Journal of Engineering and Technology for Industrial Applications

ITEGAM-JETIA

ISSN ONLINE: 2447-0228

Manaus, v.12 n.57, p. 1181-1196. January/February, 2026.

DOI: https://doi.org/10.5935/jetia. v12i57.2703

RESEARCH ARTICLE OPEN ACCESS

FUZZY ADAPTIVE SPEED AND POSITION CONTROL FOR PERMANENT MAGNET SYNCHRONOUS MOTORS

Bentchikou Ibrahim[1], Tlemçani Abdelhalim[2], Hassan Nouri[3], Boudjema Fares[4], Boukhetala Djamel[5], Ould cherchali Noureddine[6], Fekir Mohamed[7], Mahdab Salim[8].

[1,7,8] Intelligent Systems Laboratory (LESI), University Djillali Bounaama , Khemis Miliana ,Algeria, Faculty of Technology
[2,6]Electrical Engineering and Automation Laboratory (LREA), Electrical Engineering Department, University of Medea, Algeria
[3]Power Systems,Electronics and Control Research Laboratory,School of Engineering,University of the West of England (UWE),Bristol BS16 1QY, UK.
[4,5]Laboratory of Process Control, National Polytechnic School, ENP

[1]https://orcid.org/0009-0008-0303-7024, [2]https://orcid.org/0000-0002-4385-671X, [3]https://orcid.org/0000-0003-2272-0351
[4]https://orcid.org/0000-0002-8619-9852, [5]https://orcid.org/0000-0003-2112-0709, [6]https://orcid.org/0009-0008-6489-1400
[7]https://orcid.org/0000-0001-9743-9543, [8]https://orcid.org/0009-0007-8691-977X

Email: b.bentchikou@univ-dbkm.dz, h_tlemcani@yahoo.fr, Hassan.Nouri@uwe.ac.uk,fboudjma@yahoo.fr, djamel.bokhetala@g.enp.edu.dz, nacherchali@yahoo.fr, m.fekir@univ-dbkm.dz, s.mahdb@univ-dbkm.dz

ARTICLE INFO

Article History
Received: September 14, 2025
Revised: October 20, 2025
Accepted: December 15, 2026
Published: February 28, 2026

Keywords:
Permanent Magnet Synchronous Machine (PMSM),
Direct Torque Control (DTC),
Fuzzy Adaptive Control (FAC),
Fuzzy Logic System (FLS),
Model Reference Adaptive Control (MRAC).

ABSTRACT

The use of knowledge-based linguistic regulators constitutes a powerful tool for controlling complex processes. The synthesis of most of these regulators is primarily based on the experience of the operator or process engineer, on which the regulator's performance strongly depends. Much of the research dedicated to linguistic knowledge-based regulators has focused on developing specialized regulators for specific applications. These studies do not provide a synthesis methodology enabling a general analysis of control schemes' performance, particularly their stability. Studies on fuzzy systems have shown that certain classes possess the quality of being universal function approximations. This significant property has opened new avenues for the application of fuzzy systems in control. Consequently, many research efforts have been directed toward combining fuzzy systems with control techniques such as adaptive control. In these control schemes, the fuzzy system serves to approximate nonlinear functions. In recent years, fundamental contributions in adaptive control—both theoretical and practical—have provided essential insights for a better understanding of adaptive systems. The primary objective of adaptive control is the synthesis of adaptation laws to automatically adjust loop regulators, ensuring that a desired performance level is achieved or maintained despite unknown, poorly known, or time-varying process parameters.Simulations of MATLAB/SIMULINK environment of the present work shows the efficacy.

Copyright ©2026 by authors and Galileo Institute of Technology and Education of the Amazon (ITEGAM). This work is licensed under the Creative Commons Attribution International License (CC BY 4.0).

I. INTRODUCTION

Accurate and high-performance control of torque and speed in Permanent Magnet Synchronous Motors (PMSMs) is a fundamental challenge that has driven modern electrical engineering. Requiring simultaneous speed, precision, robustness, and energy efficiency [1], [2], the development of high-performance control algorithms is essential for applications ranging from industrial robotics to electric vehicles. This pursuit of performance has led to a marked evolution in control strategies, with each new approach seeking to overcome the limitations of its predecessors. Historically, scalar control (V/f), simple but lacking dynamic performance, was initially dominant. A first revolution occurred with the development of Vector Control (Field-Oriented Control - FOC) in the 1970s [3]. By decoupling and independently regulating flux and torque, much like a direct current (DC) machine, FOC provided, for the first time, exceptional response dynamics and precise low-speed torque control.

However, this performance comes at the cost of implementation complexity, sensitivity to motor parameter variations (notably rotor resistance), and a critical reliance on high-performance processors for real-time mathematical transformations. Vector control, also known as Field-Oriented Control (FOC) [4], [5]. Is an advanced technique for controlling AC (alternating current) electric motors, predominantly employed in high-performance variable-speed drives. While this method offers significant advantages such as the independent regulation of torque and magnetic flux, analogous to the control of a DC motor, which ensures a rapid and precise dynamic response, it is also characterized by several substantial drawbacks. These disadvantages primarily include its computational complexity.

The necessity for real-time mathematical transformations (Park and Clarke transforms) demands powerful microcontrollers (e.g., ARM Cortex-M4, DSPs). Furthermore, its performance is highly dependent on the precision of positional and current sensors (e.g., encoders, resolvers) or on complex sensorless algorithms. Any error in flux estimation severely degrades system performance. A critical limitation is that flux estimation via voltage integration becomes increasingly inaccurate at very low frequencies (< 0.5 Hz) due to measurement errors and integral drift. Additionally, the elevated hardware and software costs associated with FOC implementation present a significant economic disadvantage [4], [5].

To overcome these drawbacks, a second revolution emerged in the 1980s with Direct Torque Control (DTC). [6], [7]. Its fundamental principle is radically different: it is based on the direct selection of a voltage vector from a switching table to maintain flux and torque within hysteresis bands. DTC is appealing due to its conceptual simplicity, its elimination of both a PWM modulator and coordinate transformations, and its intrinsic robustness. Its dynamic response is extremely fast, even surpassing that of FOC [7], [8]. A key feature of DTC is that transistor switching is only triggered when the torque or flux deviates from its tolerance band. This approach minimizes the inverter's switching frequency, reduces switching losses, and enhances energy efficiency, particularly in high-power applications.

Perhaps the most essential advantage of DTC is its robustness to parametric variations [8]. This means it is considerably less sensitive to variations in motor parameters (such as stator resistance) compared to vector control. It operates based on a direct estimation of flux and torque derived from voltage and current measurements, without explicit dependence on precise parametric models. A plurality of control methodologies has consequently been developed, each distinguished by specific structural and functional characteristics. Among these are direct methods [9], which adjust controller parameters online via adaptation mechanisms; indirect methods [10], which estimate process parameters to synthesize the control law; and model-free approaches [11], which entirely dispense with an explicit mathematical model through a purely data-driven approach.

The choice and efficacy of each strategy intrinsically depend on the nature, complexity, and degree of knowledge of the system under consideration.A diverse array of control strategies has been documented in the literature for Permanent Magnet Synchronous Motor (PMSM) control, encompassing proportional-derivative (PD) control [12], proportional-integral-derivative (PID) control [13], sliding mode control (SMC) , fuzzy logic control (FLC) [14], neural network (NN) based control, among others.In reference [15], Aliman et al. introduced a particle swarm optimization-based initialization method for a fuzzy-logic augmented PD controller, designed for passive mode rehabilitation exercises using a lower-limb exoskeleton.

A separate investigation analyzed the influence of intelligent control strategies, wave frequency, applied voltage, and grapheme nanoplatelet weight fraction on wave propagation characteristics in cylindrical micro-shells reinforced with graphene nanoplatelets. Reference [16] proposes a robotic system for bilateral upper-limb rehabilitation, integrating mirror therapy principles with virtual stimulation technology. This system enhances training effectiveness for hemiplegic patients by improving response speed, disturbance rejection, and trajectory tracking accuracy. Meanwhile, study [17] presents a novel fractional-order PID controller for mobile robot navigation, employing a deep deterministic policy gradient (DDPG) algorithm combined with a dynamic controller, demonstrating notable real-time performance efficacy.

Compared to other intelligent control methods [18], [19], the AFLC method has been used to control the dynamics of different systems, because it can take the human experience into account in the design of the learning mechanism. By [20] presented a fuzzy adaptive passive control method for a robot-assisted stroke rehabilitation therapy to improve initiative, safety, and motor skills among stroke patients. In [21] proposed a FLC-based adaptive fault-tolerant controller to mitigate the adverse effects caused by simultaneous additive and multiplicative actuator faults and mismatched nonlinearity in Markov jump systems. However, this method requires a high number of computational resources to accomplish the set target. The automated guided vehicle model with a navigation system is presented in [22] and utilizes fuzzy logic control and computer vision to assist with lane keeping.

