

FUZZY SYSTEMS IN MOTOR CONTROL SOLUTIONS: A COMPARATIVE ANALYSIS OF FUZZY LOGIC VS. PI REGULATORS IN DYNAMIC LOAD SCENARIOS

Mark WENDLER*, József KOPJÁK**, Gergely SEBESTYÉN***

*Doctoral School of Applied Informatics and Applied Mathematics, Óbuda University, Bécsi út 96/B, 1034 Budapest, Hungary, E-mail: mark.wendler@phd.uni-obuda.hu

**Kandó Kálmán Faculty of Electrical Engineering, Óbuda University, Bécsi út 96/B, 1034 Budapest, Hungary, E-mail: kopjak.jozsef@kvk.uni-obuda.hu

***Kandó Kálmán Faculty of Electrical Engineering, Óbuda University, Bécsi út 96/B, 1034 Budapest, Hungary, E-mail: sebestyen.gergely@kvk.uni-obuda.hu

ABSTRACT

This paper presents a comprehensive comparative analysis of fuzzy logic and conventional PI controllers in motor control applications, focusing on dynamic load scenarios. We investigate the integration of fuzzy logic controllers within field-oriented control (FOC) architectures, particularly examining their performance in speed regulation, oscillation reduction, and transient response. Through systematic experimentation with a sensorless PMSM drive system, we demonstrate how fuzzy controllers can outperform traditional PI regulators in handling nonlinearities and varying operating conditions. The study includes detailed analysis of control surface optimization, revealing how strategic modifications to membership functions can significantly reduce speed oscillations while maintaining responsiveness. Our results show that the implemented fuzzy speed controller achieves 28.57% faster settling time compared to its PI counterpart, albeit with a 2% overshoot trade-off. Furthermore, we identify key subsystems within FOC architectures where fuzzy logic implementation offers the most substantial benefits, including open-loop start-up sequences and flux control. The paper concludes with practical insights into computational requirements for embedded implementations and discusses future directions for intelligent control systems in motor drive applications.

Keywords: embedded systems, motor control, BLDC, Field oriented control, regulator, fuzzy control, estimator,

1. INTRODUCTION

Motor control is a cornerstone of modern electromechanical systems, directly influencing efficiency, precision, and adaptability in applications ranging from industrial automation to embedded electronics. Traditional control methods, such as proportional-integral (PI) regulators, rely on linear models and fixed parameters, often struggling with nonlinearities and dynamic load variations. To address these limitations, intelligent control strategies—particularly fuzzy logic—have emerged as powerful alternatives, leveraging human-like reasoning to handle uncertainty and complex system dynamics. Additionally Fuzzy systems were playing main roles in research and development on new AI based control technologies as well [1], [2].

This article investigates the role of fuzzy logic in motor control, comparing its performance against conventional PI regulators in dynamic load scenarios. Also identifying what part of the control loops can be replaced and improved by Fuzzy controllers of the complex motor control system. Through simulation-based analysis, the advantages or disadvantages of fuzzy controllers in adaptability, robustness, and transient response.

2. FUZZY LOGIC OVERVIEW

2.1. Fuzzy Logic overview and usage in Motor Control

In 1965, a Berkeley professor named Lotfi Zadeh dropped an intellectual bombshell. Frustrated by the rigidity of binary logic (where everything must be 100% true or false), he proposed a radical idea: What if machines could think in shades of gray? His paper, Fuzzy Sets,

introduced a world where a temperature could be "slightly hot" (0.7 true) or a motor's speed "almost optimal" (0.9 true)—just like human intuition [3], [4].

2.2. Key Concepts of Fuzzy systems [4]

Fuzzification: Turning Numbers into abstract description

Fuzzy Sets: The foundational concept where elements can partially belong to a set.

Fuzzy Inference Systems: These systems use fuzzy logic to map inputs to outputs based on a set of fuzzy rules.

Fuzzy Control Systems: Widely used in industrial and consumer applications to handle imprecise inputs and achieve smooth control.

2.3. Fuzzy logic fundamentals

Fuzzy logic is a mathematical approach that handles the concept of partial truth, with values ranging between completely true and completely false. This contrasts with classical logic, which operates on binary true/false (1/0) values [4].

1. Fuzzy Sets:

- **Definition:** A fuzzy set is a set without a sharp boundary. An element can partially belong to a fuzzy set with a certain degree of membership.
- **Membership Function:** Defines how each element in the input space is mapped to a membership value between 0 and 1. Common shapes include triangular, trapezoidal, and Gaussian.

2. Membership Degree:

- **Range:** Values range from 0 (not a member) to 1 (full member).
- **Example:** For the fuzzy set "High speed rotating rotor" a Permanent Magnet Synchronous Motor, 4000 rotation per minute might have a membership degree of 0.8, while another motor rotating 1000 rotation per minute might have a membership degree of 0.3.

3. Fuzzy Inference System (FIS):

- **Components:** Comprises a rule base, a database, a decision-making unit, and a fuzzification/defuzzification interface.
- **Rule Base:** Contains a set of if-then rules that describe how to perform inference. **Example:** If the temperature is high, then the fan speed is high.
- **Fuzzification:** Converts crisp inputs into fuzzy values using membership functions.
- **Inference:** Processes the fuzzified inputs according to the fuzzy rules to produce fuzzy outputs.
- **Defuzzification:** Converts the fuzzy outputs back into crisp values. Common methods include centroid (center of gravity) and max membership principle.

4. Types of Fuzzy Inference Systems:

- **Mamdani FIS:** Commonly used in control systems, employs min-max operations and centroid defuzzification.
- **Sugeno FIS:** Uses weighted average for defuzzification, often applied in optimization and adaptive control.

