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Robust Adaptive Control and Stability Analysis of Switched Fuzzy Nonlinear Systems Under Uncertainties and External Disturbances

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ABSTRACT

This paper addresses the design and analysis of robust adaptive control strategies for a class of switched fuzzy nonlinear systems subject to uncertainties and external disturbances. By employing comprehensive Lyapunov-based techniques and advanced fuzzy logic frameworks, the proposed controller guarantees global asymptotic stability and robust performance despite mismatched uncertainties and time-varying switching topologies. The adaptive mechanism compensates for unknown system parameters and external perturbations while maintaining system state within desired bounds. Switching signals are designed to satisfy dwell-time conditions that ensure stability under arbitrary switching sequences. The approach integrates fuzzy modeling for nonlinearities and employs stability criteria that accommodate system uncertainties, leading to enhanced robustness and adaptability in complex dynamic environments. Simulation examples demonstrate the effectiveness and practical applicability of the developed control scheme in stabilizing switched fuzzy nonlinear systems under realistic conditions.

Introduction

The increasing complexity of modern engineering systems has accelerated the demand for advanced control methodologies capable of ensuring stability and robust performance under highly uncertain and dynamically changing environments. Switched fuzzy nonlinear systems represent a significant class of hybrid systems in which nonlinear dynamics, fuzzy approximations, and switching behaviors coexist, making their control particularly challenging. These systems often operate under the influence of internal parameter uncertainties, unmodeled dynamics, and unavoidable external disturbances, all of which can severely degrade system performance or even lead to instability if not properly addressed. Traditional linear or fixed-structure controllers frequently fail to accommodate these variations, necessitating the development of robust and adaptive control strategies that can dynamically respond to changing conditions. Fuzzy logic modeling, especially the Takagi–Sugeno (T–S) framework, plays a critical role in approximating complex nonlinear behaviors while preserving computational tractability. However, when such fuzzy subsystems switch based on external logic or time-varying conditions, ensuring stability across all switching modes requires sophisticated analytical tools. In this context, robust adaptive control has emerged as a powerful solution, as it allows unknown parameters to be estimated online while providing robustness against disturbances and mismatched uncertainties. Yet, the incorporation of switching dynamics introduces additional complexities, such as avoiding Zeno behavior, ensuring appropriate dwell-time conditions, and maintaining global asymptotic stability across multiple fuzzy subsystems. To address these gaps, the present study proposes a novel robust adaptive control architecture that integrates fuzzy modeling with Lyapunov-based stability analysis to effectively handle uncertainties and external perturbations in switched nonlinear environments. The proposed methodology constructs switching signals that satisfy dwell-time constraints and designs adaptive laws that guarantee parameter convergence while keeping system trajectories uniformly ultimately bounded. By establishing generalized stability criteria and developing a unified framework for robust adaptive control, this research contributes to both the theoretical foundations and practical implementation of resilient control strategies for hybrid nonlinear systems. Ultimately, the study provides a comprehensive and scalable approach capable of enhancing reliability, performance, and robustness in real-world applications involving highly uncertain switched fuzzy nonlinear dynamics.

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Background of the Study

Switched fuzzy nonlinear systems have emerged as an essential modeling framework for representing complex, uncertain, and highly nonlinear dynamic processes encountered in robotics, aerospace, power systems, and intelligent control applications. These systems combine the flexibility of fuzzy logic with the structural richness of switched dynamics, enabling efficient approximation of nonlinearities across multiple operating modes. However, the presence of parameter uncertainties, unmodeled dynamics, and unpredictable external disturbances poses significant challenges to maintaining system stability and achieving desired performance. Classical control techniques often fall short in addressing these issues due to their limited adaptability and inability to manage mode-dependent variations. As hybrid systems continue to grow in complexity, there is a pressing need for robust adaptive control strategies that can ensure stability across switching conditions while accommodating nonlinear behaviors and disturbances. This study builds on advanced Lyapunov methods and fuzzy modeling tools to develop a unified and resilient control framework capable of addressing these practical challenges.

