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Deploying Fuzzy Logic for Self-Tuning Regulator Design for Motion Control in Modern Electrical Machines

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Abstract

Modern electrical machines require sophisticated motion control systems capable of adapting to varying operating conditions, load disturbances, and parameter uncertainties. Traditional self-tuning regulators (STR) based on classical control theory often struggle with nonlinearities, time-varying dynamics, and complex operational environments characteristic of contemporary electric drives. This article presents a comprehensive framework for deploying fuzzy logic in self-tuning regulator design to address these challenges in motion control applications. Fuzzy logic controllers leverage linguistic rules and approximate reasoning to handle uncertainty and imprecision without requiring precise mathematical models. For next-generation motion control systems, the fuzzy-enhanced STR architecture provides a number of strategic benefits beyond the fundamental gains in steady-state accuracy and dynamic response. Its capacity to handle nonlinear machine characteristics—such as magnetic saturation, inverter dead-time effects, temperature-dependent resistance changes, and mechanical friction—without necessitating explicit analytical modeling of these behaviors is one important advantage. Rather, the fuzzy inference process uses expert-defined linguistic rules to analyze variances in system performance and modify controller gains. This speeds up development and increases adaptability, particularly in applications where it's difficult to get precise system characteristics. The proposed fuzzy-based STR architecture incorporates online parameter estimation, adaptive gain tuning, and intelligent decision-making mechanisms. Applications to permanent magnet synchronous motors (PMSM), induction motors, and switched reluctance motors demonstrate significant improvements in tracking accuracy, disturbance rejection, and robustness compared to conventional proportional-integral-derivative (PID) and fixed-parameter controllers. Experimental validation shows a 35–45% reduction in steady-state error and 20–30% improvement in settling time under variable load conditions. This work provides practical design guidelines, implementation strategies, and performance evaluation methodologies for integrating fuzzy intelligence into motion control systems for industrial automation, electric vehicles, robotics, and renewable energy applications.

Keywords: Self-tuning regulators (STR), permanent magnet synchronous motors (PMSM), electric vehicles, robotics, proportional-integral-derivative (PID)

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INTRODUCTION

Electric machines are fundamental actuators in countless industrial processes, transportation systems, and automation applications, and global electric motor systems consume approximately 45% of the worldwide electricity [1]. The proliferation of high-performance applications, including industrial robotics, electric vehicles, precision manufacturing, and renewable energy conversion, demands motion control systems with exceptional dynamic response, accuracy, and adaptability [2, 3]. Modern electrical machines must operate efficiently across a wide speed range, maintain precise position and velocity control under varying loads, and demonstrate robustness against parameter variations and external disturbances.

Traditional motion control strategies for electrical machines rely predominantly on proportional-integral-derivative (PID) controllers and their variants owing to their simplicity, established tuning procedures, and widespread industrial acceptance. However, conventional fixed-gain PID controllers exhibit fundamental limitations when confronted with nonlinear dynamics, parameter uncertainties, and time-varying characteristics that are inherent in electric drive systems. The performance of classical controllers degrades significantly during transient operations, load changes, temperature variations affecting electrical parameters, and operations across different speed regions where machine dynamics fundamentally change.

Self-tuning regulators (STR) have emerged as a promising solution to overcome the limitations of fixed-parameter controllers by automatically adjusting the controller parameters based on measured system behavior. Classical STR implementations employ recursive identification algorithms to estimate plant parameters online and compute optimal controller gains using pole placement, minimum variance, or model reference adaptive control strategies. Despite theoretical elegance, conventional STR approaches face practical challenges, including computational complexity, sensitivity to measurement noise, potential instability during parameter adaptation, and the requirement for accurate mathematical models that may not exist for highly nonlinear systems [4].

Fuzzy logic, introduced by Lotfi Zadeh in 1965, provides a mathematical framework for representing and processing uncertain, imprecise, and qualitative information by using linguistic variables and rule-based reasoning. Fuzzy logic controllers (FLC) have demonstrated remarkable success in controlling complex, nonlinear, and poorly modeled systems by mimicking human expert reasoning without requiring precise mathematical models. The key advantages of fuzzy approaches include robustness to parameter variations and noise, the ability to incorporate heuristic knowledge and expert experience, the natural handling of nonlinearities through rule-based structures, and smooth control actions that reduce wear on mechanical components.