The authors demonstrate that a light intensity range between 110 and 150 lux is ideal. In [23], a new fuzzy nonsingular fast terminal sliding mode control is introduced for pendubots, offering speedy response, finite time convergence, and singularity avoidance with genetic algorithm optimization. By [24] proposed fuzzy-logic systems for finite-time stabilization in stochastic nonlinear systems, and presented a unique adaptive control approach to address approximation mistakes and ensure system mean square stability. In [25] solved control problems in an uncertain n-link robotic system using singularity-free adaptive fuzzy fixed-time control and introduced an enhanced error conversion mechanism and barrier Lyapunov function. In [26], [27], a robust FLC has been designed to guarantee a high stability and provide high disturbance rejection capacity**.**

These theoretical and methodological advances have sparked a marked resurgence of interest in recent scientific literature, as evidenced by several notable publications [28], [29], confirming the relevance and growing importance of adaptive fuzzy logic control across various scientific and engineering disciplines. The fundamental objective of this control paradigm is to ensure asymptotic and precise tracking of a predefined reference trajectory, while satisfying robust optimal performance criteria under operational constraints and modeling uncertainties.

Evolving fuzzy systems build and adapt fuzzy models, such as predictors and controllers, by progressively updating their rule-base structure from data streams. On the occasion of the 60th anniversary of fuzzy set theory, commemorated at the Fuzz-IEEE 2025 conference, several fundamental contributions were presented in this area [30], focusing on adaptive and fuzzy modeling and control.Subsequently, it highlights the emergence and importance of evolving intelligent systems for fuzzy modeling and control, emphasizi ng their advantages for handling non-stationary environments. The main challenges and future directions are also addressed.

The aforementioned applications motivated the adoption of Adaptive Fuzzy Logic Control (AFLC) for our Permanent Magnet Synchronous Machine (PMSM). To equip our system with real-time self-tuning capabilities, this paper proposes the integration of a Direct Torque Control (DTC) structure with an AFLC. This synergy aims to combine the robustness and simplicity of DTC with the flexibility and learning capacity of AFLC. The core concept involves equipping the fuzzy controller with an online parameter adaptation mechanism, enabling continuous self-optimization to maintain high performance and minimize torque ripple across a wide range of operating conditions. The efficacy of this approach was successfully validated through extensive simulations conducted in the Matlab/Simulink environment, which yielded robust and high-performance results.

II. PMSM MODEL

II.1 THE DYNAMIC BEHAVIOR OF PERMANENT MAGNET SYNCHRONOUS MACHINES (PMSM) IN THE D-Q REFERENCE FRAME IS DESCRIBED BY THE FOLLOWING SYSTEM OF EQUATIONS [31]

$$\begin{aligned} \frac{di_d}{dt} &= -\frac{R}{Ld} i_d + \frac{L_q}{L_d} p\Omega i_q + \frac{1}{L_d} v_d \\ \frac{di_q}{dt} &= -\frac{R}{L_q} i_q - \frac{L_d}{L_q} p\Omega i_d - \frac{\phi_f}{L_q} p\Omega + \frac{1}{L_q} v_q \\ \frac{d\Omega}{dt} &= \frac{3p}{2J}(\phi_f i_q + (L_d - L_q) i_d i_q) - \frac{1}{J} T_r - \frac{F_c}{J}\Omega \end{aligned} \tag{1}$$

Or: Vd, Vq, id, iq represent the stator voltages and currents returned to the axis d and q. The mechanical equation of the machine is written as:

$$J\frac{d\omega_r}{dt} = (T_{em} - T_r - T_f) \tag{2}$$

With:

$$T_f = f_c \omega_r$$

ω_r : Mechanical speed of the machine
Tr : Resistant torque
Tem: Electromagnetic torque
Tf : Friction torque
J : Moment of inertia
p : Number of pairs of poles
ω : Electrical speed of the rotor
f_c : Friction coefficient

II.2 THE MAIN APPLICATIONS OF PERMANENT MAGNET SYNCHRONOUS MOTORS

Permanent magnet synchronous machines are generally used for low-power applications such as tooling machines, positioning systems, motion or torque transmission devices, attraction, fixation, and repulsion devices, measuring instruments, magnetic recording devices, devices for acting on free electrons or ions, and in robotics.

II.3 DYNAMIC MODELING OF THE VOLTAGE INVERTER

Under ideal conditions (neglecting dead time, switching delays, and voltage distortion), a three-phase inverter admits only eight possible switch configurations. These generate eight phase voltage combinations, which map to eight discrete stator voltage vectors in the αβ reference frame for motor control [32].

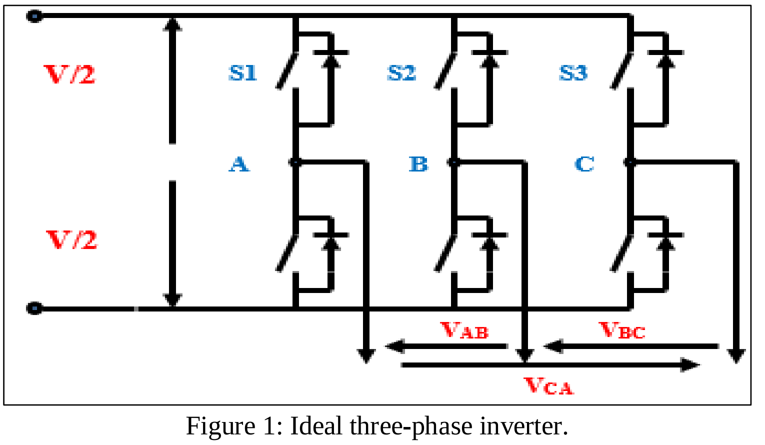

Figure 1: Ideal three-phase inverter.
Source: Authors, (2026).

III. DIFFERENT TECHNIQUES OF CONTROL

Since DTC (Direct Torque Control) is a well-established method studied in prior works, we will not discuss it in detail here, reserving our analysis for the novel Direct and Indirect Adaptive Fuzzy Logic Control.

III.1 SPEED AND POSITION CONTROL OF PMSM USING FUZZY ADAPTIVE ALGORITHMS

III.1.1 Direct Identification-Based Fuzzy Adaptive Control

The synthesis of the decentralized fuzzy adaptive control scheme we have proposed considers the direct decentralized dynamic model of each subsystem. Reformulating this model in a new form will enable us to propose an alternative control law structure. This law is determined using the so-called computed torque method.

III.1.1.1 Fuzzy Model Parameter Estimation

Consider a nonlinear system defined by a collection of m nth-order differential equations, such that:

$$\begin{aligned} x_i^{(n)} &= F_i(X) + G_i(X)u_i \\ y_i &= x_i ; i = 1\ldots, m \end{aligned} \tag{3}$$

With:

$$X = \left[x^{(n-1)}, \ldots, x\right]^T, x = [x_1, \ldots x_m]^T \; et \; u = [u_1, \ldots, u_m]^T \tag{4}$$

The operating principle of the direct identification-based fuzzy adaptive control scheme is as follows:

Fuzzy systems are employed to estimate the nth-order derivatives of the system outputs.
The estimator (the fuzzy model) sends the estimated parameters to the controller, which then generates the control signal using these parameters through the computed torque method.

The nth-order derivative of output yi is represented by a first-order Sugeno fuzzy system, expressed in the following form [33], [34]:

$$\hat{y}_i^{(n)} = f_i(X; \beta_i) \tag{5}$$

A fuzzy rule in the fuzzy system has the following form:

$$\begin{aligned} &R_k : si \; x_1^{(n-1)} \; est \; F_{l(l,n-1)} \; et \ldots et \; x_m^{(n-1)} \; est \; F_{l(m,n-1)} \; et \ldots et \; x_1 \; est \; F_{l(l,0)} et \ldots et \; x_m \; est \; F_{l(m,0)} \\ &Then : \hat{y}_i^{(n)^k} = a(0,k) + a(1,n-1,k)x_1^{(n-1)} + \ldots + a(m,n-1,k)x_m^{(n-1)} + \ldots + a(1,0,k)x_1 \ldots \\ &\qquad + a(m,0,k)x_m + b(k)u_i \end{aligned} \tag{6}$$

With:

$$1 \le l(q, j) \le m(q, j); k = 1, \ldots M_i \tag{7}$$

$m(q, j)$: Represents the number of fuzzy sets associated with the input $x_q^{(j)}$ of the fuzzy system Is the total number of fuzzy rules. The output of the fuzzy system is given by the following relation

$$\hat{y}_i^{(n)} = \frac{\sum_{k=1}^{M_i} \mu_k \hat{y}^{(n)}{}_i^k}{\sum_{k=1}^{M_I} \mu_k} \tag{8}$$

Where μ_k represents the confidence degree or activation level of rule R_k , given by:

$$\mu_k = \mu_{F_{l(1,n-1)}} \times \mu_{F_{l(2,n-1)}} \times \ldots \times \mu_{F_{l(m-1,0)}} \times \mu_{F_{l(m,0)}} \tag{9}$$

The estimation of the fuzzy system parameters - including both premise and consequence parameters - is performed using a modified gradient-based learning algorithm. This algorithm adaptively adjusts the fuzzy system parameters $f_i(.)$ to minimize the instantaneous error between the actual value and the fuzzy system output $\hat{y}_i^{(n)}$. The error function is defined as:

$$e_i(t) = y_i^{(n)} - \hat{y}_i^{(n)} \tag{10}$$

The adaptation law is expressed by the following equation:

$$\hat{\beta}_i(t) = \hat{\beta}_i(t-1) + p(t)\psi(t)e_i(t) \tag{11}$$

$$\psi(t) = \frac{\partial f_i(X.\beta_i)}{\partial \beta_i} / _{\hat{\beta}(t-1)}$$

Where represents the estimation algorithm gain, determined by the following relation:

$$p(t) = \frac{\alpha_1 I}{\alpha_2 + \psi^T(t)\psi(t)}; \alpha_1 \rangle 0, \alpha_2 \rangle 0 \tag{12}$$