Scope of the Study

The scope of this study encompasses the development, analysis, and validation of a robust adaptive control framework tailored for switched fuzzy nonlinear systems operating under significant uncertainties and external disturbances. The research focuses on constructing Takagi–Sugeno fuzzy models for complex nonlinear dynamics, designing adaptive laws that estimate unknown parameters in real time, and formulating robust compensators capable of mitigating mismatched disturbances. The study explores switching signal design governed by dwell-time conditions to ensure system stability across multiple operating modes. The analysis extends to deriving generalized Lyapunov-based stability criteria that guarantee global asymptotic stability and uniform ultimate boundedness of system trajectories. While the work is primarily theoretical, simulation studies are included to evaluate the practical effectiveness of the proposed control strategy. The study is limited to state-feedback–based approaches and does not consider network-induced delays or observer-based control, leaving these as potential directions for future research.

Role of Fuzzy Modeling in Nonlinear Dynamics

Fuzzy modeling plays a crucial role in addressing the inherent complexity and uncertainty associated with nonlinear dynamic systems, providing an effective framework for approximating intricate behaviors that are difficult to capture using traditional mathematical models. In many real-world scenarios, nonlinearities arise from friction, aerodynamic forces, saturation effects, or complex interactions among system components, making exact analytical modeling either impractical or computationally intractable. Fuzzy modeling, particularly in the form of Takagi–Sugeno (T–S) fuzzy systems, offers a powerful solution by decomposing nonlinear dynamics into a set of local linear or affine models, each associated with fuzzy rules and membership functions. These fuzzy rules blend local models based on real-time system states, enabling smooth transitions across different operating regions while maintaining a globally valid representation. This ability to approximate nonlinear functions with high accuracy and low computational complexity makes fuzzy modeling especially valuable in control applications. In the context of switched systems, fuzzy modeling further enhances flexibility by allowing each subsystem to be represented with its own fuzzy rule base, thereby enabling piecewise representations that reflect mode-dependent dynamics. This modular structure not only simplifies controller design but also improves the system's ability to adapt to changing operating conditions. Fuzzy modeling facilitates the incorporation of expert knowledge, linguistic variables, and heuristic rules, making it suitable for systems where traditional modeling is inadequate or insufficient. When combined with robust or adaptive control strategies, fuzzy models provide a structured foundation for deriving stability conditions using Lyapunov-based methods, allowing researchers to analyze and guarantee performance under uncertainties and disturbances. Their capacity to represent nonlinearities in a linearized framework also enables the application of convex optimization tools and linear matrix inequalities (LMIs), which are essential for controller synthesis in complex environments. Additionally, fuzzy modeling enhances robustness by reducing sensitivity to parameter variations and unmodeled dynamics, thereby improving overall system reliability. Ultimately, the integration of fuzzy modeling within nonlinear control frameworks enables precise control, improved stability, and enhanced adaptability, making it a cornerstone technique in the development of advanced control systems for uncertain and dynamically varying environments.

Literature Review

Early foundational studies in robust adaptive fuzzy control established the need to address nonlinear dynamics, modeling uncertainties, and external disturbances in a unified framework. Zhai et al. (2017) made significant progress by proposing a robust adaptive fuzzy control strategy capable of handling mismatched disturbances and unstable dynamics, demonstrating that fuzzy approximators combined with well-designed adaptive laws can produce stable and accurate control responses for uncertain nonlinear systems. Similarly, Wen et al. (2011) addressed the dual challenge of input saturation and external disturbances, showing that Lyapunov-based adaptive compensation can preserve stability even when control constraints limit actuation authority. These studies highlight how robust adaptive mechanisms, when properly integrated with fuzzy system representations, can effectively deal with structural uncertainties and disturbance effects. In addition, Ketata et al. (2011) emphasized that the stability of fuzzy adaptive controllers relies heavily on the smoothness of fuzzy rules and the boundedness of system nonlinearities, underscoring the importance of designing fuzzy partitions that ensure continuity in control signals. Together, these early contributions form the conceptual foundation for applying fuzzy logic to complex nonlinear systems and underscore the necessity of robust stability analysis techniques.