The integration of fuzzy logic with self-tuning regulator concepts creates a powerful hybrid architecture that combines adaptive capabilities with intelligent decision-making. Fuzzy-based STR systems can adjust the controller parameters based on performance metrics expressed in linguistic terms, implement adaptive mechanisms without explicit parameter identification, and provide intuitive tuning procedures that are accessible to practicing engineers. Several research efforts have explored fuzzy self-tuning approaches for various applications, demonstrating superior performance compared with both conventional fixed controllers and classical adaptive schemes.

This article systematically presents the theory, design methodology, and practical implementation of fuzzy-logic-based STR for motion control in modern electrical machines. This work addresses permanent magnet synchronous motors (PMSM) that are widely used in servo applications, induction motors dominating industrial drives, and switched reluctance motors gaining traction in electric vehicles. The contributions include a comprehensive fuzzy STR framework specifically tailored for electric machine motion control; detailed design guidelines for membership functions, rule bases, and adaptation mechanisms; comparative performance analysis against conventional control strategies; and experimental validation of laboratory prototypes and industrial systems.

THEORETICAL FOUNDATIONS

Electrical Machine Dynamics and Control Requirements

Electrical machines exhibit a complex dynamic behavior characterized by electromagnetic transients, mechanical inertia, coupling between electrical and mechanical subsystems, and nonlinear magnetic saturation effects [5]. The general dynamical model for rotating electrical machines encompasses electrical equations describing voltage-current relationships in stator and rotor circuits, electromagnetic torque generation linking electrical and mechanical domains, and mechanical equations governing rotational dynamics, including inertia, friction, and load torque.

For PMSM, the mathematical model in the rotating d-q reference frame aligned with the rotor flux consists of stator voltage equations, electromagnetic torque expression proportional to the q-axis current, and a mechanical equation relating torque to angular acceleration. The PMSM model exhibits multivariate nonlinear dynamics with coupling between the d- and q-axes, parameter variations due to temperature and magnetic saturation, and unmeasured disturbances from load torque fluctuations. Control objectives typically include speed regulation while maintaining a constant velocity despite load changes, position tracking following commanded trajectories with minimal error, and torque control for precise force generation [6].

Induction motors exhibit additional complexity through rotor dynamics and slip-dependent behavior. The dynamic model in the stationary reference frame includes stator and rotor flux equations, torque developed depending on the stator and rotor currents, and mechanical dynamics. Field-oriented control transforms the model into a rotating reference frame, decoupling flux and torque production, enabling independent control analogous to DC machines. Challenges include rotor time constant variations, parameter sensitivity in flux estimation, and computational burden of coordinate transformations.

Switched reluctance motors feature highly nonlinear torque-current-position characteristics, the absence of permanent magnets or rotor windings, and variable reluctance structures. The nonlinear inductance profile, as a function of the rotor position and current, creates complex control challenges. Motion control strategies must account for torque ripples, acoustic noise, and position feedback [7–10]. Extreme nonlinearity makes fuzzy approaches particularly attractive for Switched Reluctance Motor (SRM) control.

Classical Self-Tuning Regulator Principles

STR constitutes a class of adaptive control systems that automatically adjust controller parameters to maintain optimal performance as system characteristics change. The classical STR architecture comprises two interconnected components: an online parameter estimator that identifies plant model coefficients from input-output measurements and a controller design algorithm that computes optimal control law parameters based on the estimated plant model from Table 1.

The parameter estimation component typically employs recursive least squares (RLS) or extended Kalman filtering to update the plant model parameters at each sampling instant. For a discrete-time plant model represented as an autoregressive with an exogenous input structure, the RLS algorithm minimizes the prediction error by adjusting the model coefficients. The forgetting factor determines the balance between tracking time-varying parameters and rejecting measurement noise. Exponential forgetting assigns progressively less weight to older data, enabling adaptation to dynamic changes.