III.1.1.2 Control Law Computation

Once the estimation step is completed, the estimator (the fuzzy model) sends the estimated parameters to the fuzzy controller. These parameters are used to construct the controller's rule base. Consequently, a rule of the proposed controller takes the following form:

$$R_k : si\ x_1^{(n-1)}\ est\ F_{l(l,n-1)}\ et...et\ x_m^{(n-1)}\ est\ F_{l(m,n-1)}\ et...et\ x_1\ est\ F_{l(1,0)}\ et...et\ x_m\ est\ F_{l(m,0)}$$
$$Then\ \ num(u_i) = v_i - y'(k)\, et\ \ den(u_i) = b(k)$$

With:

$$v_i = y_{di}^{(n)} + k_n\left(y_{di}^{(n-1)} - y_i^{(n-1)}\right) + ... + k_1(y_{di} - y_i)$$
$$y'(k) = a(0,k) + a(1,n-1,k)x_1^{(n-1)} + ... + a(m,n-1,k)x_m^{(n-1)} + ... + a(1,0,k)x_1 + ... + a(m,0,k)x_m$$

Where:

The coefficients k_i are chosen such that the polynomial $s^n + k_n s^{n-1} ... + k_1$ is a Hurwitz polynomial (i.e., its roots have negative real parts). [12]. The control input applied to subsystem i is given by the following relation:

$$u_i = \frac{num(u_i)}{den(u_i)} \tag{13}$$

Where:

$$num(u_i) = \frac{\sum_{k=1}^{M_i} \mu_k (v_i - y'(k))}{\sum_{k=1}^{M_i} \mu_k} \tag{14}$$

And:

$$den(u_i) = \frac{\sum_{k=1}^{M_i} \mu_k b(k)}{\sum_{k=1}^{M_i} \mu_k} \tag{15}$$

From this, it follows that:

$$u_i = \frac{\sum_{k=1}^{M_i} \mu_k (v_i - y'(k))}{\sum_{k=1}^{M_i} \mu_k (b(k))} \tag{16}$$

Figure 2 presents a schematic overview of the direct-identification-based adaptive fuzzy control principle.

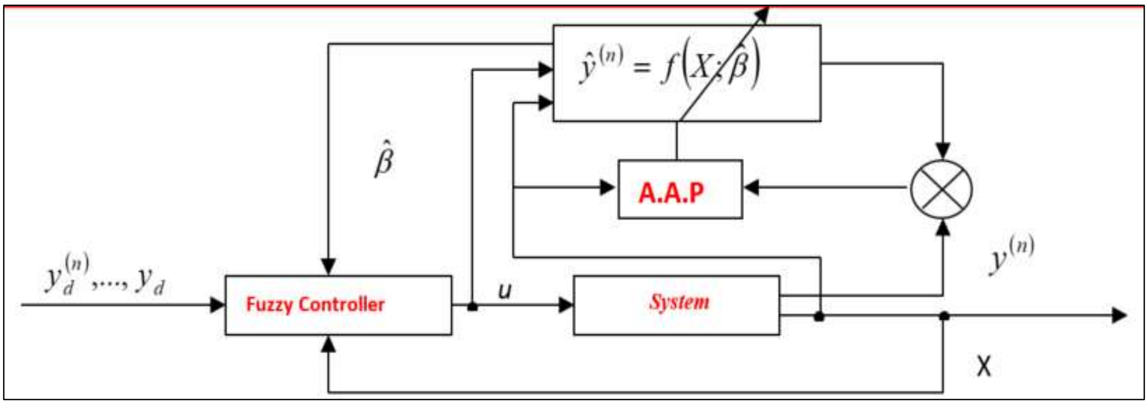

Figure 2: Structure of direct-identification-based adaptive fuzzy control.
Source: Authors, (2026).

✓ Application to Permanent Magnet Synchronous Motor

a) Speed Regulation

The control structure can be represented by the schematic diagram in Figure 3. The adaptive fuzzy controller generates the current i_{qref} , which is multiplied by a coefficient $\left(\frac{3p\phi_f}{2}\right)$ to produce the electromagnetic torque T_{emref} . This torque, along with the reference flux Φ_{ref} , is then utilized in the Direct Torque Control (DTC) scheme to generate the inverter control signals.

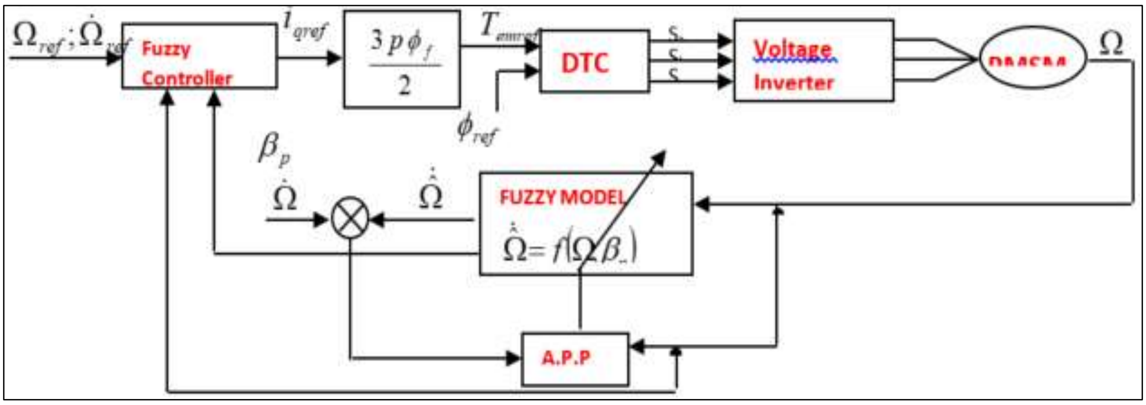

Figure 3: Speed control structure using the adaptive fuzzy control method based on direct identification.
Source: Authors, (2026).

We have:

$$J\frac{d\Omega}{dt} + f\Omega = \frac{3p\phi_f}{2}i_q - T_r \tag{17}$$

Hence:

$$\frac{d\Omega}{dt} = \frac{3p\phi_f}{2J}i_q - \frac{T_r}{J} - \frac{f}{J}\Omega \tag{18}$$

This equation can be described by the following equation:

$$\frac{d\Omega}{dt} = F(X) + G(X)i_q \tag{19}$$

With:

$$F(X) = -\left(\frac{T_r}{J} + \frac{f\Omega}{J}\right); G(X) = \frac{3p\phi_f}{2J}; X = [\Omega] \tag{20}$$

In adaptive fuzzy control based on direct identification, the speed derivative is approximated by a fuzzy system, such that:

$$\hat{\dot{\Omega}} = \frac{\sum_{k=1}^{3}\mu_k \hat{\dot{\Omega}}_k}{\sum_{k=1}^{3}\mu_k} \tag{21}$$

Where: μ_k represents the confidence degree of rule R_k , and $\hat{\dot{\Omega}}_k$ is its consequent. This consequent is defined

By:

$$\dot{\hat{\Omega}}_k = a(0,k) + a(1,k)\Omega + b(k)i_{qref}$$

The adaptive fuzzy controller provides the desired current i_{qref} , which is expressed as:

$$i_{qref} = \frac{\sum_{k=1}^{3} \mu_k (v - y'_k)}{\sum_{k=1}^{3} \mu_k b(k)} \tag{22}$$

Where: $v - y'_k$ and $b(k)$ are, respectively, the numerator and denominator of rule R_k of the fuzzy controller. Their expressions are given by:

$$v = \dot{\Omega}_{ref} + k_\Omega(\Omega_{ref} - \Omega)$$
$$y_k = a(0,k) + a(1,k)\Omega$$

From which, the reference electromagnetic torque is obtained by the equation: [3]

$$T_{emref} = \frac{\sum_{k=1}^{3} \mu_k (v - y'_k)}{\sum_{k=1}^{3} \mu_k b(k)} \times \frac{3p\phi_f}{2} \tag{23}$$

b) Position Control

The control adjustment structure of this system is illustrated in Figure 4.

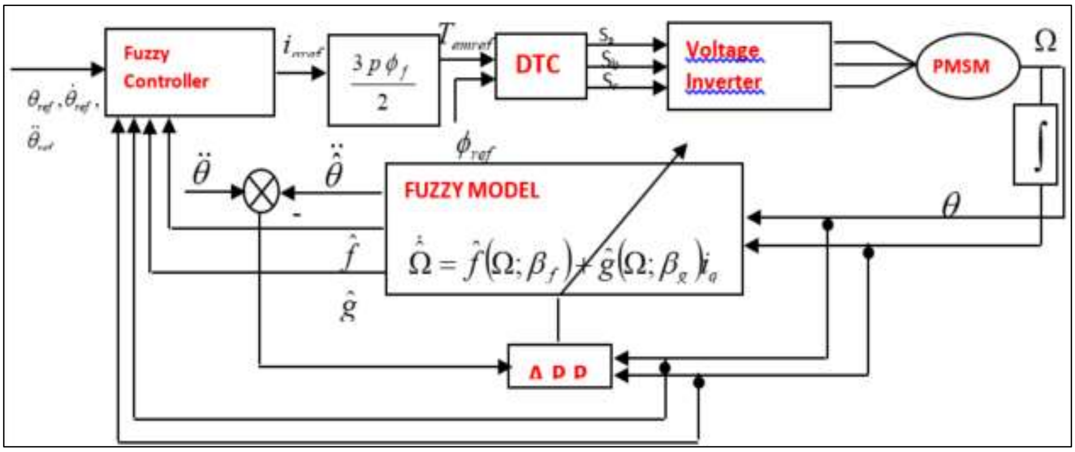

Figure 4: Position control structure using indirect adaptive fuzzy linearizing control method.
Source: Authors, (2026).

