions for the torque error (ΔT_e) and the stator-flux error ($\Delta \phi_s$).


Fig. 6. Membership functions for the output variable representing the voltage modulus.

TABLE III. PROPOSED TABLE FOR SELECTING THE VOLTAGE-VECTOR MODULUS.

$\Delta T_e / \Delta \phi_s$	NL	NM	NS	NZ	PS	PM	PL
NL	PL	PM	PS	PS	PS	PM	PL
NM	PL	PM	PS	PS	PS	PM	PL
NS	PL	PM	PS	NZ	PS	PM	PL
NZ	PL	PM	PS	NZ	PS	PM	PL
PS	PL	PM	PS	NZ	PS	PM	PL
PM	PL	PM	PS	PS	PS	PM	PL
PL	PL	PM	PS	PS	PS	PM	PL

C. Fuzzy logic speed controller (FLC)

Speed loops are conventionally closed with PI controllers, which need an accurate model of the plant and well-tuned gains to deliver high performance. As a result, any unforeseen change in load or operating conditions can bring overshoot, speed and torque oscillation, long recovery times and a general loss of drive quality [38]. A fuzzy-logic controller (FLC) is introduced to counter these effects within the DTC scheme, curbing flux and torque ripple and giving precise speed regulation.

The proposed FLC uses the speed error and its rate of change as inputs, defined by:

$$e(k) = \Omega_{ref}(k) - \Omega(k) \quad (13)$$

$$de(k) = e(k) - e(k-1) \quad (14)$$

The controller output is the reference torque the machine must develop, i.e. the output of the speed loop. The structure of the fuzzy speed controller is shown in Figure 7.

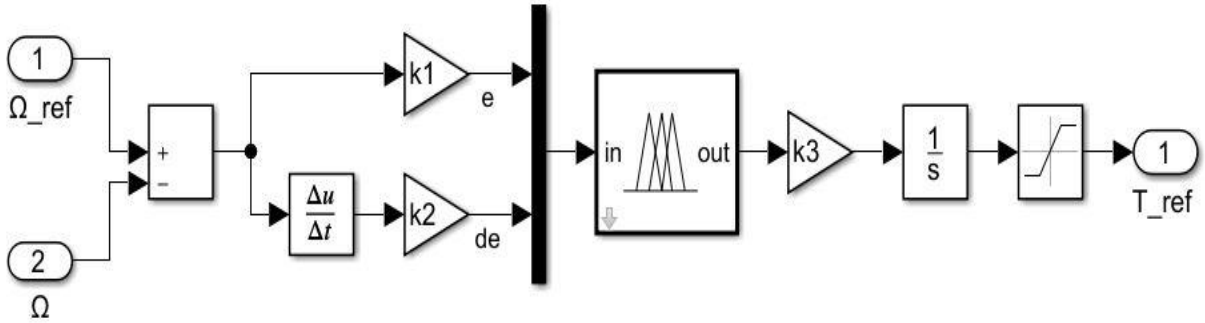
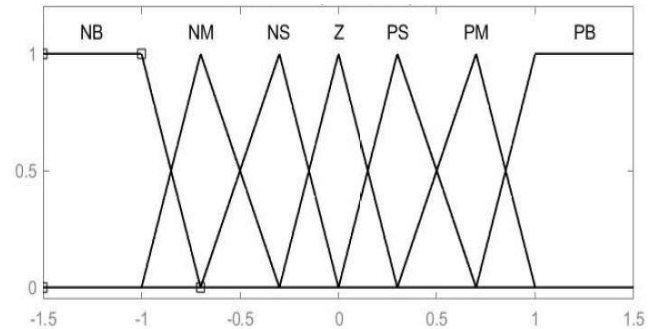


Fig. 7. Structure of the fuzzy-logic speed controller.

In this study the speed error, its derivative and the reference torque are described by fuzzy sets belonging to seven classes: Negative Big (NB), Negative Medium (NM), Negative Small (NS), Zero (Z), Positive Small (PS), Positive Medium (PM) and Positive Big (PB). The degree of membership of each input or output in a class is set by the membership functions, for which triangular and trapezoidal shapes were adopted, as displayed in Figure 8.


 Fig. 8. Membership functions for the speed error e , its derivative de and the reference torque T_{ref} .

The inference rules of the fuzzy speed controller are listed in Table IV.