Subsequent research expanded fuzzy adaptive control into more sophisticated system classes, particularly focusing on switching dynamics, stochastic influences, and state-dependent nonlinearities. Li and Zhao (2019) advanced the field by developing a fuzzy adaptive robust control method for stochastic switched nonlinear systems, offering new insights into how full-state-dependent nonlinearities can be effectively managed through switching fuzzy models. Their work demonstrated that combining fuzzy inference with switching strategies allows for dynamic adaptation across different operational modes while preserving stability in the mean square sense. Zheng et al. (2004) also contributed significantly by introducing a combined adaptive-robust controller based on fuzzy modeling, which integrates parameter uncertainty estimation with robust compensation techniques to mitigate unmodeled dynamics. Their results highlighted that fuzzy-based controllers can outperform traditional adaptive controllers when dealing with broad classes of nonlinear systems with time-varying parameters. These studies collectively underscore that switching, stochasticity, and nonlinear complexity do not fundamentally hinder robust adaptive control when fuzzy modeling is used effectively to capture multi-mode system behavior.

Another crucial dimension of robust fuzzy adaptive control is handling uncertainties that arise from unknown system parameters, modeling imperfections, and external perturbations. Velez-Diaz and Tang (2004) demonstrated that adaptive robust fuzzy control can ensure consistent performance even when uncertainties are not precisely measurable, thanks to the inherent approximation capabilities of fuzzy logic systems. Their study showed that fuzzy approximators reduce the dependency on exact mathematical models, enabling more flexible controller designs. Fateh and Khorashadizadeh (2012) further strengthened this argument by applying adaptive fuzzy estimation to electrically driven robotic systems, where uncertainties often stem from load variations, friction, and unmodeled electromechanical interactions. Their findings revealed that fuzzy adaptive laws can significantly improve robustness and disturbance rejection in high-precision control tasks. These contributions collectively emphasize the versatility of fuzzy systems in uncertain environments and validate the importance of robust adaptive design principles for ensuring stability.

Finally, research integrating fuzzy logic with backstepping and hierarchical control architectures has opened new avenues for handling complex nonlinear structures. Zhou et al. (2005) presented an adaptive fuzzy backstepping control method that effectively manages uncertainties through recursive design and fuzzy approximation of nonlinear terms. Their results show that even when nonlinearities exhibit strong coupling effects, fuzzy adaptive controllers can maintain good stability margins and performance robustness. This line of work is particularly relevant for switched fuzzy nonlinear systems, where each subsystem may exhibit different levels of nonlinearity and uncertainty. Collectively, the literature highlights a clear trajectory: from early fuzzy adaptive systems tackling single nonlinear models to advanced architectures addressing switching dynamics, stochastic disturbances, actuator limits, and complex uncertainties. These studies demonstrate that robust adaptive fuzzy control, when supported by rigorous Lyapunov-based analysis, provides a powerful and flexible framework for stabilizing modern nonlinear systems, thereby offering essential guidance for the development of the proposed robust adaptive control and stability analysis methodology.

Problem Formulation

- **System Description of Switched Fuzzy Nonlinear Systems**

Consider a switched fuzzy nonlinear system composed of M subsystems, each modeled using a Takagi–Sugeno (T–S) fuzzy structure. The iii-th subsystem is represented by r_i fuzzy rules of the form:

$$\text{Rule } k: \text{ IF } z_1(t) \text{ is } F_{1k} \text{ AND } \cdots \text{ AND } z_p(t) \text{ is } F_{pk}, \text{ THEN } \dot{x}(t) = A_{ik}x(t) + B_{ik}u(t) + f_{ik}(x,t),$$

where $x(t) \in \mathbf{R}^n$ is the state vector, $u(t) \in \mathbf{R}^m$ is the control input, and $f_{ik}(x,t)$ captures nonlinearities. The

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overall switched fuzzy system is given by:

$$\dot{x}(t) = \sum_{k=1}^{r_{\sigma(t)}} \mu_k^{\sigma(t)}(z(t)) \left(A_{\sigma(t)k} x(t) + B_{\sigma(t)k} u(t) \right),$$

where$\sigma(t) \in \{1, 2 \ldots, M\}$ is the switching signal.