From Equation (19), we obtain:

$$i_{qref} = \frac{2J}{3p\phi_f}\frac{d\Omega}{dt} + (f\Omega + T_r)\frac{2}{3p\phi_f} \tag{24}$$

Given that $\dot{\theta} = \Omega$, it follows:

$$i_{qref} = \frac{2J}{3p\phi_f}\ddot{\theta} + (f\dot{\theta} + C_r)\frac{2}{3p\phi_f} \tag{25}$$

Equation (24) allows us to write:

$$i_q = F(X)\ddot{\theta} + G(X) \tag{26}$$

Where:

$$F(X) = \frac{2J}{3p\phi_f}; G(X) = (f\dot{\theta} + C_r)\frac{2}{3p\phi_f}; X = [\theta, \dot{\theta}] \tag{27}$$

From Equation (25), we have:

$$\ddot{\theta} = F(X) + G(X)i_q \tag{28}$$

Where:

$$F(X) = -\left(\frac{C_r}{J} + \frac{f\Omega}{J}\right); G(X) = \frac{3p\phi_f}{2J}; X = [\dot{\theta}] \tag{29}$$

To implement the proposed method, we replace $\ddot{\theta}$ with a first-order Sugeno fuzzy system:

$$\ddot{\theta} = f\left(\dot{\theta}, \beta\right) \tag{30}$$

This system has a single input $\dot{\theta}$. In our application, three membership functions are assigned to this input. The fuzzy system output is expressed as:

$$\ddot{\theta} = \frac{\sum_{k=1}^{3} \mu_k \ddot{\theta}_k}{\sum_{k=1}^{3} \mu_k} \tag{31}$$

Where μ_k is the firing strength of rule R_K and $\ddot{\theta}_k$ is its consequent, defined by:

$$\ddot{\theta}_k = a(0,k) + a(1,k)\dot{\theta} + b(k) i_{qref} \tag{32}$$

The adaptive fuzzy controller output is given by:

$$i_{qref} = \frac{\sum_{k=1}^{3} \mu_k (v - y'_k)}{\sum_{k=1}^{3} \mu_k b(k)} \tag{33}$$

Where:

$$\begin{aligned} v &= \ddot{\theta}_{ref} + k_{1\theta}\left(\dot{\theta}_{ref} - \dot{\theta}\right) + k_{2\theta}\left(\theta_{ref} - \theta\right) \\ y'_k &= a\left(0,k\right) + a\left(1,k\right)\dot{\theta} \end{aligned} \tag{34}$$

With $v - y'_k$ and $b(k)$ being respectively the numerator and denominator of the fuzzy controller's rule R_K
Thus, we obtain the reference electromagnetic torque through:

$$C_{emref} = \frac{\sum_{k=1}^{3} \mu_k (v - y'_k)}{\sum_{k=1}^{3} \mu_k b(k)} \times \frac{3p\phi_f}{2} \tag{35}$$

We observe that the adaptation algorithm requires speed derivative measurement, which is computed through numerical differentiation - an approach that may prove problematic with noisy measurements.

- Numerical Simulation

To demonstrate the proposed control method's effectiveness, we conducted numerical simulations. The coefficients governing the PMSM's desired response were set to 220.852, 45, and 708.75 respectively. Figures (5, a-c) respectively illustrate the PMSM's dynamic and static performance during , a speed regulation at 157 rad/s (no-load) , Load conditions and Rotation reversal. Results analysis reveals:

Excellent reference tracking and disturbance rejection, mere 0.39% speed deviation during disturbances, Rapid 0.018s disturbance recovery, Robust flux-torque decoupling maintained under severe operating conditions

Figures (6, a-c) demonstrate position regulation performance for, 5 rad reference (no-load) and load conditions as well as Position reversal. We also note Precise position reference tracking, fast disturbance rejection (0.2s recovery), minimal 0.086% position deviation during disturbances. The stator flux magnitude successfully reaches its reference value while maintaining an essentially circular trajectory. The flux-torque decoupling remains unaffected even under severe operating conditions.

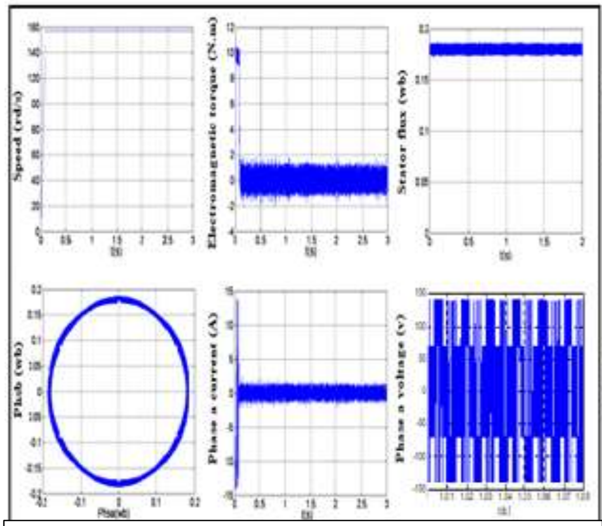

Figure (5.a): Dynamic behavior of the PMSM at no load

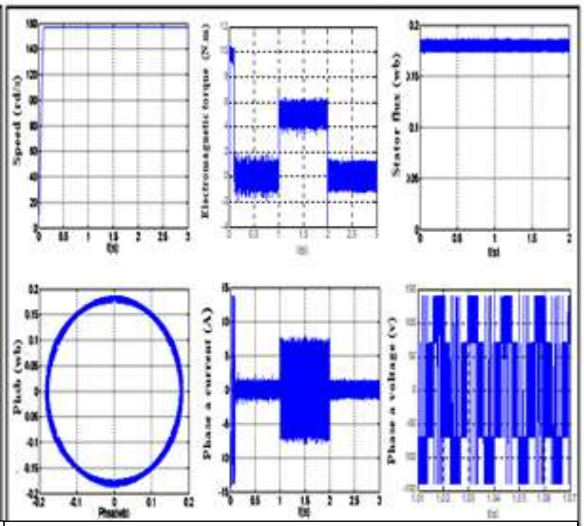

Figure (5.b): Dynamic behavior of the PMSM during startup under load variation

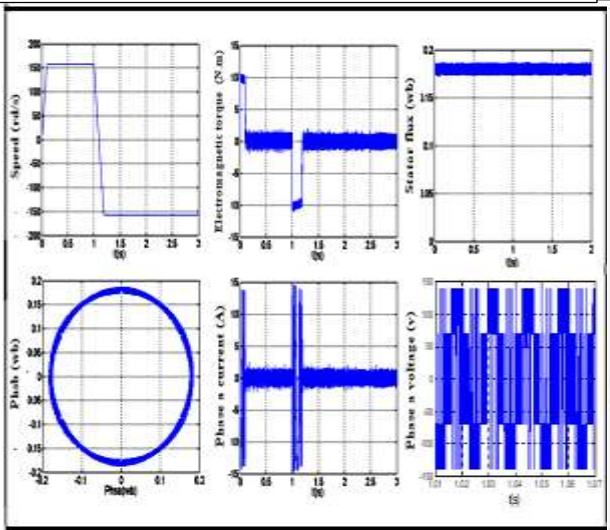

Figure (5.c): Dynamic behavior of the PMSM during a reversal of the direction of rotation.

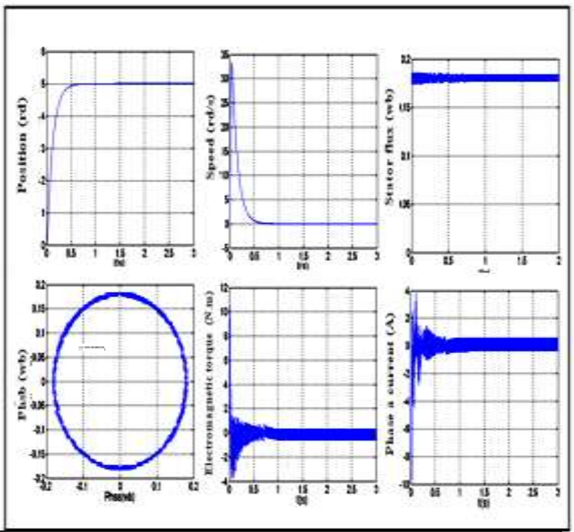

Figure (6.a): Dynamic behavior of the PMSM during no-load positioning

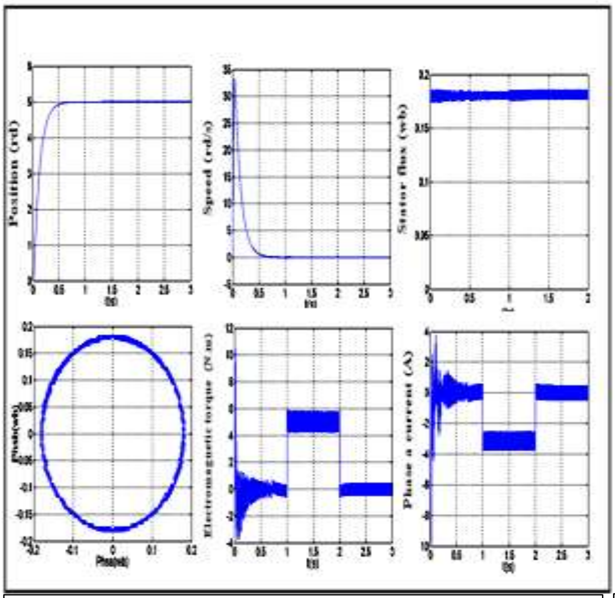

Figure (6.b): Dynamic behavior of the PMSM during positioning with load variation