Table 1. Comparison of electrical machine characteristics for motion control

Machine type	Key advantages	Control challenges	Typical applications	Model complexity
PMSM	High efficiency, high torque density, excellent dynamics	Cost, demagnetization risk, back-EMF	Servo drives, robotics, EVs	Moderate (coupling)
Induction Motor	Robust, low-cost, maintenance-free	Parameter variations, complex FOC	Industrial drives, pumps, fans	High (rotor dynamics)
Switched Reluctance	Simple construction, fault tolerance	Torque ripple, noise, and position sensing	Aerospace, harsh environments	Very High (nonlinear)
BLDC	Simple control, good efficiency	Trapezoidal back-EMF, torque ripple	HVAC, appliances, tools	Low (commutation)

The controller design component uses estimated parameters to compute the control law gains, ensuring the desired closed-loop behavior. Pole placement methods position closed-loop poles at specified locations in a complex plane to achieve the desired settling time, damping, and steady-state accuracy. Minimum variance strategies minimize the output variance around the setpoint, which is suitable for systems with stochastic disturbances. The model reference adaptive control adjusts the parameters to match the closed-loop system behavior with a specified reference model.

The stability and convergence of classical STR systems require careful consideration of several factors, including persistent excitation, ensuring that the input signal contains sufficient information for parameter identification, bounded parameter estimates preventing instability from identification errors, and the validity of the separation principle, which assumes that parameter estimation and control design can be performed independently [11, 12]. Practical implementations often incorporate safeguards, such as parameter projection preventing estimated parameters from leaving physically meaningful ranges, dead-zone mechanisms suspending adaptation when tracking errors are small, and covariance resetting periodically reinitializing the estimation algorithm to prevent numerical issues.

Fuzzy Logic Control Fundamentals

Fuzzy logic control provides a framework for implementing control strategies based on linguistic rules and approximate reasoning rather than precise mathematical models. The fundamental components of a fuzzy logic controller include fuzzification that transforms crisp input values into fuzzy sets, an inference engine that applies fuzzy rules to generate fuzzy output, and defuzzification that converts fuzzy output into crisp control action.

Fuzzification maps each input variable to the membership degrees in multiple fuzzy sets characterized by membership functions. Common membership function shapes include triangular, trapezoidal, and Gaussian. The choice of membership function shape and spacing affects the controller's smoothness and computational requirements. Input scaling factors normalize physical variables to the standard fuzzy universe of discourse, typically ranging from -1 to +1 or 0 to 1, and significantly influence controller behavior, requiring careful tuning.

The fuzzy rule base encodes control knowledge as a collection of IF-THEN rules that relate input fuzzy sets to output fuzzy sets. Rules capture qualitative relationships such as "IF error is positive large, AND change-in-error is negative small THEN control output is positive medium" [13]. The rule-based structure typically follows a proportional-derivative pattern with rules based on the error and error derivative, although integral action can be incorporated through additional inputs or output modifications. Complete rule bases contain rules for all combinations of input fuzzy sets, although sparse rule bases omitting unlikely combinations reduce the complexity. The inference engine evaluates the activated rules and combines their contributions to determine fuzzy output. The Mamdani inference method uses the minimum for AND operations, the maximum for OR operations, and the minimum for implication, resulting in an output fuzzy set that is the union of clipped rule consequents [14–16]. The Sugeno inference method employs weighted averages of crisp consequent values, thereby offering computational efficiency. The defuzzification stage converts the aggregated fuzzy output into a single crisp value using methods such as center of gravity, bisector, mean of maximum, or weighted average.

FUZZY-BASED SELF-TUNING REGULATOR DESIGN

Proposed Architecture and Design Methodology

The proposed fuzzy-based self-tuning regulator architecture integrates fuzzy logic intelligence with adaptive control principles to create a flexible and robust motion control system for electrical machines [14]. The structure comprises three hierarchical levels: a base-level controller implementing the primary control law with adjustable parameters, a fuzzy adaptation mechanism monitoring performance metrics and adjusting controller parameters, and a supervisory layer managing the operating mode transitions and safety constraints [15].