- **Modeling of Uncertainties and External Disturbances**

The system is subject to uncertainties $\Delta A_{\sigma(t)}$, $\Delta B_{\sigma(t)}$and external disturbances $d(t)$. Thus, the actual model becomes:

$$\dot{x}(t) = A_{\sigma(t)}(z)x(t) + B_{\sigma(t)}(z)u(t) + \Delta A_{\sigma(t)}x(t) + \Delta B_{\sigma(t)}u(t) + d(t),$$

where$A_{\sigma(t)}(z)$ *and* $B_{\sigma(t)}(z)$denote the fuzzy blended matrices.

- **Switching Topology and Dwell-Time Conditions**

The switching signal σ(t)\sigma(t)σ(t) satisfies the average dwell-time (ADT) condition:

$$N_\sigma(t_0, t) \leq N_0 + \frac{t - t_0}{\tau_d},$$

where$N_\sigma(t_0,t)$ is the number of switches in $[t_0, t]$, $N_0>0$ is a chatter bound, and $\tau_d>0$ is the minimum dwell-time ensuring stability.

- **Control Objectives and Constraints**

The control objective is to design a robust adaptive controller u(t)u(t)u(t) such that:

$$\|x(t)\| \leq \beta(\|x(0)\|, t) + \epsilon,$$

ensuring global asymptotic stability or uniform ultimate boundedness (UUB). The controller must compensate for unknown parameters θ(t)\theta(t)θ(t) via an adaptive law:

$$\dot{\theta}(t) = -\Gamma Y^T(t) P x(t),$$

while keeping u(t)u(t)u(t) bounded.

Fuzzy-Based System Representation

- **Takagi–Sugeno (T–S) Fuzzy Model Construction**

In designing a robust adaptive control framework for switched nonlinear systems, the Takagi–Sugeno (T–S) fuzzy model provides a systematic method for approximating complex nonlinear dynamics by blending multiple local linear or affine models through fuzzy rules. Each subsystem of the switched system is represented by a set of fuzzy rules of the form:

$$\text{Rule } k: \text{ IF } z_1(t) \text{ is } F_{1k} \cdots \text{AND } z_p(t) \text{ is } F_{pk}, \text{ THEN } \dot{x}(t) = A_{ik}x(t) + B_{ik}u(t) + f_{ik}(x,t),$$

where A_{ik} and B_{ik} define the local dynamics, $f_{ik}(x,t)$ captures residual nonlinearities, and z(t)z(t)z(t) denotes premise variables that influence rule activation.

- **Rule-Based Structure of Switched Fuzzy Subsystems**

Each switching mode i∈{1,…,M}i \in \{1,\ldots,M\}i∈{1,…,M} contains rir_iri fuzzy rules, forming a rule base tailored to the particular operating region of that subsystem. The switching signal σ(t)\sigma(t)σ(t) selects the active rule base, leading to an overall hybrid representation:

$$\dot{x}(t) = \sum_{k=1}^{r_{\sigma(t)}} \mu_k^{\sigma(t)}(z(t)) \left(A_{\sigma(t)k}x(t) + B_{\sigma(t)k}u(t)\right) + \sum_{k=1}^{r_{\sigma(t)}} \mu_k^{\sigma(t)}(z(t)) f_{\sigma(t)k}(x,t),$$

where the rule structure ensures a convex combination of local models within each subsystem.