TABLE IV. RULE BASE FOR SPEED CONTROL.

e / de	NB	NM	NS	Z	PS	PM	PB
NB	NB	NB	NB	NB	NM	NS	Z
NM	NB	NB	NB	NM	NS	Z	PS
NS	NB	NB	NM	NS	Z	PS	PM
Z	NB	NM	NS	Z	PS	PM	PB
PS	NM	NS	Z	PS	PM	PB	PB
PM	NS	Z	PS	PM	PB	PB	PB
PB	Z	PS	PM	PB	PB	PB	PB

III. SIMULATION RESULTS AND DISCUSSION

The behaviour of the complete PV pumping system with the induction motor under FL-DTC was examined in MATLAB/Simulink, and the main results are discussed below.

Figure 9 presents the three-phase stator currents. Their balanced, sinusoidal form in steady state confirms sound operation. A transient with over-currents appears at start-up but is rapidly contained by the DTC action, which finely shapes the applied voltages and so limits the electromechanical stress on the machine.

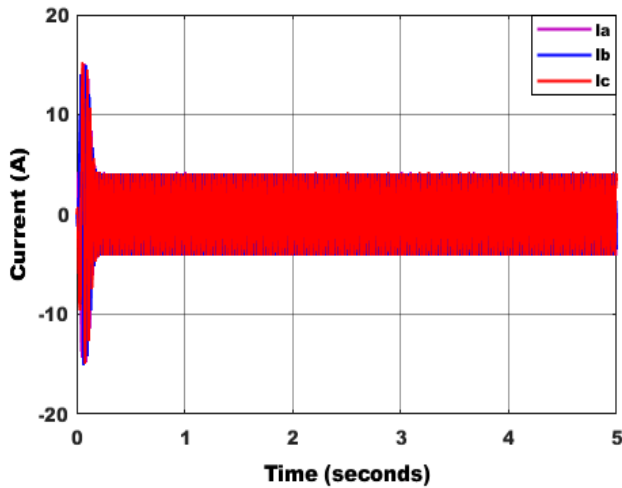


Fig. 9. Three-phase stator currents.

The α and β stator-flux components in Figure 10 evolve quickly toward a stable regime with clean sinusoidal shapes, evidence of accurate flux control in the stationary frame. The circular locus traced in the α - β plane, Figure 11, is the signature of DTC operation and reflects effective regulation of both the flux amplitude and its angle.

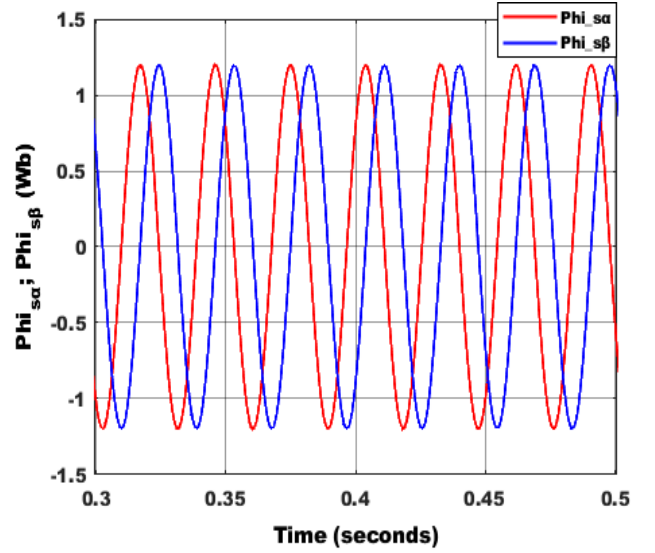


Fig. 10. Alpha and beta components of the stator flux.

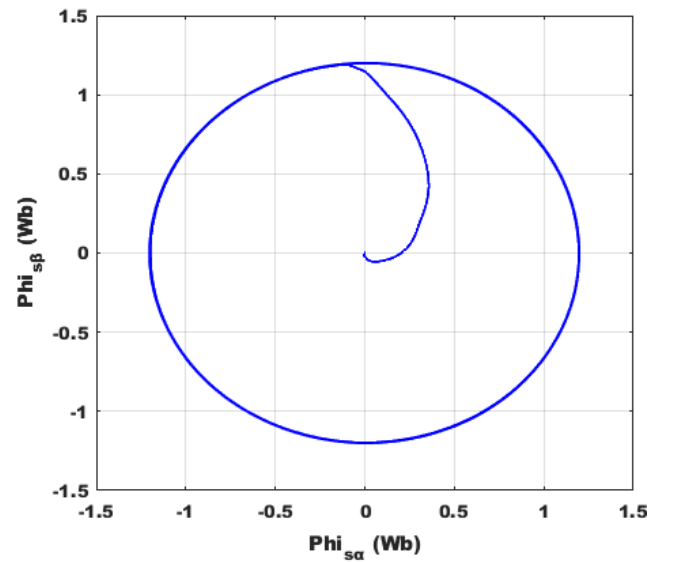


Fig. 11. Circular trajectory of the stator flux.