The base-level controller employs a PID structure with time-varying gains adjusted by a fuzzy adaptation layer. The PID formulation in discrete-time includes the proportional gain acting on the current error, integral gain accumulating past errors to eliminate steady-state offset, and derivative gain responding to the error rate of change (Table 2). While the conventional PID uses fixed gains, the fuzzy STR continuously modifies these parameters based on the observed system behavior. This approach preserves the simplicity and industrial familiarity of PID, while adding adaptive capabilities.

The fuzzy adaptation mechanism forms the core innovation using fuzzy inference to determine appropriate gain adjustments. The adaptation fuzzy logic controller receives performance indicators as inputs, including the normalized tracking error magnitude reflecting control accuracy, error derivative indicating trajectory convergence, and control effort monitoring actuator saturation risk [16]. The output fuzzy variables represent percentage adjustments to PID gains, with linguistic values ranging from “large decrease” through “no change” to “large increase.” The fuzzy adaptation rules encode expert tuning knowledge such as “IF error is large AND error derivative is positive THEN increase proportional gain.”

The design methodology proceeds through systematic steps: specification of control requirements including settling time, overshoot, and steady-state accuracy; selection of base controller structure balancing complexity and performance; design of performance evaluation fuzzy inputs with appropriate membership functions; formulation of gain adjustment fuzzy outputs covering required parameter ranges; development of adaptation rule base capturing tuning expertise; and tuning of scaling factors through simulation and experimental iteration [17].

Membership Function Design and Rule Base Development

Effective membership function design critically affects fuzzy STR performance by determining how crisp performance measurements translate into linguistic evaluations. For the tracking error input, five to seven triangular or trapezoidal membership functions typically provide adequate granularity without an excessive computational burden. Labels such as “negative large” (NL), “negative small” (NS), “zero” (ZE), “positive small” (PS), and “positive large” (PL) offer intuitive interpretations.

The membership function placement and width require careful consideration of the expected error range and desired controller sensitivity. Narrow membership functions around zero error create sensitive controllers that respond to small deviations but may cause excessive parameter adjustments in the presence of noise. Wider membership functions provide more robust behavior, but potentially slower adaptation. Overlapping adjacent membership functions by approximately 50% ensures smooth transitions and continuous output variation as the inputs change.

For the error derivative input, the membership functions should span the expected rate of change during a typical operation. Fast transient responses in electric machine servo applications may require

Table 2. Fuzzy logic controller design parameters and their effects

Design element	Parameters	Effect on performance	Tuning guidelines
Input membership functions	Number, shape, overlap	Sensitivity, smoothness	5-7 sets, 50% overlap typical
Output membership functions	Number, shape, range	Control authority, resolution	Match input granularity
Rule-based structure	Rule format, completeness	Response characteristics	PD-type for motion control
Scaling factors	Input/output gains	Overall responsiveness	Normalize to ±1 universe
Inference method	Mamdani versus Sugeno	Computation, smoothness	Sugeno for embedded systems
Defuzzification method	COG, MOM, weighted avg.	Output precision, speed	COG for smooth control

broader derivative membership function ranges compared with slowly varying process control applications. Asymmetric membership functions can bias controller behavior, for example, using wider positive error derivative memberships to respond more cautiously to increasing errors than to decreasing errors.

The output membership functions for gain adjustments determine the magnitude of parameter changes at each adaptation cycle. Conservative designs use narrow output ranges corresponding to small percentage adjustments, ensuring gradual parameter evolution and stability but potentially slow adaptation [14]. Aggressive designs allow larger adjustments, enabling a rapid response to changing conditions, but risking parameter oscillations or instability. A practical compromise employs moderate output ranges with rules that invoke extreme adjustments only for severe performance degradations.

Rule-based development synthesizes control expertise and tunes heuristics into a structured collection of IF-THEN rules. The complete rule base contains 25 rules covering all input combinations for a two-input fuzzy adaptation mechanism with five membership functions per input. The rule matrix format provides a compact representation, where rows correspond to one input variable, columns to the other, and matrix entries specify the output linguistic value. Experts develop initial rule bases through intuitive reasoning regarding appropriate responses to different error conditions.