3. MOTOR CONTROL AND FUZZY SYSTEMS IN APPLIED TECHNOLOGY

Significant contribution is found in electrical motor control systems in speed control, position control, and torque control. Multiple articles present versatile use cases of fuzzy logic-based controls. As a typical example, the sensorless rotor position estimation algorithm eliminates the need for physical sensors, reducing cost and complexity while maintaining high accuracy and reliability in motor control. In the next sections there are listed a few use cases and studies of Fuzzy systems utilized in different kind of motor control applications [5], [6], [7].

3.1. Fuzzy Logic Rotor Position Estimation in Switched Reluctance Motors

The paper "Fuzzy Logic Rotor Position Estimation Based Switched Reluctance Motor DSP Drive with Accuracy Enhancement" explores the use of fuzzy logic to enhance the accuracy of rotor position estimation in

SRMs. The integration of a fuzzy logic-based algorithm with a digital signal processor (DSP) facilitates real-time control and improves overall performance by compensating for nonlinearities and uncertainties in the motor model [8].

3.2. Hybrid Fuzzy Sliding Mode Control

"Design of the Fuzzy Sliding Mode Controller for DC Motor" presents a hybrid control strategy that integrates fuzzy logic with sliding mode control. This combination enhances the robustness of sliding mode control while providing the adaptability of fuzzy logic, resulting in a highly resilient and efficient motor control system capable of handling a wide range of operating conditions [9].

3.3. Fuzzy Logic in Educational Robotics

Understanding the theoretical advancements in fuzzy logic and AI-assisted motor control is crucial, but practical applications and educational projects provide valuable insights into real-world implementations and challenges [10], [11].

The article "An Undergraduate Fuzzy Logic Control Lab Using a Line Following Robot" describes an educational setup for teaching fuzzy logic control using a line-following robot. This practical approach allows students to gain hands-on experience with fuzzy logic principles and their application in motor control, bridging the gap between theory and practice [10], [11].

3.4. Fuzzy Control of Self-Balancing Robots

"Fuzzy Control of Self-Balancing Robots: A Control Laboratory Project" extends this educational approach to more complex systems, such as self-balancing robots. This project illustrates the effectiveness of fuzzy control in maintaining balance and stability, showcasing the potential of fuzzy logic in dynamic and nonlinear control systems [12].

3.5. Sensorless Control Techniques

"Sensorless Control of Interior Permanent Magnet Machine Drives with Zero-Phase-Lag Position Estimation" contributes to the broader understanding of sensorless control strategies. This knowledge can be integrated with fuzzy logic and neuro-fuzzy systems to develop advanced motor control solutions that are both cost-effective and highly efficient [13], [14], [15].

3.6. Adaptive Neuro Fuzzy inference system

The integration of fuzzy logic with neural networks has led to the development of Adaptive Neuro-Fuzzy Inference Systems (ANFIS), which combine the interpretability of fuzzy systems with the learning capabilities of neural networks. This hybrid approach is particularly effective in modeling and controlling nonlinear systems where traditional methods may fall short [16].

The study "ANFIS Based Speed Controller for a Direct Torque Controlled Induction Motor Drive" demonstrates

how ANFIS can be applied to motor control tasks, offering improved adaptability and precision. By training the system on input-output data, the controller can automatically adjust fuzzy rules and membership functions, resulting in enhanced performance under varying load conditions. This approach highlights the potential of neuro-fuzzy systems in intelligent motor drive applications, especially where system dynamics are complex or poorly defined [16].

4. FUZZY INTEGRATION WITHIN MOTOR CONTROL ALGORITHMS

4.1. Fuzzy controllers in basic motor control loops

The main motor control loops are the following for motor control applications (Fig. 1).

Numerous studies have explored the practical implementation of fuzzy logic in various motor control loops. The most common and effective areas for integrating fuzzy control are within the core elements of motor control loop diagrams—namely, position control, angular velocity

(speed) control, and current control [17], [18].

Each of these control loops plays a critical role in modern industrial and automation systems. For instance, speed control is widely used in applications like fan drives, where maintaining a constant rotational speed is essential for performance and energy efficiency. Similarly, in process control environments, servo motors are employed to regulate torque or maintain consistent pressure levels, with fuzzy controllers enhancing stability and adaptability under varying load conditions [17], [19].

Position control, on the other hand, is vital in precision-dependent systems such as robotic arms, CNC machines, and automated manipulators. These applications benefit greatly from fuzzy logic's ability to handle uncertainties and dynamic changes without the need for exact system modeling [8].

By applying fuzzy logic to these fundamental control loops, systems can achieve higher resilience, better accuracy, and improved overall performance in real-world, nonlinear environments.

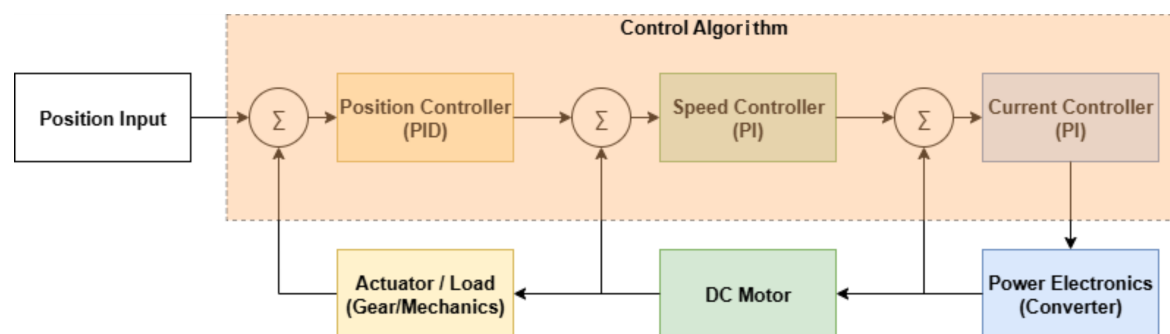


Fig. 1 Typical motion control loops diagram

4.2. Speed control

Speed control is one of the most common applications of fuzzy logic in motor systems. FLCs regulate speed by continuously adjusting the control input (e.g., voltage or current) based on fuzzy rule sets that relate error (the difference between desired and actual speed) and change in error to control actions. This allows for more intuitive and flexible handling of dynamic variations, load changes, and non-linearities compared to traditional methods.