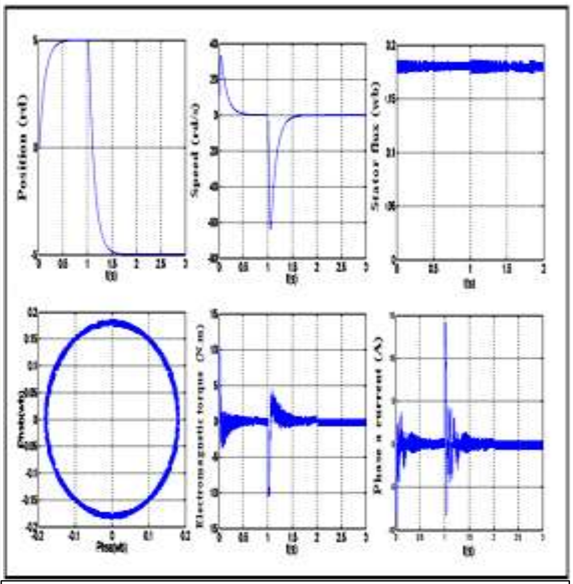

Figure (6.c): Dynamic behavior of the PMSM during position reversal

Source: Authors, (2026).

III.1.2 Indirect Identification-Based Fuzzy Adaptive Control

In this section, we propose a novel approach to indirect adaptive fuzzy control, combining fuzzy systems with the so-called computed torque method. Fuzzy systems are employed to provide a representative model of the direct dynamics of the system to be controlled. The control law is then derived from this model using the computed torque method. [13]

III.1.2.1 System Identification Using Fuzzy Systems

Consider again the system described by equation (3).

$$\begin{aligned} x_i^{(n)} &= F_i(X) + G_i(X)u_i \\ y_i &= x_i; \quad i = 1,\dots,m \end{aligned} \tag{36}$$

The objective of the proposed control strategy is to generate a local control law based on (36) (a decentralized control structure), using estimates of the functions. F_i and $G_i$the control synthesis is performed in two steps:

- System identification: The model of the system to be controlled is identified using fuzzy systems.
- Control computation: The control law is derived via the computed torque method using the identified fuzzy model.

From Equation (40), we can write:

$$\hat{x}_i^{(n)} = f_i(X;\beta_{fi}) + g_i(X;\beta_{gi})u_i \tag{37}$$

The functions $f(.)_i$ *and* $g_i(.)$ are first-order Sugeno fuzzy systems with linguistic descriptions of the following form: [24]

- For fuzzy system $f_i(\cdot)$ **:**

$$\begin{aligned} &R_K^f : si\ x_l^{(n-1)}\ est\ F_{l(l,n-1)}^{\mathbf{f}}\ et...et\ x_m^{(n-1)}\ est\ F_{l(m,n-1)}^{f}\ et...et\ x_i\ est\ F_{l(1,0)}^{\mathbf{f}}\ et\ x_m\ est\ F_{l(m,0)}^{f} \\ &Alors\quad s_f(k) = a_f(o,k) + a_f(1,n-1,k)x_1^{(n-1)} + \dots + a_f(m,n-1,k)x^{n-1}_m + \dots + a_f(1,0,k)x_1 \dots \\ &\qquad + a_f(m,0,k)x_m \end{aligned} \tag{38}$$

- For fuzzy system **:** $g(\cdot)$:

$$\begin{aligned} &R_K^g : si\ x_l^{(n-1)}\ est\ F_{l(l,n-1)}^{\mathbf{g}}\ et...et\ x_m^{(n-1)}\ est\ F_{l(m,n-1)}^{g}\ et...et\ x_i\ est\ F_{l(1,0)}^{\mathbf{g}}\ et\ x_m\ est\ F_{l(m,0)}^{g} \\ &Alors\quad s_g(k) = a_g(o,k) + a_g(1,n-1,k)x_1^{(n-1)} + \dots + a_g(m,n-1,k)x^{n-1}_m + \dots + a_g(1,0,k)x_1 \dots \\ &\qquad + a_g(m,0,k)x_m \end{aligned} \tag{39}$$

The final outputs of the fuzzy systems $f_i(.)$ *and* $g_i(.)$are respectively given by:

$$f_i(X;\beta_{fi}) = \frac{\sum_{k=1}^{M_{fi}} \mu_{fk} s_f(K)}{\sum_{k=1}^{M_{fi}} \mu_{fk}} \tag{40}$$

$$g_i(X;\beta_{gi}) = \frac{\sum_{k=1}^{M_{gi}} \mu_{gk} s_g(k)}{\sum_{k=1}^{M_{gi}} \mu_{gk}} \tag{41}$$

Where:

$$\mu_{fK} = \mu_{l(1,n-1)}^{f} \times \mu_{Fl(2,n-1)}^{f} \times \dots \times \mu_{Fl(m-1,0)}^{f} \times \mu_{Fl(m,0)}^{f} \tag{42}$$

$$\mu_{gK} = \mu_{l(1,n-1)}^{g} \times \mu_{Fl(2,n-1)}^{g} \times \dots \times \mu_{Fl(m-1,0)}^{g} \times \mu_{Fl(m,0)}^{g} \tag{43}$$

The unknown parameters $\beta_i = \lfloor \beta_{fi}, \beta_{gi} \rfloor$are estimated recursively using a modified gradient learning algorithm. In this algorithm, the parameters β_i are adjusted to minimize the instantaneous error between. $y_i^{(n)} et\ \hat{y}_i^{(n)}$ This error is given by: [35]

$$e_i(t) = y_i^{(n)} - \hat{y}_i^{(n)} \tag{44}$$

The proposed adaptation law takes the form [22]:

$$\hat{\beta}_i(t)=\hat{\beta}_i(t-1)+p(t)\psi(t)e_i(t)$$
$$\psi(t)=\frac{\partial y_i^{(n)}}{\partial \beta_i}=\left[\frac{\partial f_i(\cdot)}{\partial \beta_{fi}};\frac{\partial g(\cdot)}{\partial \beta_{gi}}\right] \quad (45)$$

Where:

$$p(t)=\frac{\alpha_1 I}{\alpha_2+\psi^T(t)\psi(t)};\alpha_1>0,\alpha_2>0$$

III.1.2.2 Control Law Computation

Our objective is to design a control law such that each subsystem tracks its reference y_{id} . For this purpose, the control law, computed via the computed torque method, is given by:

$$u_i=\frac{v_i-f_i(X;\beta_{fi})}{g_i(X;\beta_{gi})} \quad (46)$$

Where:

$$v_i=y_{di}^{(n)}+k_n\left(y_{di}^{(n-1)}-y_i^{(n-1)}\right)+\ldots+k_1(y_{di}-y_i)$$

The coefficients k_i are selected such that the polynomial $s^n+k_n s^{n-1}\ldots+k_1$ is a Hurwitz polynomial (roots with negative real parts). This control law ensures critical damping for the error dynamics. Figure (7) schematically illustrates the principle of the proposed control strategy. [35].

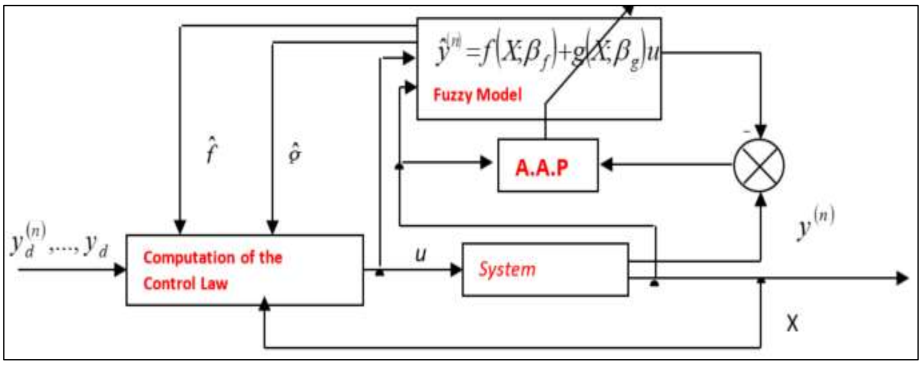

Figure 7: Principle of indirect adaptive fuzzy linearizing control.
Source: Authors, (2026).

✓ **Application to PMSM (Permanent Magnet Synchronous Motor)**

a) Speed Regulation

The structure of the indirect adaptive fuzzy linearizing control is illustrated in Figure (8). The adaptive fuzzy controller generates the current i_{qref} , which is multiplied by a coefficient $\left(\frac{3p\phi_f}{2}\right)$ to produce the electromagnetic torque T_{emref} . This torque, along with the reference flux Φ_{ref} , are then utilized in the Direct Torque Control (DTC) scheme to generate the inverter switching commands.