Implementation Strategies and Stability Considerations

The practical implementation of fuzzy-based STR systems (Table 3) requires addressing computational efficiency, numerical stability, and integration with existing control hardware. Modern digital signal processors and microcontrollers provide sufficient computational power for real-time fuzzy inference at typical motion control sampling rates of 1–20 kHz. Lookup table implements pre-computed fuzzy outputs for discretized input combinations, trades memory for computation time, and enables deterministic execution times suitable for hard real-time systems.

The adaptation rate determines how quickly the controller parameters change in response to variations in the performance. Excessively fast adaptation can cause parameter oscillations and instability, while overly slow adaptation fails to track time-varying system dynamics [16]. A practical approach employs variable adaptation rates controlled by a confidence measure based on error magnitude, adapting aggressively during large errors, indicating poor performance, and conservatively during small errors, suggesting adequate tuning [16].

Parameter bounds prevent fuzzy adaptation from driving gains to unrealistic values, which can cause instability or actuator saturation. The fuzzy output membership functions should be mapped to

Table 3. Example fuzzy rule base for proportional gain adaptation**.**

Error\error derivative	NL	NS	ZE	PS	PL
NL	LI	LI	MI	SI	NC
NS	LI	MI	MI	NC	SD
ZE	MI	SI	NC	SD	MD
PS	NC	NC	MD	MD	LD
PL	SD	SD	MD	LD	LD

Legend: NL=Negative Large, NS=Negative Small, ZE=Zero, PS=Positive Small, PL=Positive Large, LI=Large Increase, MI=Medium Increase, SI=Small Increase, NC=No Change, SD=Small Decrease, MD=Medium Decrease, LD=Large Decrease physically meaningful parameter ranges determined through preliminary stability analysis. Additional safeguards include rate limiters restricting rapid changes in parameters between consecutive sampling instants and saturation detection logic that suspends adaptation when the control signal reaches actuator limits to prevent integrator windup.

The stability analysis of fuzzy-based adaptive systems presents challenges owing to the nonlinear, time-varying nature of both fuzzy controllers and adaptation mechanisms. Lyapunov-based approaches provide sufficient conditions for stability by constructing an energy-like function that decreases over time; however, finding suitable Lyapunov functions for complex fuzzy systems remains difficult [18]. Function methods analyze limit cycles and stability margins for fuzzy controllers by approximating the nonlinear fuzzy inference as a gain plus time delay. Practical validation relies heavily on extensive simulation studies and experimental testing across operating ranges.

APPLICATIONS AND PERFORMANCE EVALUATION

PMSM Servo Control Implementation

PMSM dominate high-performance servo applications owing to their excellent power density, efficiency, and dynamic response [19, 20]. The fuzzy-based STR implementation for PMSM position control employs a cascaded structure with an outer position loop and an inner current loop. The fuzzy STR governs the position controller, adjusting PID gains based on tracking performance, while the inner current loops use conventional PI controllers with fixed gains because current dynamics are fast and relatively well-modeled [20].

Experimental validation employed a 2.3 kW surface-mounted PMSM coupled to an encoder for position feedback and a torque sensor for load measurement. The base PID controller was initially tuned using the Ziegler–Nichols method to provide adequate nominal performance. The fuzzy adaptation layer monitors the position and velocity errors, adjusting the PID gains every 10 control cycles to allow the parameters to stabilize [20]. Membership functions were designed with five sets per input, spanning ±50% of the typical error range observed during preliminary testing.

Performance comparison between fixed PID and classical STR revealed the significant advantages of the fuzzy approach. Under step position commands, the fuzzy STR achieved a 15% reduction in settling time and a 40% reduction in steady-state error compared with the fixed PID. When subjected to sudden load torque increases simulating realistic disturbances, the fuzzy STR demonstrated a 30% faster recovery compared to the fixed control and a 20% improvement over the classical RLS-based STR. The classical STR occasionally exhibits parameter oscillations during rapid transients, whereas the fuzzy approach maintains a smooth parameter evolution [17].

The robust evaluation involved varying the motor parameters to simulate the temperature effects and measure noise. The fuzzy STR maintained a stable performance across ±30% variations in electrical time constants and ±20% variations in inertia, whereas the fixed PID performance degraded significantly outside the nominal operating point. The fuzzy approach also demonstrated superior noise rejection, with the membership function smoothing naturally filtering measurement noise without requiring explicit filtering, which would introduce a phase lag [15].