In separately excited DC motors and permanent magnet synchronous motors (PMSMs), FLCs have shown superior performance, especially in transient states such as startup, sudden load variation, or directional changes. Studies have demonstrated that FLCs reduce overshoot, improve settling time, and maintain better speed regulation under disturbances [20]. Their ability to function without requiring a precise model of the motor system makes them particularly attractive in real-world industrial applications.

4.3. Position control

Position control involves regulating the angular position of a motor shaft and is critical in applications such as

robotics, CNC machines, and actuators. Fuzzy logic controllers excel here due to their capacity to incorporate experiential knowledge of motor behavior into rule sets. Instead of relying on exact system equations, fuzzy position controllers use input variables such as position error and rate of change of error to determine the control output.

This approach is especially useful in systems with variable dynamics or uncertain parameters, where traditional control strategies might fail or require complex tuning. For instance, fuzzy controllers have been applied to universal motor drives and high-precision applications where eliminating steady-state error is crucial [21], [22]. The adaptive nature of FLCs allows them to maintain accurate position tracking even under load variations or changes in system characteristics.

4.4. Torque control

Fuzzy logic is also effectively used in torque and flux control, particularly in field-oriented control (FOC) and direct torque control (DTC) strategies for AC motors like PMSMs and induction motors. In such systems, controlling electromagnetic torque and flux linkage accurately is

essential for smooth and efficient motor operation [23].

Fuzzy logic helps mitigate torque ripple and flux oscillations—common issues in conventional DTC schemes—by refining the switching logic and decision-making process. Fuzzy-based DTC strategies use fuzzy rule sets to estimate optimal voltage vectors and minimize error between reference and actual torque/flux values. This results in smoother torque production, reduced vibration,

and better dynamic performance, especially at low speeds or during rapid transients [23].

4.5. Fuzzy Control in more complex Field-Oriented Motor Control algorithms

There is the most typical sensorless field oriented motor control block diagram on Figure 2. The parts that might be improved by fuzzy controllers are highlighted in red color.

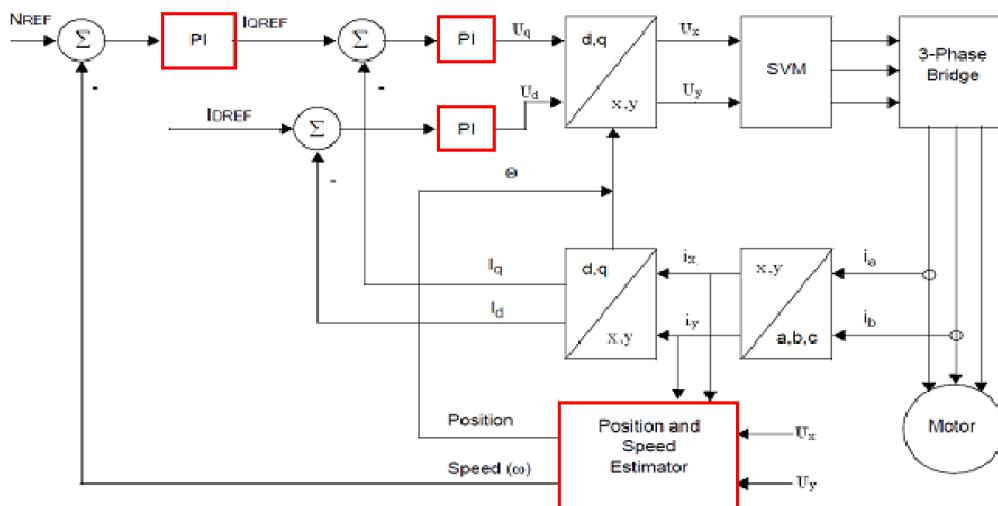


Fig. 2 Field Oriented Control Block diagram [24]

4.6. Estimators in Sensorless Field-Oriented Control

In sensorless FOC, estimators are essential for calculating rotor position and speed in the absence of physical sensors like encoders or resolvers. These estimators rely on voltage and current measurements to reconstruct motor states, often using mathematical models such as back-EMF observers, model reference adaptive systems (MRAS), or extended Kalman filters (EKF) [19], [22].

Fuzzy logic enhances these estimation techniques by improving their robustness against model inaccuracies, parameter variation, and measurement noise. For example, fuzzy observers can be designed to adjust estimation parameters dynamically based on fuzzy rules, allowing better tracking of the rotor position and speed under nonlinear conditions or abrupt load changes. This adaptability is especially valuable in low-speed or zero-speed scenarios, where traditional estimators struggle due to weak back-EMF signals [19], [22].

Integrating fuzzy logic into sensorless estimators thus leads to more reliable and accurate state estimation, enabling smoother and more stable operation across the entire speed range.