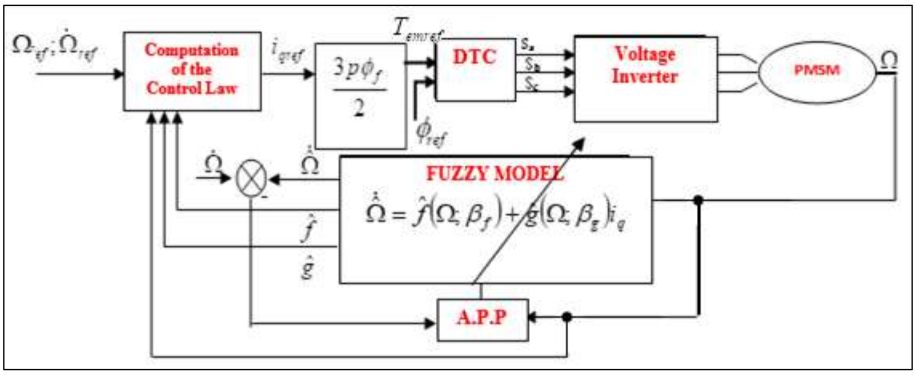

Figure 8: Speed control structure using the indirect adaptive fuzzy linearizing control method.
Source: Authors, (2026).

Considering equation (36), the selected model for identifying the speed derivative has the following form:

$$\dot{\Omega} = f(\Omega;\theta_f) + g(\Omega;\theta_g)i_q \tag{47}$$

With: $f(.)\ and\ g(.)$ are fuzzy systems with unknown parameters. These systems are characterized by a single input, with three membership functions assigned to this input. [35]. The final outputs of the fuzzy systems $f(.)\ et\ g(.)$ are respectively given by:

$$f(\Omega;\beta_f) = \frac{\sum_{k=1}^{3}\mu_{fk}s_f(k)}{\sum_{k=1}^{3}\mu_{fk}}$$
$$g(\Omega;\beta_g) = \frac{\sum_{k=1}^{3}\mu_{gk}s_g(k)}{\sum_{k=1}^{3}\mu_{gk}} \tag{48}$$

Where: $\mu_{fk}\ and\ \mu_{gk}$ represent the confidence degrees of rules $R_{fk}\ and\ R_{gk}$ for the fuzzy systems $f(.)\ and\ g(.)$. While $s_f(k)\ and\ s_g(k)$ are the consequences of these rules, defined as:

$$s_f(k) = a_f(0,k) + a_f(1,k)\Omega$$
$$s_g(k) = a_g(0,k) + a_g(1,k)\Omega \tag{49}$$

The output provided by the adaptive fuzzy controller is expressed as:

$$i_{qref} = \frac{v - f(\Omega;\beta_f)}{g(\Omega;\beta_g)} \tag{50}$$

With:

$$v = \dot{\Omega}_{ref} + k\Omega(\Omega_{ref} - \Omega)$$

From this, we obtain the reference electromagnetic torque through the equation:

$$T_{emref} = \frac{3p\phi_f}{2}\frac{v - f(\Omega;\beta_f)}{g(\Omega;\beta_g)} \tag{51}$$

b) Position Control

The control structure for position regulation is illustrated in Figure (9).

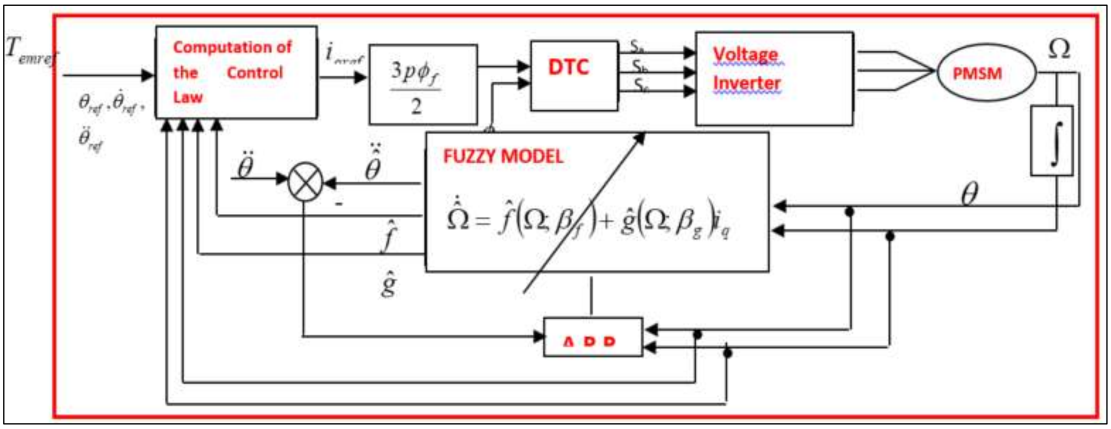

Figure 9**:** Position control architecture using indirect adaptive fuzzy linearization control methodology.
Source: Authors, (2026).

Based on equation (28), the selected identification model for $\ddot{\theta}$ is formulated as:

$$\ddot{\theta} = f(\dot{\theta};\beta_f) + g(\dot{\theta};\beta_g)i_q \tag{52}$$

Where $f(\dot{\theta};\beta_f)\ and\ g(\dot{\theta};\beta_g)$ represent fuzzy inference systems characterized by a single input variable. In the present study, we implement three Gaussian membership functions for this input. The aggregated outputs of these fuzzy systems are mathematically expressed as: [36]

$$f(\dot{\theta},\beta_f)=\frac{\sum_{k=1}^{3}\mu_{fk}s_f(k)}{\sum_{k=1}^{3}\mu_{fk}}$$
$$g(\dot{\theta},\beta_g)=\frac{\sum_{k=1}^{3}\mu_{gk}s_g(k)}{\sum_{k=1}^{3}\mu_{gk}} \quad (53)$$

The control signal generated by the adaptive fuzzy controller is given by:

$$i_{qref}=\frac{v-f(\dot{\theta},\beta_f)}{g(\dot{\theta},\beta_g)} \quad (54)$$

With:

$$v=\ddot{\theta}_{ref}+k_{1\theta}(\dot{\theta}_{ref}-\dot{\theta})+k_{2\theta}(\theta_{ref}-\theta)$$

The reference electromagnetic torque is consequently derived from:

$$T_{emref}=\frac{3p\phi_f}{2}\frac{v-f(\dot{\theta},\beta_f)}{g(\dot{\theta},\beta_g)} \quad (55)$$

Remark 1: The adaptation algorithm necessitates real-time measurement of the angular velocity derivative. While numerically estimated in this implementation, we note that such approximation may introduce significant errors under noisy measurement conditions, potentially c]ompromising control performance.

- Numerical Simulation and Performance Analysis

The closed-loop system dynamics were rigorously evaluated through numerical simulations investigating both speed and position regulation using the proposed indirect adaptive fuzzy linearization approach. The critical control parameters, determining the PMSM's dynamic response characteristics, were optimally tuned to 620.54, 61.5704, and 473.86 respectively. The transient and steady state performance metrics, illustrated in Figures (10, a-c) and (11, a-c) demonstrate:

➢ Exceptional disturbance rejection capability:
➢ Maximum speed deviation: 0.55% of nominal value
➢ Maximum position error: 0.46% of reference
➢ Perturbation recovery time constants: 5ms (speed) and 290ms (position)
➢ Robust flux-torque decoupling
➢ Complete independence maintained even under severe operational regimes
➢ No observable coupling effects during rapid torque transients

➢

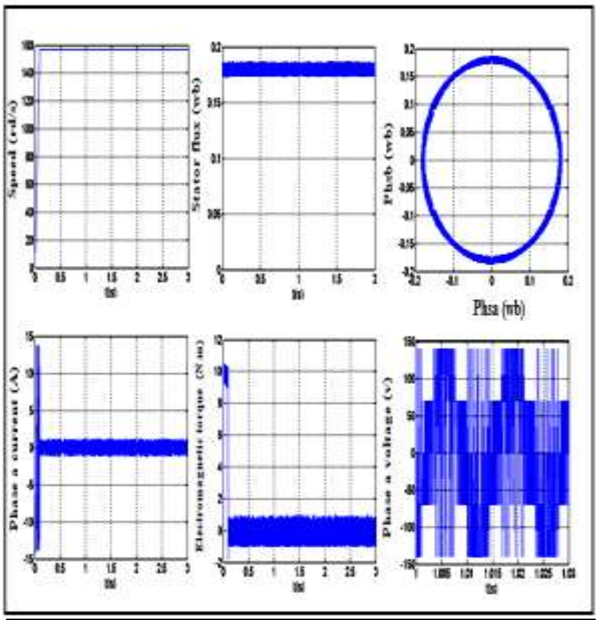

Figure (10.a): Dynamic behavior of the PMSM under no-load conditions

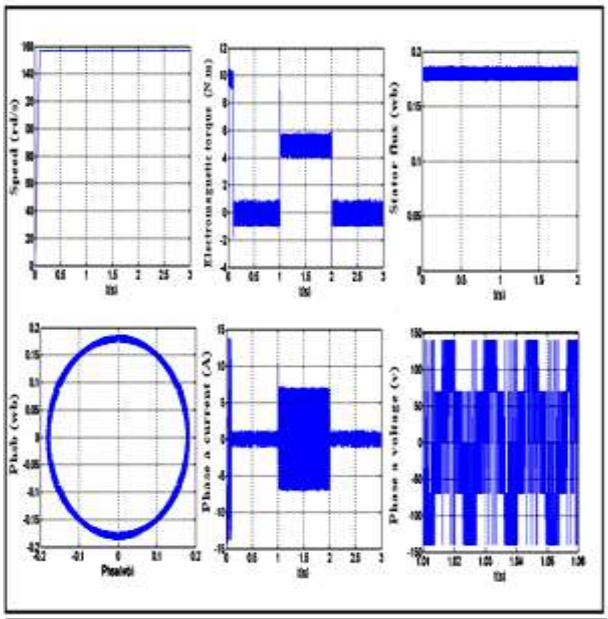

Figure (10.b): Dynamic response of the PMSM during startup under variable load conditions