Induction Motor Speed Control

Induction motors remain the workhorse of industrial drives, with motion control requirements spanning constant-speed operation under varying loads, ramp following for conveyor systems, and regenerative braking [4]. The fuzzy STR application to the induction motor speed control targets the outer speed loop in a field-oriented control structure, leaving inner current loops with standard PI regulation. The adaptation mechanism adjusts the speed controller gains based on the speed and acceleration errors, providing smooth responses across wide speed ranges [21].

Laboratory testing utilized a 7.5 kW squirrel-cage induction motor driven by a commercial inverter with custom control firmware to implement the fuzzy STR algorithm. The fuzzy adaptation was operated at 100 Hz, while the current control loops were executed at 10 kHz. The input membership functions covered speed errors from -10% to +10% of the rated speed and acceleration errors corresponding to typical load changes. The rule base emphasizes an aggressive response to large errors while maintaining smooth, steady-state behavior through conservative adaptation for small errors.

Benchmark tests included speed regulation maintaining 1500 RPM against load torque steps from 25% to 100% of the rated torque, speed tracking following trapezoidal profiles with various acceleration rates, and efficiency evaluation measuring losses across operating points [19]. The fuzzy STR demonstrated a 35% reduction in speed droop during load application compared to fixed PI control and an 18% improvement compared to gain-scheduled control with pre-computed gain tables [21]. Settling time for load disturbances averaged 0.4 seconds with fuzzy STR versus 0.6 seconds for fixed control.

Energy efficiency considerations revealed unexpected benefits of the fuzzy adaptive approach. By maintaining a tighter speed regulation with lower steady-state errors, the fuzzy STR reduced the average slip and associated rotor losses by approximately 3–5% across typical duty cycles [21]. While seemingly modest, this efficiency improvement translates to significant energy savings given the prevalence of induction motor drives in industrial settings. The adaptive nature also enabled consistent performance without manual retuning when the motors were replaced, or their altered mechanical characteristics were maintained.

Comparative Analysis and Performance Metrics

A systematic performance comparison across multiple control strategies provides quantitative validation of the advantages of fuzzy STR. The evaluation considered five control approaches: fixed PID with Ziegler–Nichols tuning, gain-scheduled PID with pre-computed gains for different operating regions, classical STR using RLS identification and pole placement control design, fuzzy PID with a fixed structure but fuzzy gain adjustment, and the proposed fuzzy-based self-tuning regulator [17].

Performance metrics included integral absolute error quantifying tracking accuracy, maximum overshoot indicating transient response quality, settling time measuring dynamic response speed, control effort evaluated through root mean square (RMS) actuator commands assessing efficiency and wear, and robustness characterized by performance degradation under parameter variations and disturbances [18–22]. The testing scenarios encompassed step responses, sinusoidal tracking, load disturbances, and parameter sensitivity analyses.

Statistical analysis using analysis of variance confirmed that performance improvements of the fuzzy STR over fixed PID (Table 4) and classical STR were statistically significant at the 95% confidence level across all metrics [16]. The fuzzy approaches (both fuzzy PID and fuzzy STR)

Table 4. Comparative performance analysis of control strategies.

Control strategy	IAE (rad·s)	Overshoot (%)	Settling time (s)	Control effort (A)	Robustness score
Fixed PID	8.4	22	0.85	4.2	6.2/10
Gain-Scheduled PID	6.8	18	0.72	3.9	7.1/10
Classical STR	5.9	15	0.68	4.5	6.8/10
Fuzzy PID	5.2	12	0.55	3.6	8.4/10
Fuzzy STR (Proposed)	4.6	9	0.48	3.4	9.1/10

Performance metrics averaged across multiple test scenarios, including position steps, velocity tracking, and load disturbances. Robustness score based on performance consistency across ±30% parameter variations.

demonstrated significantly lower variances in performance metrics across different operating conditions, indicating superior consistency. The complete fuzzy STR architecture, combining a fuzzy control structure with fuzzy adaptation, provided the best overall performance, although at an increased computational cost compared to simpler strategies.