4.7. Open-Loop Start-Up in Sensorless FOC

One of the key challenges in sensorless FOC is the motor start-up phase, especially at low or zero speed where

back-EMF is insufficient for reliable position estimation. Open-loop start-up methods are commonly employed during this stage, where predefined voltage or current patterns are applied to initiate rotor motion until estimators can take over [1], [22].

Fuzzy logic can significantly enhance open-loop start-up by introducing intelligent decision-making based on observed current and voltage behavior. A fuzzy controller can determine optimal start-up sequences, adjust voltage vectors, or manage current ramping rates based on fuzzy rules derived from empirical behavior, improving reliability and reducing the risk of torque oscillations or misalignment [1], [22].

5. COMPARATIVE ANALYSIS

As an initial step and learning curve, the analysis focuses on replacing a conventional PI speed controller with a fuzzy logic controller. This substitution establishes a robust, deterministic baseline system for evaluating embedded control performance. The experiments and methodologies are inspired by foundational studies in fuzzy control theory [6], although technological updates were necessary to align with modern systems. Furthermore, previous work in paper [17] involving fuzzy speed controller design and MATLAB adaptations were made to suit newer hardware and microcontrollers. The motor model employs field-oriented control (FOC) with encoder-based and sensorless operation modes. Ensuring the

accuracy and robustness of the position estimator was critical to isolating the speed controller's performance, therefore the encoder based mode were used during the experiments. A simplified schematic of the system, shown

in Figure 3, includes a parallel connection of a classic PI and Fuzzy PI controllers to facilitate direct comparison under varying load profiles.

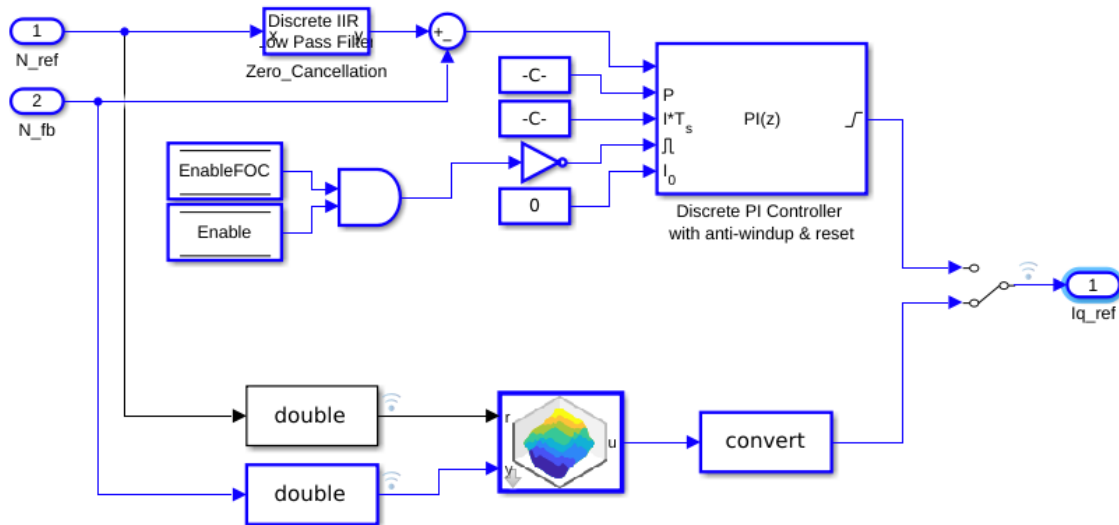


Fig. 3 Speed control model with changeable controller (PID/Fuzzy)

The system has the following inputs and outputs:

- N_{ref} (Input 1): Speed reference signal in fixed point representation - Generated test scenario, see later at section 5.2
- N_{fb} (Input 2): Measured motor speed in rpm and fixed point representation [scaled to rpm/4000]
- $I_{q,ref}$ (Output 1): The requested torque output connected to the field oriented control current controller loop input reference.

5.1. Implemented Fuzzy Inference system

The Figure 4 illustrates the structure of the fuzzy inference system (FIS) used in this analysis, which forms the basis for interpreting system behavior and generating control actions.

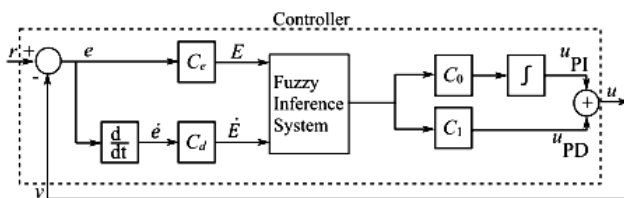


Fig. 4 Fuzzy inference system inputs and outputs

In this configuration, the input r represents the speed reference provided to the system, while y corresponds to the measured motor speed, forming part of the feedback

loop. The fuzzy controller processes the error and its rate of change to generate the output u , which serves as the I_q torque reference for the motor control loop.

The FIS is a Mamdani-type controller designed to regulate motor torque based on two inputs:

Inputs:

- SPEEDERROR (speed deviation from setpoint):
 - Terms: TooSlow, LittleSlow, SpeedOK, LittleFast, TooFast
- SPEED_ERR_CHANGE (rate of error change):
 - Terms: ErrorChangeDecrease, ErrorChangeIncrease

Output:

- TORQUE (control action):
 - Terms: DecreaseSignificant, IncreaseSignificant, DecreaseLittle, Sustain, IncreaseLittle

Rule Examples:

1. IF SPEEDERROR is TooSlow THEN TORQUE is IncreaseSignificant
2. IF SPEEDERROR is TooFast THEN TORQUE is DecreaseSignificant
3. IF SPEEDERROR is LittleFast THEN TORQUE is DecreaseLittle
4. IF SPEEDERROR is LittleSlow THEN TORQUE is IncreaseLittle

5. IF SPEEDERROR is SpeedOK THEN TORQUE is Sustain (stability zone)

The fuzzy rule base operates exclusively on the SPEEDERROR input for decision making. While the SPEED_ERR_CHANGE input was experimentally evaluated, its inclusion produced only marginal modifications to the control surface characteristics, demonstrating negligible impact on system behavior. Consequently, this additional input parameter was determined to be non-essential for the scope of the present investigation.