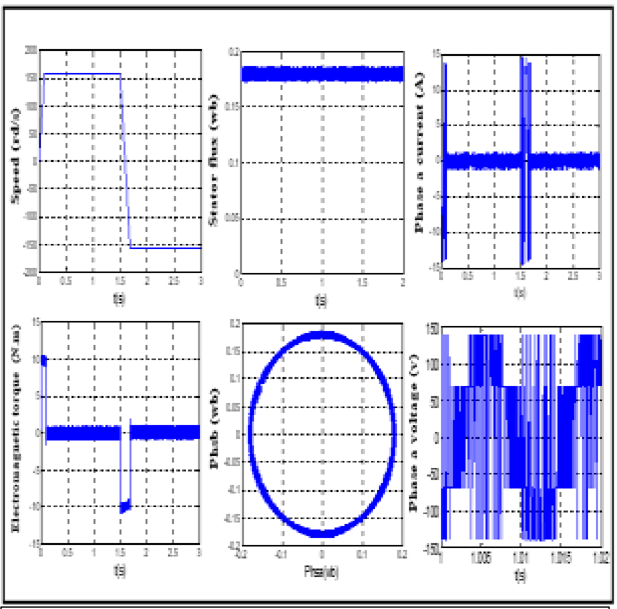

Figure (10.c): Dynamic behavior of the PMSM during rotational direction reversal

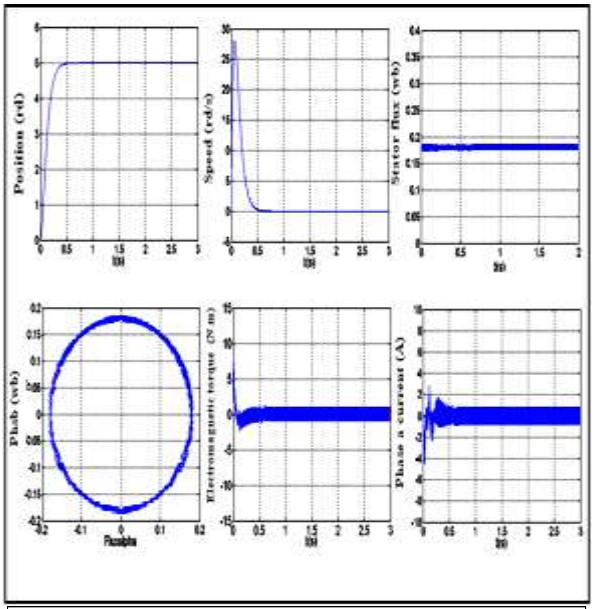

Figure (11.a): Dynamic positioning performance of the PMSM under no-load conditions

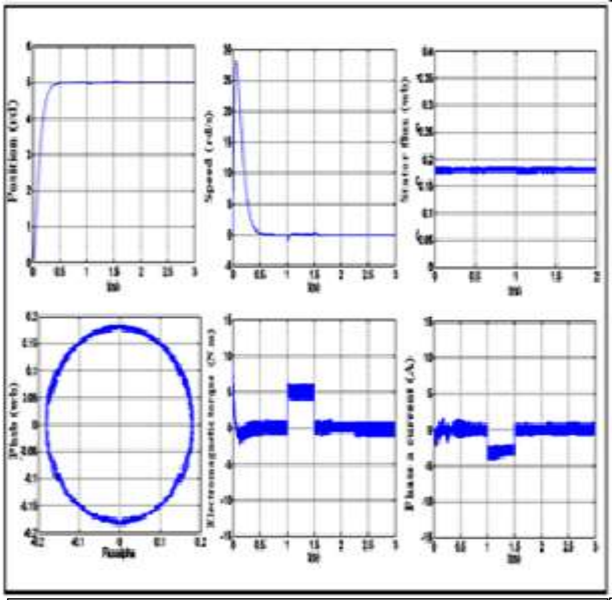

Figure (11.b): Dynamic positioning performance of the PMSM under variable load conditions

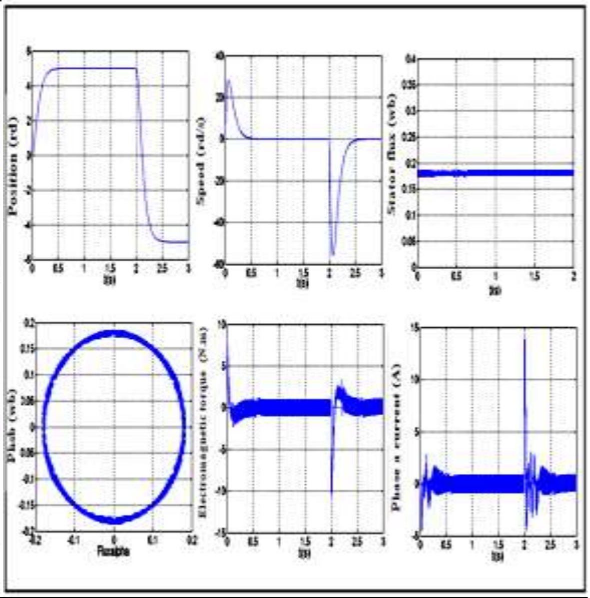

Figure (11.c): Dynamic positioning behavior of the PMSM during position reversal

Source: Authors, (2026).

IV. CONCLUSIONS

This research has systematically investigated two adaptive fuzzy control approaches for permanent magnet synchronous motors (PMSMs): direct and indirect adaptive fuzzy control methodologies. The study demonstrates how fuzzy systems can effectively approximate unknown continuous nonlinear functions in both control paradigms, while maintaining complete independence from prior knowledge of the PMSM's dynamic model structure or parameters. Our contributions include:

Direct Adaptive Fuzzy Control: A novel control architecture where fuzzy logic systems directly generate control signals through online adaptation.

Indirect Adaptive Fuzzy Linearization Control: An identification-based approach employing fuzzy systems for model approximation and linearization

Both decentralized control strategies exhibit:

Robust position and speed regulation capabilities

Model-free operation without requiring parametric knowledge

Fuzzy rule bases derived directly from the corresponding fuzzy models

Consistent operation across various dynamic regimes

However, these techniques require the measurement of the machine's speed derivative, which is calculated numerically, which can be detrimental in the case of noisy measurements. The study establishes a theoretical framework for advanced fuzzy control applications in PMSM drives, particularly suitable for industrial applications requiring both precision and robustness under uncertain operating conditions. Future work should focus on experimental validation and computational optimization for real-time implementation.

V.AUTHOR'S CONTRIBUTION

Conceptualization: Bentchikou Ibrahim, Tlemçani Abdelhalim, Hassan Nouri, Boudjema Fares, Boukhetala Djamel,Ould cherchali Noureddine ,Fekir Mohamed, Mahdab Salim.
Methodology: Bentchikou Ibrahim, Tlemçani Abdelhalim, Hassan Nouri, Boudjema Fares, Boukhetala Djamel,Ould cherchali Noureddine ,Fekir Mohamed, Mahdab Salim .
Investigation: Bentchikou Ibrahim, Tlemçani Abdelhalim, Hassan Nouri, Boudjema Fares, Boukhetala Djamel,Ould cherchali Noureddine ,Fekir Mohamed, Mahdab Salim.
Discussion of results : Bentchikou Ibrahim, Tlemçani Abdelhalim, Hassan Nouri, Boudjema Fares, Boukhetala Djamel,Ould cherchali Noureddine ,Fekir Mohamed, Mahdab Salim.
Writing–Original Draft: Bentchikou Ibrahim, Tlemçani Abdelhalim, Hassan Nouri, Boudjema Fares, Boukhetala Djamel,Ould cherchali Noureddin ,Fekir Mohamed,Mahdab Salim.
Writing –Review and Editing: Bentchikou Ibrahim, Tlemçani Abdelhali, Hassan Nouri, Boudjema Fares, Boukhetala Djamel,Ould cherchali Noure ,Fekir Mohamed, Mahdab Salim.
Resources: Bentchikou Ibrahim, Tlemçani Abdelhalim, Hassan Nouri, Boudjema Fares, Boukhetala Djamel,Ould cherchali Noureddine ,Fekir Mohamed, Mahdab Salim .
Supervision: Bentchikou Ibrahim, Tlemçani Abdelhalim, Hassan Nouri, Boudjema Fares, Boukhetala Djamel,Ould cherchali Noureddine ,Fekir Mohamed, Mahdab Salim .
Approval of the final text: Bentchikou Ibrahim, Tlemçani Abdelhalim, Hassan Nouri, Boudjema Fares, Boukhetala Djamel,Ould cherchali Noureddi ,Fekir Mohamed, Mahdab Salim.

VI. REFERENCES

[1] I,.Bentchikou; K, Halbaoui.; F, Boudjema.; D,Boukhetala and A, Tlemçani.“ Alternative hybrid control of switched systems. an application to machine dc fed by multicellular converter”, Revue Roumaine des Sciences Techniques, Série Électrotechnique et Énergétique, Vol. 67, 3, pp. 247–252, Bucarest, 2022, ISSN 0035-4066.