Figure 12 shows the favourable speed dynamics: the motor reaches the 1000 rpm setpoint in under 0.5 s. The rapid, overshoot-free rise, free of oscillation, illustrates the responsiveness and stability brought by the fuzzy regulator embedded in the DTC scheme and helps preserve the mechanical integrity of the pump over the long term.

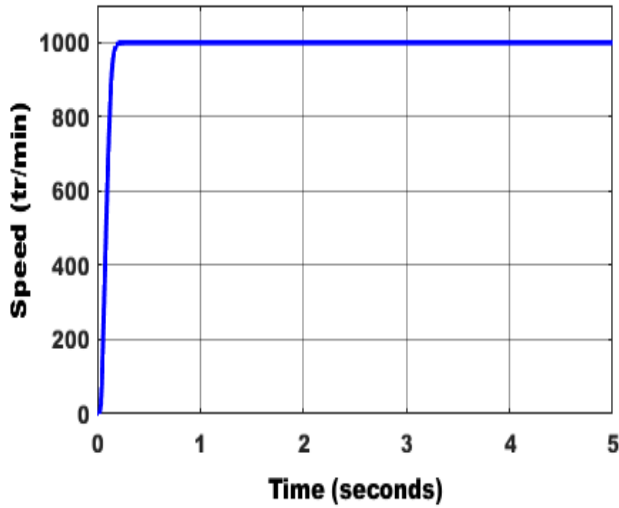


Fig. 12. Induction-motor speed under FL-DTC control.

The torque waveform in Figure 13 starts with a peak near 35 N·m needed to overcome the pump inertia, then falls quickly to about 5 N·m, the value required in steady state. The smooth transition and small residual ripple confirm that FL-DTC regulates the torque steadily and precisely.

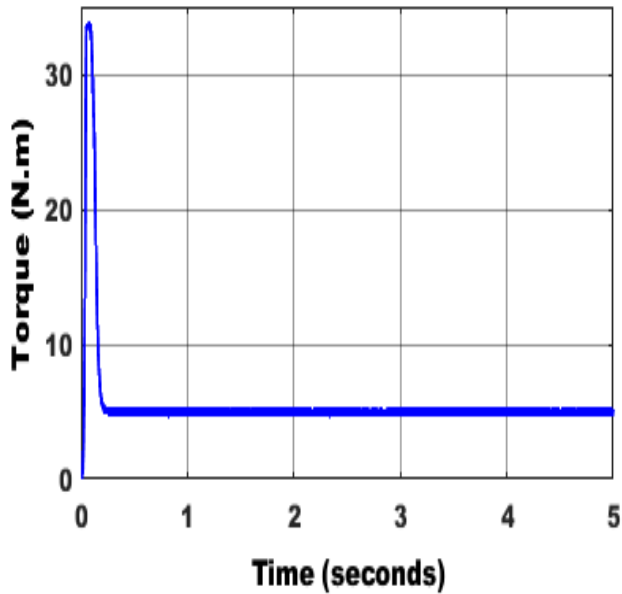


Fig. 13. Electromagnetic torque of the induction motor under FL-DTC control.

Figure 14 shows the stator-flux magnitude settling rapidly to roughly 1.2 Wb. This prompt, reliable regulation demonstrates the ability of FL-DTC to manage torque and flux independently; holding the flux at its optimum is essential for maximising efficiency and minimising losses.

The mechanical and hydraulic powers of the pumping unit appear in Figure 15. The fast transient and the close agreement between the two curves point to efficient power transfer from the motor to the pump. This matching secures a steady water flow, which is decisive for pumping in isolated locations.

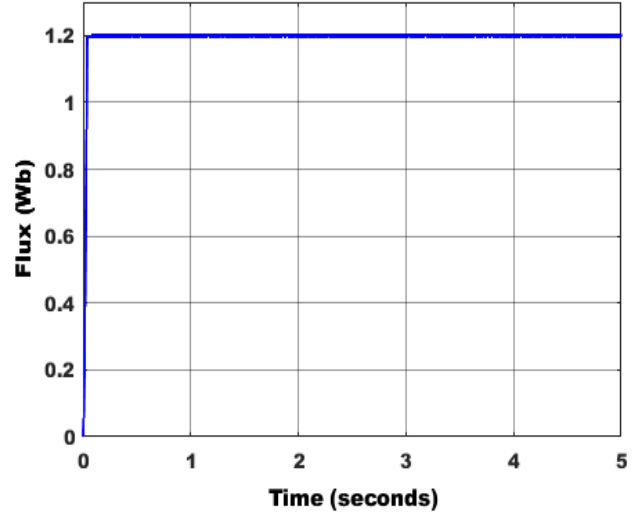


Fig. 14. Stator flux of the induction motor under FL-DTC control.