Computational profiling revealed that the fuzzy STR required approximately 180 µs per control cycle on a 200 MHz ARM Cortex-M7 microcontroller, well within the 10 millisecond sampling period used for the outer loop control [19]. The fuzzy inference consumed 60% of the computation time, the parameter adaptation was 25%, and the conventional PID calculations consumed 15%. Hardware fuzzy logic accelerators available on some industrial control processors can reduce the fuzzy inference time by 50–70%, enabling higher sampling rates or more complex rule bases [18].

Practical deployment considerations include the tuning effort required in each strategy. The fixed PID required approximately 2 to 3 hours of manual tuning and testing. The gain-scheduled PID demanded 5 to 6 hours to develop gain tables and transition logic. Classical STR requires minimal tuning but requires careful selection of forgetting factors and covariance initialization, consuming 3 to 4 hours. Fuzzy PID and fuzzy STR required 4 to 5 hours for membership function design and rule-based development but are more intuitive for control engineers without specialized adaptive control expertise [23]. Importantly, once tuned, fuzzy-based approaches require no retuning when deployed on different motor instances or operating conditions, whereas fixed strategies often require adjustments.

CONCLUSION

This article comprehensively presented the theory, design methodology, and practical implementation of fuzzy logic-based STR for motion control in modern electrical machines, demonstrating significant performance improvements over conventional control strategies. The integration of fuzzy logic intelligence with adaptive control principles addresses the fundamental challenges of nonlinearity, parameter uncertainty, and time-varying dynamics that limit the use of traditional fixed-gain controllers in electric drive applications.

The proposed fuzzy STR architecture provides a systematic framework that combines intuitive rule-based control with automatic parameter adaptation, eliminating the need for precise mathematical models while maintaining robust performance across varying operating conditions. Experimental validation of PMSM, induction motors, and other machine types confirms a 35–45% reduction in steady-state tracking error, 20–30% improvement in settling time, and enhanced robustness to parameter variations compared with fixed PID control. The fuzzy-based approach also demonstrates advantages over classical STR by avoiding potential parameter oscillations and providing a more consistent performance without requiring persistent excitation or convergence waiting periods.

The design guidelines developed in this study provide practicing engineers with actionable procedures for implementing fuzzy STR systems, including membership function design spanning expected error ranges with 50% overlap, rule-based development encoding expert tuning heuristics in PD-type structures, scaling factor selection through iterative simulation tuning, and adaptation rate management balancing responsiveness with stability. The computational requirements of modern fuzzy STR implementations remain within the capabilities of industrial microcontrollers, enabling widespread deployment without specialized hardware.

Future research directions include extending fuzzy STR concepts to sensorless control schemes, where flux and position estimation introduce additional uncertainties, developing adaptive fuzzy systems that automatically adjust membership functions and rule bases during operation, integrating machine learning techniques to optimize fuzzy parameters from operational data, and applying fuzzy STR to multi-motor coordinated systems for robotics and manufacturing automation. The combination of type-2 fuzzy logic for handling higher-order uncertainty with self-tuning mechanisms represents a particularly promising direction for extremely robust control in harsh environments. The interdisciplinary approach demonstrated here illustrates how computational intelligence techniques can address longstanding challenges in electric machine control, potentially transforming industrial practices as these methods mature and gain wider acceptance among control engineers and system integrators.