[2] V. Sri Charan, D. Kiran Kumar, “speed control of pmsm drive using model predictive control based field oriented control:”, JETIA, v.11 n.52, p. 1 -8.March/April, 2025

[3] A. N. Halisyah, D. Adiputra, and F. A. Al. "Field oriented control driver development based on BTS7960 for physiotherapy robot implementation". International Journal of Electrical and Computer Engineering (IJECE), vol. 14, no. 2, pp. 1486–1495, 2024. DOI: 10.11591/ijece.v14i2.pp1486-1495.

[4] E. Benmalek, M. Rayyam, A. Gege, O. Ennasiri, and A. Ezzaidi. "AI-BASED FIELD-ORIENTED CONTROL FOR INDUCTION MOTORS". Informatyka, Automatyka, Pomiary w Gospodarce i Ochronie Środowiska, vol. 14, no. 4, pp. 75–81, 2024. DOI: 10.35784/iapgos.6253.

[5] T. Le. "A Robust Control Strategy for Effective Field-Oriented Control of PMSMs". Engineering, Technology & Applied Science Research, vol. 14, no. 6, pp. 18469–18475, 2024. DOI: 10.48084/etasr.8893.

[6] M. P. Kazmierkowski; L. Malesani; L. Zarri et A. Tani. "Direct Torque Control of PWM Inverter-Fed AC Motors - Survey and Recent Advances", IEEE Transactions on Power Electronics, vol. 38, no. 1, pp. 1-20, 2024. DOI:10.1109/TPEL.2023.3304561.

[7] S. Vazquez; J. I. Leon; L. G. Franquelo et M. Reyes. "Predictive Torque Control for High-Performance Drives: A Comparative Study with DTC and FOC", IEEE Transactions on Industrial Electronics, vol. 71, no. 3, pp. 2105-2118, 2025. DOI:10.1109/TIE.2024.3356789.

[8] M. Ahmed et al. "DTC flou adaptatif pour PMSM", IEEE Trans. on Transportation Electrification, vol. 10, no. 1, 2024. DOI: 10.1109/TTE.2023.3304561.

[9] M. Ogharandukun, F. I. Onah, N. B. Ngang et E. Chijioke. "Adaptive Control-Based Technique for Enhancing Energy Efficiency of a Wind Energy Generator". European Journal of Engineering and Environmental Sciences, vol. 8, no. 1, pp. 21–29, 2024. DOI: 10.5281/zenodo.12787161.

[10] V. Stepanyan et K. Krishnakumar. "Adaptive Control with Reference Model Modification". Journal of Guidance, Control, and Dynamics, vol. 35, no. 4, pp. 1370–1374, 2012. DOI: 10.2514/1.55756.

[11] T. Yucelen et A. J. Calise. "Derivative-Free Model Reference Adaptive Control". Journal of Guidance, Control, and Dynamics, vol. 34, no. 4, pp. 933–950, 2011. DOI: 10.2514/1.53234.

[12] K. J. Åström and T. Hägglund. "The future of PID control". Control Engineering Practice, Vol. 9, No. 11, pp. 1163–1175, 2001. DOI: 10.1016/S0967-0661(01)00062

[13] T. Jin, X. Yang, C. Qi, Y. Wu, Y. Zhang and W. Xu. "Model reference adaptive PID control for enhanced stability and posture control of unmanned underwater vehicles". Ocean Engineering, Vol. 330, 121218, 2025. DOI: 10.1016/j.oceaneng.2025.121218.

[14] N. Essounbouli. "Contrôleur flou adaptatif pour robots mobiles", JofeSys vol. 21, no. 1, 2025.

[15] N. Aliman, R. Ramli, S.M. Haris, M.S. Amiri, M. Van, A robust adaptive-fuzzyproportional-derivative controller for a rehabilitation lower limb exoskeleton, EngSci. Technol. Int. J. 35 (2022) 101097.

[16] W. Xiao, K. Chen, J. Fan, Y. Hou, W. Kong, G. Dan, AI-driven rehabilitation and assistive robotic system with intelligent PID controller based on RBF neural networks, Neural Comput. Appl. 35 (22) (2023) 16021–16035.

[17] M. Gheisarnejad, M.H. Khooban, An intelligent non-integer PID controller-based deep reinforcement learning: implementation and experimental results, IEEE TransInd. Electron. 68 (4) (2020) 3609–3618.

[18] J. Hu, H. Zhang, H. Liu, X. Yu, A survey on sliding mode control for networked control systems, Int. J. Syst. Sci. 52 (6) (2021) 1129–1147.

[19] A.G. Loukianov, J.R. Dominguez, B. Castillo-Toledo, Robust sliding mode regulation of nonlinear systems, Automatica 89 (2018) 241–246

[20] Y. Hu, J. Meng, G. Li, D. Zhao, G. Feng, G. Zuo, et al., Fuzzy adaptive passive control strategy design for upper-limb end-effector rehabilitation robot, Sensors 23 (8) (2023) 4042.

[21] H. Yang, Y. Jiang, S. Yin, Adaptive fuzzy fault-tolerant control for Markov jump systems with additive and multiplicative actuator faults, IEEE Trans. Fuzzy Syst. 29 (4) (2020) 772–785.

[22] M. Munadi, B. Radityo, M. Ariyanto, Y. Taniai, Automated guided vehicle (AGV) lane-keeping assist based on computer vision, and fuzzy logic control under varying light intensity, Results Eng. 21 (2024) 101678. Results in Engineering 24 (2024) 102916 13

[23] V.T. Nguyen, H.B. Giap, N.T. Tran, N.H. Manh, V.A. Nguyen, A study on fuzzy nonsingular fast terminal sliding mode control for pendubot with uncertainties, in: Springer ICISN, 2023, pp. 12–18.

[24] F. Wang, B. Chen, Y. Sun, Y. Gao, C. Lin, Finite-time fuzzy control of stochastic nonlinear systems, IEEE Trans. Cybern. 50 (6) (2019) 2617–2626.

[25] Y. Pan, P. Du, H. Xue, H.K. Lam, Singularity-free fixed-time fuzzy control for roboticsystems with user-defined performance, IEEE Trans. Fuzzy Syst. 29 (8) (2020) 2388–2398.

[26] X. Su, F. Xia, J. Liu, L. Wu, Event-triggered fuzzy control of nonlinear systems with its application to inverted pendulum systems, Automatica 94 (2018) 236–248.

[27] H. Zhang, Y. Liu, Y. Wang, Observer-based finite-time adaptive fuzzy control for nontriangular nonlinear systems with full-state constraints, IEEE Trans. Cybern. 51 (3) (2020) 1110–1120.

[28] M. Van, Y. Sun, S. Mcllvanna, M.N. Nguyen, M.O. Khyam, D. Ceglarek, Adaptive fuzzy fault tolerant control for robot manipulators with fixed-time convergence, IEEE Trans. Fuzzy Syst. 31 (9) (2023) 3210–3219.

[29] V.T. Nguyen, Q.C. Nguyen, M.Van, V.T. Nguyen, D.H.Pham, & D.C Nguyen, ‘’Novel adaptive fuzzy control for pendubot with actuator faults and uncertainties: design and experiments’’ Results in Engineering, 24, Article 102916 ://doi.org/10.1016/j.rineng.2024.102916

[30] L.Daniel , S.Igor , G.Fernando ‘’From Model-Based and Adaptive Control to Evolving Fuzzy Control’’2025 IEEE International Conference on Fuzzy Systems

[31] I.Bentchikou, F. Boudjema, D. Boukhetala ,A.Tlemçani, N. Ould Cherchali " Investigation in the Technique of Adaptive Predictive Control Fed by a Hybrid Inverter Applied to a Permanent Magnetic Synchronous Machine", Nonlinear Dynamics and Systems Theory. An International Journal of Research and Surveys . Volume 16, Number 1, 2016. ISSN 1562-8353.

[32] A. Tlemçani; F. Boudjema; D. Boukhetala. "Nonlinear Backstepping Control Strategy for PMSM with Uncertain Load Torque", International Journal of Electrical Power & Energy Systems, vol. 155, 109567, 2024.

[33] P. Du, K. Sun, S. Zhao, and H. Liang, ‘‘Observer-based adaptive fuzzy control for time-varying state constrained strict-feedback nonlinear systems with dead-zone,’’ Int. J. Fuzzy Syst., vol. 21, no. 3, pp. 733–744, Apr. 2019.

[34] S. Ha, L. Chen, H. Liu, and S. Zhang, ‘‘Command filtered adaptive fuzzy control of fractional-order nonlinear systems,’’ Eur. J. Control, vol. 63, pp. 48–60, Jan. 2022.

[35] X. You, S. Dian, K. Liu, B. Guo, G. Xiang, and Y. Zhu, ‘‘Command filter-based adaptive fuzzy finite-time tracking control for uncertain fractional-order nonlinear systems,’’ IEEE Trans. Fuzzy Syst., vol. 31, no. 1, pp. 226–240, Jan. 2023.

[36] A. Bounemeur and M. Chemachema, ‘‘Finite-time output-feedback fault tolerant adaptive fuzzy control framework for a class of MIMO saturated nonlinear systems,’’ Int. J. Syst. Sci., vol. 56, no. 4, pp. 733–752, Mar. 2025.