Throughout the analysis phase, multiple membership function configurations were evaluated while maintaining a consistent rule base to isolate their individual effects. This methodological approach ensured that observed behavioral changes could be directly attributed to membership function variations rather than rule modifications. The impact of these different configurations manifests clearly in the resulting control surfaces, which demonstrate:

- A basic, simple implementation producing conventional fuzzy control characteristics
- An optimized configuration specifically designed to minimize output oscillations

The comparative analysis reveals how membership function refinement alone can significantly enhance system performance, particularly in oscillation reduction, without requiring rule base alterations.

5.2. Fuzzy speed control analyses

A key objective was to evaluate the controllers under dynamic, real-world conditions rather than simple step responses. As demonstrated in the fuzzy control literature [17], fuzzy systems often outperform conventional methods in scenarios with high dynamic variability, noise, or unpredictable disturbances. To test this, a multi-stage reference signal was designed (Figure 5, blue line). Scaled from 0 to 1 (0–100%, corresponding to 0–4000 RPM), the reference begins with a step increase at 1 second to 0.4 (1600rpm), followed by a ramp decrease to 0.3 (1200 RPM). The light blue signal represents the mechanical load of the motor.

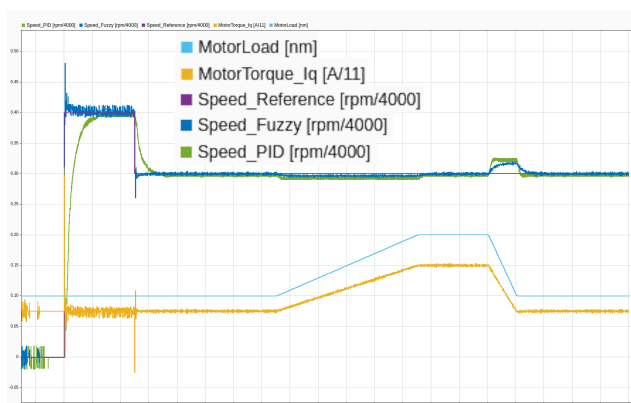


Fig. 5 PID and Fuzzy Control comparison

Further complexity is introduced via a variable load profile (light blue in Figure 5), combining gradual and abrupt torque changes to simulate real-world environmental perturbations. The orange is the torque produced that is proportional to the motor current (Iq). The driving inverter board full scale current reading is 11A, it is also scaled to 0 to 1. As the (Figure 5, orange line) shows there is a dynamic change in the load condition during the test scenario. This design highlights asymmetrical dynamics: motor deceleration involves distinct inertial and load characteristics compared to acceleration, challenging controllers tuned solely for one regime.

Results from the PI (Figure 5, Green line) and Fuzzy controller (Figure 5, Dark Blue line) controllers reveal marked differences in performance. Despite nearly identical gain coefficients—adjusted only to accommodate fixed-point arithmetic constraints in the fuzzy inference system—the fuzzy controller exhibits superior robustness, even with a basic control surface (Figure 6). Tests with refined membership functions and control surfaces yielded further improvements described in the next section.

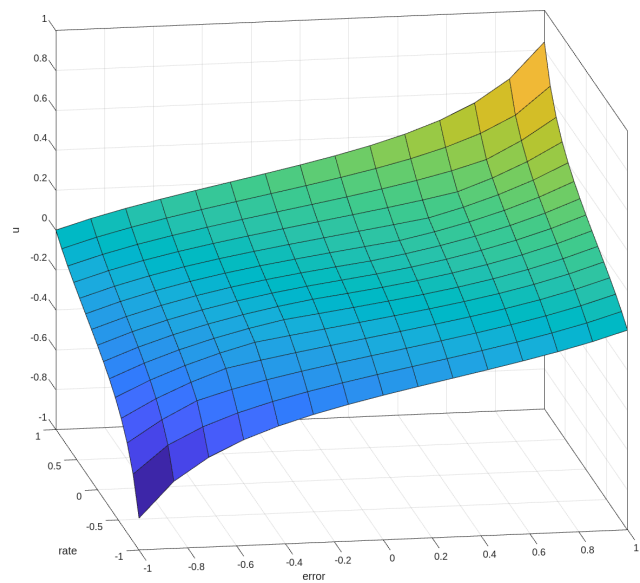


Fig. 6 Simple fuzzy control surface

5.3. Improved control surface to reduce oscillations around setpoint

When the motor speed reached the set point, an oscillation started. This can be seen in figure 5, with time 1.0-1.5 seconds on the dark blue line and the orange line. The orange signal is proportional to the generated motor torque; therefore, this creates direct audible noise and mechanical stress. The same can be seen in the figure 7, the dark blue signal the speed is oscillating around the set point. Compared to the green signal, the classical PI motor speed controller is much slower than the blue Fuzzy controller. Drawback is still the significant overshoot and the oscillation, but it is utilising the basic control surface.

To demonstrate that the magnitude is significant after settling time, below is a short calculation that represents the relative magnitude oscillation of angular velocity signal.