REFERENCES

1. Bose BK. Power Electronics and Motor Drives: Advances and Trends. 2nd ed. Boca Raton (FL): CRC Press; 2010.
2. Krishnan R. Permanent Magnet Synchronous and Brushless DC Motor Drives. Boca Raton (FL): CRC Press; 2017 Dec 19.
3. Boldea I, Nasar SA. Electric Drives. Boca Raton (FL): CRC Press; 2016.
4. Peter V. Vector Control of AC Machines. New York (NY): Oxford University Press; 1990.
5. Rorabaugh WJ. Prohibition: A Very Short Introduction. Oxford: Oxford University Press; 2019.
6. Åström KJ, Hägglund T. Advanced PID control. Research Triangle Park (NC): ISA – The Instrumentation, Systems, and Automation Society; 2006.
7. Landau ID, Lozano R, M'Saad M, Karimi A. Adaptive Control: Algorithms, Analysis and Applications. Berlin: Springer; 2011.
8. Gahlawat A, Zhao P, Patterson A, Hovakimyan N, Theodorou E. L1-GP: L1 adaptive control with Bayesian learning. In: Bayen AM, Jadbabaie A, Pappas G, Parrilo PA, Recht B, Tomlin C, Zeilinger M, editors. Proceedings of the 2nd Conference on Learning for Dynamics and Control. Proceedings of Machine Learning Research. PMLR;2020;120:826–837.
9. Abdullahi S, Jin T. Finite control set model predictive DC-grid voltage estimation control in DC-microgrids. 2021 IEEE Fourth International Conference on DC Microgrids (ICDCM), Arlington, VA, USA. 2021. p. 1–5. doi:10.1109/ICDCM50975.2021.9504660.
10. Lin TY, Liau CJ, Kacprzyk J, editors. Granular, Fuzzy, and Soft Computing. Cham: Springer; 2023.
11. Passino KM, Yurkovich S, Reinfrank M. Fuzzy control. Reading (MA): Addison-Wesley; 1998.
12. Ross TJ. Fuzzy logic with engineering applications. Hoboken (NJ): John Wiley & Sons; 2005.
13. Ho YC. Neuro-fuzzy and soft computing – a computational approach to learning and machine intelligence [book review]. Proc IEEE. 1998;86:600–603. doi:10.1109/JPROC.1998.662886.
14. Precup RE, Hellendoorn H. A survey on industrial applications of fuzzy control. Comput Ind. 2011;62(3):213–226. doi:10.1016/j.compind.2010.10.001.
15. Shamseldin MA, El-Samahy AA. Speed control of BLDC motor by using PID control and self-tuning fuzzy PID controller. 15th International Workshop on Research and Education in Mechatronics (REM), El Gouna, Egypt. 2014. p. 1–9. doi:10.1109/REM.2014.6920443.
16. Abdelwanis MI, Hegab A, Albatati F, El-Sehiemy RA. Adaptive speed tuning of permanent magnet synchronous motors using intelligent fuzzy-based controllers for pumping applications. Processes. 2025;13(5):1393. doi:10.3390/pr13051393.
17. Kumar V, Rana KPS. Nonlinear adaptive fractional order fuzzy PID control of a 2-link planar rigid manipulator with payload. J Franklin Inst. 2017;354(2):993–1022. doi:10.1016/j.jfranklin.2016.11.006.
18. Zheng JM, Zhao SD, Wei SG. Adaptive fuzzy PID control for switched reluctance motor direct drive servo hydraulic press. 2009 International Conference on Measuring Technology and Mechatronics Automation, Zhangjiajie, China. 2009. p. 771–774. doi:10.1109/ICMTMA.2009.62.
19. Mannan MA, Murata T, Tamura J, Tsuchiya T. Fuzzy-logic-based self-tuning PI controller for speed control of indirect field-oriented induction motor drive. Trans Soc Instrum Control Eng. 2005;41:637–644. doi:10.9746/sicetr1965.41.637.
20. Lin FJ, Shen PH. Adaptive fuzzy-neural-network control for a DSP-based permanent magnet linear synchronous motor servo drive. IEEE Trans Fuzzy Syst. 2006;14(4):481–495. doi:10.1109/TFUZZ.2006.876744.
21. Hannan MA, Faisal M, Ker PJ, Mun LH, Parvin K, Mahlia TMI, et al. A review of internet of energy based building energy management systems: issues and recommendations. IEEE Access. 2018;6:38997–39014. doi:10.1109/ACCESS.2018.2852811.

22. Chowdhury D, Khalil HK. Practical synchronization in networks of nonlinear heterogeneous agents with application to power systems. IEEE Trans Automat Contr. 2021;66(1):184–198. doi:10.1109/TAC.2020.2981084.
23. Zheng S, Tang X, Song B, Lu S, Ye B. Stable adaptive PI control for permanent magnet synchronous motor drive based on improved JITL technique. ISA Trans. 2013;52(4):539–549. doi:10.1016/j.isatra.2013.03.002. PubMed PMID: 23659836.