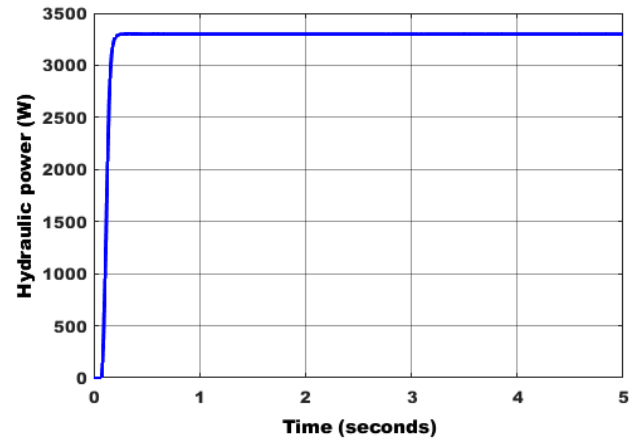
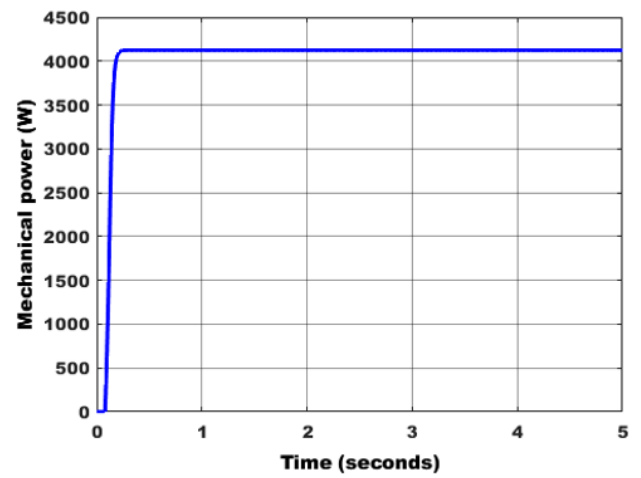


Fig. 15. Mechanical and hydraulic power of the pump.

Figure 16 confirms that the FLC-MPPT block tracks the maximum power point well: after a brief transient the PV voltage, current and power settle around their optimal values. This behaviour reflects the capacity of the fuzzy regulator to reposition the operating point quickly so as to harvest the most energy. Although the curves correspond to steady conditions, real-time MPP tracking of this kind is what keeps the plant efficient when the sunlight varies in practice.