- $\omega_{ref} \approx 0.404$ setpoint of the motor speed. Purple signal on graph. (Set by test scenario)
- $\omega_{max} \approx 0.415$ Maximum of rotor angular velocity after settling time
- $\omega_{min} \approx 0.395$ Minimum of rotor angular velocity after settling time

$$A = \frac{\omega_{max} - \omega_{min}}{2} = 0.02$$

$$\text{Oscillation [\%]} = \left(\frac{A}{\omega_{ref}} \right) \times 100 \approx 5\% \quad (1)$$

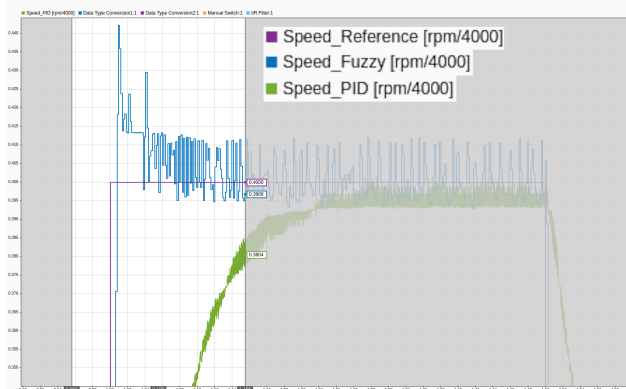


Fig. 7 Speed step response with the basic/simple control surface

The improved control surface in figure 8 can be seen. The key improvement is the central feature of the surface, that is a flat platform around the origin, where both the speed error and its rate of change are close to zero. This plateau plays a crucial role in minimizing oscillations around the setpoint by creating a "dead zone" in which small deviations do not trigger corrective torque actions. By withholding control effort in this region, the system avoids overreacting to minor fluctuations, which can otherwise cause instability, actuator wear, or persistent hunting around the target speed. This design choice effectively dampens noise and provides a smoother convergence to the desired state. As the deviation increases beyond this zone, the surface gradually and smoothly ramps up the torque response, ensuring the system remains responsive and capable of correcting larger errors without introducing abrupt changes. Overall, the shape of the surface balances responsiveness with stability, making it well-suited for systems requiring precise, yet robust, control behavior.

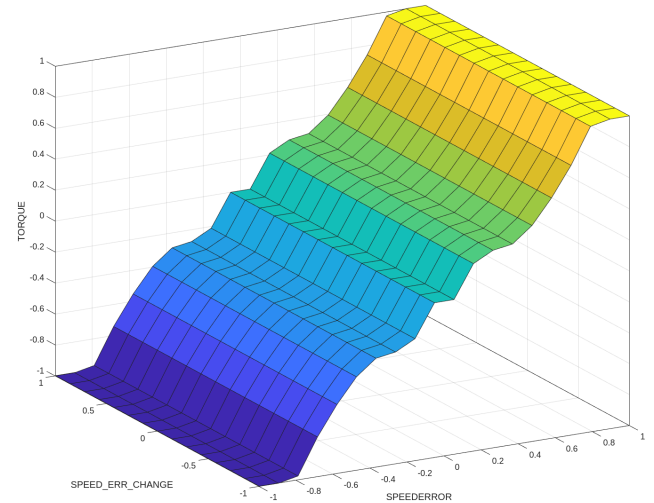


Fig. 8 Improved control surface for decreasing oscillation

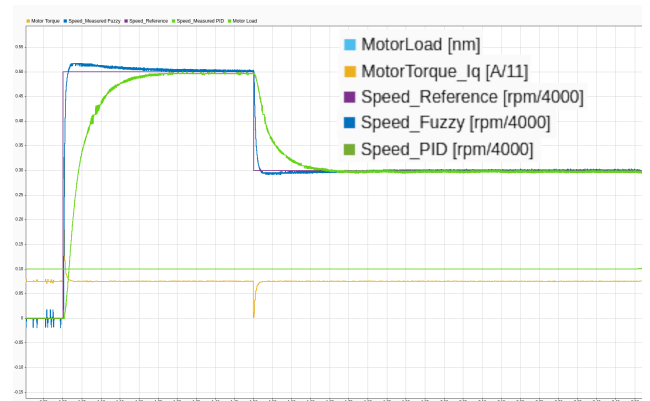


Fig. 9 Speed step response with the improved control surface

The figure 9 shows the improvement. The dark blue and the orange signals can be observed. Those shows clear improvement comparing to figure that the oscillation has disappeared and the overshoot is also limited.

In a more detailed analysis of step response performance between traditional PI and fuzzy logic speed controller, distinct behavioral differences emerge in terms of overshoot, settling time, and post-settling stability. The increased resolution of the diagram in figure 9 can be seen better. The green signal is the classical PI controller added to the diagram as reference. The fuzzy logic controller demonstrates a faster response, reaching the target value more quickly than its PI counterpart. However, this speed comes at the cost of noticeable overshoot. In contrast, the PI controller exhibits a slower, more conservative approach, with no overshoot and a smooth convergence toward the reference signal. Its post-settling behavior is markedly stable, with minimal fluctuation around the setpoint. This trade-off highlights the fuzzy controller's agility.

The table 1 summarize the metrics of the PID and fuzzy control basic control surface.

Table 1 Comparison between PI Control and Fuzzy Control

Feature	PID Control	Fuzzy Basic
Overshoot	None	Yes (10%)
Settling Time	Slow (150ms)	Fast (40ms)
Oscillation	low (1%)	high (5%)

The table 2 shows the metrics of the improved control surface simulation metrics compared to the basic control surface.

Table 2 Comparison between Fuzzy basic control surface vs improved control surface with plateau

Feature	Fuzzy Basic	Improved
Overshoot	Yes (10%)	Yes (2%)
Settling Time	Fast (40ms)	Fast (50ms)
Oscillation	high (5%)	low (1%)

6. CONCLUSION

This paper collected practical use case scenarios demonstrating the application of fuzzy logic in motor control algorithms, particularly in speed, position, and torque regulation within field-oriented control systems. A key design element of the implemented fuzzy controller was the inclusion of an integrator, consistent with conventional PI controller structures. By using identical integrator parameters for both the fuzzy and PI controllers, a balanced comparison was ensured. Despite this shared feature, the fuzzy inference system showed improved overall performance—achieving faster response times, better robustness to load disturbances, and enhanced adaptability to dynamic conditions.

The comparative analysis revealed that while the initial fuzzy controller exhibited some overshoot and oscillations, these were effectively minimized through an improved control surface design. Specifically, the introduction of a flat "dead zone" around the setpoint helped suppress unnecessary torque corrections, resulting in smoother operation and reduced mechanical stress.

These findings confirm that, with appropriate tuning and structure—such as the use of an integrator—fuzzy logic controllers can outperform traditional methods in scenarios involving non-linear dynamics, variability, and uncertainty, making them highly relevant for real-world motor control applications.

Broader motor control subsystems—such as position control, current regulation, and fault detection—presents exciting opportunities for enhancing system reliability, efficiency, and performance. Looking ahead, the potential for integrating Fuzzy and Neuro-Fuzzy controllers into start-up process especially the 3rd stage described in paper [25] contains improvement potential. By continuing to refine and expand the application of intelligent control strategies, the industry can unlock new levels of performance and cost-effectiveness, driving innovation in applications ranging from electric vehicles to industrial

automation. This work serves as a foundational step toward realizing the full potential of adaptive control in modern motor systems [26], [17], [27], [9].

REFERENCES

- [1] WENDLER, M. – KOPJÁK, J. – SZÜCS, I. – BENDIÁK, I.: “Enhancing Sensorless Start-Up in PMSM: Analysis and Optimization of Open-Loop Technique for Smooth Transitions,” in 2025 IEEE 23rd World Symposium on Applied Machine Intelligence and Informatics (SAMI 2025), Stará Lesná, Slovakia: IEEE, Jan. 2025.
- [2] “A rotor position estimation method based on fuzzy PI for SPMSM sensorless control,” presented at the IEEE International Future Energy Electronics Conference and ECCE Asia, IEEE, Jun. 2017, pp. 2148–2152. doi: 10.1109/IFEEC.2017.7992384.
- [3] DUBOIS, D. – PRADE, H. – UGHETTO, L.: “Fuzzy Logic, Control Engineering and Artificial Intelligence,” in Fuzzy Algorithms for Control, H. B. Verbruggen, H.-J. Zimmermann, and R. Babuška, Eds., Dordrecht: Springer Netherlands, 1999, pp. 17–57. doi: 10.1007/978-94-011-4405-6_2.
- [4] ZADEH, L. A.: “Fuzzy logic,” *Computer*, vol. 21, no. 4, pp. 83–93, 1988.
- [5] KIM, H. – HARKE, M. C. – LORENZ, R. D.: “Sensorless control of interior permanent-magnet machine drives with zero-phase lag position estimation,” *IEEE Trans. on Ind. Applicat.*, vol. 39, no. 6, pp. 1726–1733, Nov. 2003, doi: 10.1109/TIA.2003.818966
- [6] KÓNYA, L.: “Minősítő szabályozás (Fuzzy Control),” *Rádiótechnika*, vol. 1998, no. 2, pp. 63–65, 1998.
- [7] KÓNYA, L.: “Minősítő szabályozás (Fuzzy Control) 2.,” *Rádiótechnika*, vol. 1998, no. 3, pp. 114–117, 1998.
- [8] CHEOK, A. D. – WANG, Z.: “Fuzzy Logic Rotor Position Estimation Based Switched Reluctance Motor DSP Drive With Accuracy Enhancement,” *IEEE Trans. Power Electron.*, vol. 20, no. 4, pp. 908–921, Jul. 2005, doi: 10.1109/TPEL.2005.850958.
- [9] BESSADET, I.: “Implementation of a cascaded fuzzy sliding mode control of hybrid power filter,” *ELECTROTECHNICAL REVIEW*, vol. 1, no. 6, pp. 76–81, Jun. 2023, doi: 10.15199/48.2023.06.14.
- [10] WENDLER, M. – KOPJÁK, J.: “Mechanical Brush Commutation Motor Drive Solution for Higher Education a New Electronic Motor Control Board for University Laboratories to Support Educating the Embedded Brushed Motor Drive Solutions,” in 2024 IEEE 18th International Symposium on Applied Computational Intelligence and Informatics (SACI), Timisoara, Romania: IEEE, May 2024, pp. 000581–000586. doi: 10.1109/SACI60582.2024.10619922.