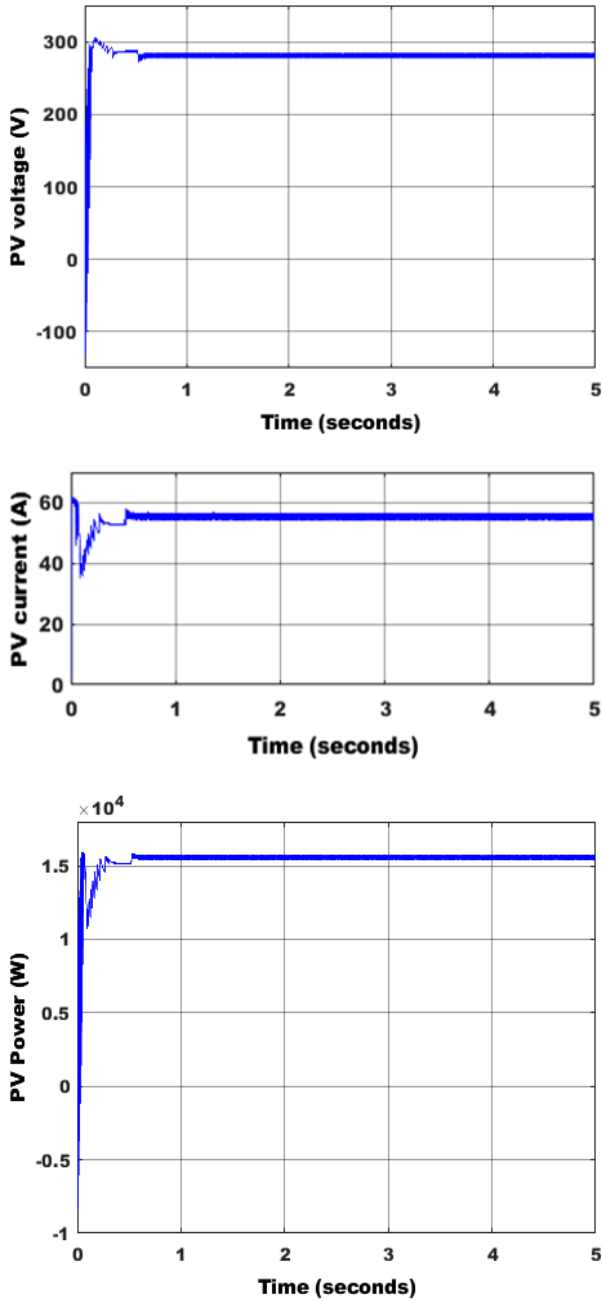


Fig. 16. Voltage, current and power of the photovoltaic system.

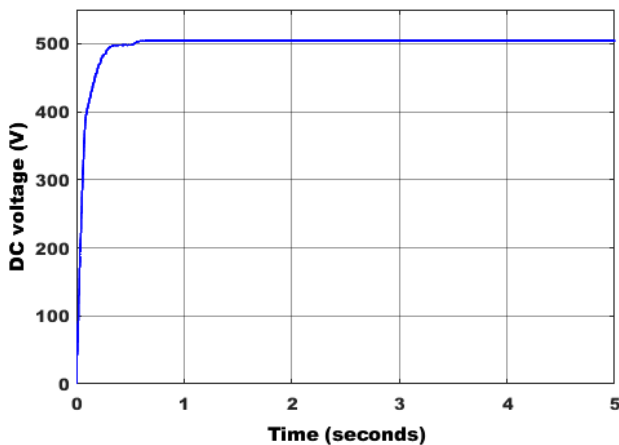


Fig. 17. DC-bus voltage.

Lastly, Figure 17 shows the regulation of the DC bus, which holds the voltage steady at the junction between the PV panels and the inverter. This stability guarantees a reliable feed to the motor as well as efficient energy conversion, shaped jointly by the FLC-MPPT controller and the motor's FL-DTC.

IV. CONCLUSION

This work addressed the design and analysis of an optimised solar pumping system built around a three-phase asynchronous motor fed by an inverter under fuzzy-logic direct torque control (FL-DTC) and paired with a fuzzy-logic maximum-power-point-tracking strategy (FLC-MPPT). The intention was to enhance both the dynamic behaviour of the motor and the overall efficiency of the installation.

The simulations returned an excellent transient response, marked by a fast start, steady-state stability and accurate regulation of torque, flux and speed. The fuzzy speed controller further refined the dynamic response, providing smooth, adaptive control under load and irradiance variations while suppressing oscillation and overshoot. The FLC-MPPT block, for its part, adapted readily to extract the maximum PV power and thus ensured an optimal supply to the motor. The stability of the DC-bus quantities and the good coordination between the subsystems together confirm the robustness and coherence of the proposed architecture.

These outcomes make the solution a promising candidate for pumping in isolated settings, particularly where energy access is scarce and where autonomy and reliability are paramount. Future work could extend the study to real-time experimentation, to the combination of additional renewable sources, or to energy optimisation through more advanced artificial-intelligence methods.

APPENDIX

TABLE V. PHOTOVOLTAIC MODULE PARAMETERS

Module: SunPower SPR-315E-WHT-D		
Parameter	Symbol	Value
Maximum power	P_{max}	315.072 W
Number of cells per module	N_{cell}	96
Open-circuit voltage	V_{OC}	64.6 V
Short-circuit current	I_{SC}	6.14 A
Voltage at maximum power point	V_{mp}	54.7 V
Current at maximum power point	I_{mp}	5.76 A
Temperature coefficient of open-circuit voltage	βV_{OC}	-0.2727 %/°C
Temperature coefficient of short-circuit current	αI_{SC}	0.061743 %/°C

TABLE VI. THREE PHASE INDUCTION MOTOR PARAMETERS

Parameter	Symbol	Value
Number of pole pairs	p	2
Rated power	P_n	1.5 kW
Rated frequency	f_n	50 Hz
Rated speed	n	1420 rpm
Rated voltage	V_n	220/380 V
Rated current	I_n	6.4/3.7 A
Stator resistance	R_s	4.85 Ω
Rotor resistance	R_r	3.805 Ω
Stator inductance	L_s	274 mH
Rotor inductance	L_r	274 mH
Mutual inductance	L_m	258 mH
Moment of inertia	J	0.031 kg·m ²
Friction coefficient	f	0.00114 kg·m ² /s

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