- [11] MENICH, P. – KOPIÁK, J.: “Optimal Fuzzy Controller, using a Genetic Algorithm for a Ball on Wheel System,” ACTA POLYTECH HUNG, vol. 20, no. 6, pp. 61–77, 2023, doi: 10.12700/APH.20.6.2023.6.4
- [12] ODRY, Á. – FULLÉR, R. – RUDAS, I. J. – ODRY, P.: “Fuzzy control of self-balancing robots: A control laboratory project,” Computer Applications in Engineering Education, vol. 28, no. 3, pp. 512–535, 2020, doi: 10.1002/cae.22219
- [13] KÁDÁR, I. – FARKAS, F. – HALÁSZ, S.: “Neuro-fuzzy Speed Controller for DC Drives Using Low Precision Shaft Encoder,” in Proceedings of 4th Joint Slovakian-Hungarian Symposium on Applied Machine Intelligence SAMI 2006, Budapest, Magyarország: Budapest Tech, BMF, pp. 426–437.
- [14] Performance Analysis of a Sensorless DC Motor Using Neuro Fuzzy Logic Control, (Jan. 27, 2023). doi: 10.1109/IITCEE57236.2023.10090872.
- [15] “Designing of Neuro-Fuzzy Controllers for Brushless DC Motor Drives Operating with Multiswitch Three-Phase Topology,” Journal of Electrical and Computer Engineering, vol. 2022, p. 7001448:1-7001448:12, Jul. 2022, doi: 10.1155/2022/7001448.
- [16] KHAN, H. – HUSSAIN, S. – BAZAZ, M. A.: “ANFIS Based Speed Controller for a Direct Torque Controlled Induction Motor Drive,” in Intelligent Systems Technologies and Applications 2016, J. M. Corchado Rodriguez, S. Mitra, S. M. Thampi, and E.-S. El-Alfy, Eds., Cham: Springer International Publishing, 2016, pp. 891–902. doi: 10.1007/978-3-319-47952-1_71.
- [17] DEVI, K. S. – DHANASEKARAN, R. – MUTHULAKSHMI, S.: “Improvement of speed control performance in BLDC motor using fuzzy PID controller,” in 2016 International Conference on Advanced Communication Control and Computing Technologies (ICACCCT), Ramanathapuram, India: IEEE, May 2016, pp. 380–384. doi: 10.1109/ICACCCT.2016.7831666
- [18] PRABU, K. J. – POONGODI, P. – PREMKUMAR, K.: “Fuzzy supervised online coactive neuro-fuzzy inference system-based rotor position control of brushless DC motor,” IET Power Electronics, vol. 9, no. 11, pp. 2229–2239, Sep. 2016, doi: 10.1049/iet-pe1.2015.0919
- [19] Permanent Magnet Synchronous Motor Rotor Position Estimation Using Fuzzy-Based Sliding Mode Observer, (May 08, 2017). doi: 10.1109/IEEEGCC.2017.8448219.
- [20] High-Performance ANFIS-Based Controller for BLDC Motor Drive, (Jan. 01, 2022). doi: 10.1007/978-981-16-3675-2_33.
- [21] NASCIMENTO, R. G. – FRICKE, K. – VIANA, F.: “Quadcopter Control Optimization through Machine Learning,” in AIAA Scitech 2020 Forum, Orlando, FL: American Institute of Aeronautics and Astronautics, Jan. 2020. doi: 10.2514/6.2020-1148.
- [22] PARASILITI, F. – PETRELLA, R. – TURSINI, M.: “Initial rotor position estimation method for PM motors,” in Conference Record of the 2000 IEEE Industry Applications Conference. Thirty-Fifth IAS Annual Meeting and World Conference on Industrial Applications of Electrical Energy (Cat. No.00CH37129), Rome, Italy: IEEE, 2000, pp. 1190–1197. doi: 10.1109/IAS.2000.881983.
- [23] JIEFAN, C. – YUE, F. – HUI, W.: “Fuzzy Direct Torque Control of Permanent Magnet Synchronous Motor,” in 2009 Sixth International Conference on Fuzzy Systems and Knowledge Discovery, Aug. 2009, pp. 107–111. doi: 10.1109/FSKD.2009.39.
- [24] KUCZMANN, M. – HORVÁTH, K.: “Tensor Product Alternatives for Nonlinear Field-Oriented Control of Induction Machines,” Electronics, vol. 13, no. 7, p. 1405, Apr. 2024, doi: 10.3390/electronics13071405.
- [25] ZHAO, K. – YANG, L. – ZHAO, S. – HU, H.: “A Hybrid Control Strategy for Sensorless PMSM with a Super-Twisting Sliding Mode Observer and a Two-stage Filter Based on Fuzzy Rules,” in IECON 2022 – 48th Annual Conference of the IEEE Industrial Electronics Society, Oct. 2022, pp. 1–7. doi: 10.1109/IECON49645.2022.9968394.
- [26] Implementation and analysis of Adaptive Neural Fuzzy Inference System based Brushless DC motor, (May 18, 2023). doi: 10.1109/IRASET57153.2023.10152892.
- [27] KUMBLA, K. K. – JAMSHIDI, M. – BENITEZ-READ, J.: “Implementation of fuzzy logic and neural networks control algorithm using a digital signal processing chip,” in Proceedings of the 1995 ACM symposium on Applied computing - SAC '95, Nashville, Tennessee, United States: ACM Press, 1995, pp. 524–528. doi: 10.1145/315891.316086.

Received April 25, 2025, accepted September 1, 2025

BIOGRAPHIES

Márk Wendler received an M.Sc. in electrical engineering from Obuda University in 2018. He is currently a PhD. student at Obuda University, Doctoral School of Applied Informatics and Applied Mathematics. His research interests include embedded systems and motor control technologies.

József Koppják completed his PhD in Computer Science at the Doctoral School of Multidisciplinary Engineering Sciences, Széchenyi István University, in 2013. Currently, he is an Associate Professor at the Faculty of Electrical Engineering at Óbuda University. Additionally, he holds

the position of Head of the Department of Hydrogen Technologies and Industrial IoT. His research interests are primarily in the fields of embedded systems, wireless sensor networks, and digital circuits.

Gergely Sebestyén received an M.Sc. in electrical

engineering from Budapest University of Technology and Economics in 2015. He currently works at the Faculty of Electrical Engineering, specifically in the Department of Hydrogen Technologies and Industrial IoT. His research interests include embedded systems, wireless sensor networks, and digital circuits.