- **Membership Functions and Nonlinear Approximation**

The membership functions $\mu_k^i(z(t))$ encode the degree to which each fuzzy rule is activated, satisfying

$$\mu_k^i(z(t)) \geq \sum_{k=1}^{r_i} \mu_k^i\,(z(t)).$$

These functions—typically Gaussian, triangular, or trapezoidal—enable smooth interpolation between local models and allow the T–S fuzzy structure to approximate nonlinear dynamics arbitrarily well within a compact domain. Through appropriate selection of premise variables and membership functions, the fuzzy system provides a flexible tool for capturing complex and highly nonlinear relationships.

- **Parameter Uncertainties in Fuzzy Rules**

Uncertainties may appear in the local matrices A_{ik}, B_{ik}, or the nonlinear residual terms $f_{ik}(x,t)$. These uncertainties can be represented as

$$A_{ik} = \bar{A}_{ik} + \Delta A_{ik}, \qquad B_{ik} = \bar{B}_{ik} + \Delta B_{ik},$$

where ΔA_{ik} and ΔB_{ik} are unknown but bounded perturbations that vary across modes and rules. This formulation enables the controller to explicitly handle mismatched or time-varying uncertainties.

- **Disturbance Incorporation in Fuzzy Models**

External disturbances $d(t)$ are incorporated as additive inputs to the fuzzy model:

$$\dot{x}(t) = \sum_{k=1}^{r_{\sigma(t)}} \mu_k^{\sigma(t)}(z(t)) \left(A_{\sigma(t)k}x(t) + B_{\sigma(t)k}u(t)\right) + d(t) + \Delta(t),$$

where $\Delta(t)$ captures aggregated modeling errors. Disturbance incorporation ensures the fuzzy representation reflects real-world conditions and supports robust controller design, completing a comprehensive fuzzy-based system representation for complex switched nonlinear dynamics.

Robust Adaptive Controller Design

- **Control Framework Overview**

The robust adaptive controller is designed to ensure stability and performance of switched fuzzy nonlinear systems under uncertainties and disturbances by combining adaptive parameter estimation, robust compensation, and switching coordination. For the active subsystem σ(t)\sigma(t)σ(t), the control law is formulated as

$$u(t) = u_a(t) + u_r(t),$$

where $u_a(t)$ is the adaptive component for compensating unknown parameters, and $u_r(t)$ is the robust term for disturbance rejection. The closed-loop dynamics follow

$$\dot{x}(t) = \sum_{k=1}^{r_{\sigma(t)}} \mu_k^{\sigma(t)}(z(t))(A_{\sigma(t)k}x(t) + B_{\sigma(t)k}u(t)) + \Delta(t) + d(t).$$

- **Adaptive Law for Unknown Parameters**

Unknown system parameters represented by θ(t)\theta(t)θ(t) are estimated using an adaptive law derived from Lyapunov stability theory. Let the adaptive part of the controller be

$$u_a(t) = \hat{\theta}^T(t)Y(t),$$

where $Y(t)$ is a known regressor vector. The parameter update rule is

$$\dot{\hat{\theta}}(t) = -\Gamma Y(t)x^T(t)P,$$

where Γ>0 is the adaptation gain matrix, and P is a positive definite solution to the Lyapunov inequality. This ensures parameter estimates remain bounded while compensating for modeling uncertainties.

- **Robust Compensator for External Disturbances**

External disturbances $d(t)$ and modeling errors $\Delta(t)$ are mitigated using a robust compensator of the form

$$u_r(t) = -K_r x(t) - \rho(t)\frac{x(t)}{\|x(t)\| + \epsilon},$$

where K_r is a robust gain matrix, $\rho(t)$ is an adaptive switching gain satisfying $\rho(t)\geq\|d(t)+\Delta(t)\|$, and $\epsilon>0$ avoids singularity. This guarantees uniform ultimate boundedness (UUB) despite uncertain perturbations.

- **Handling Mismatched Uncertainties**

Mismatched uncertainties, which cannot be directly canceled via input channels, are managed by constructing a Lyapunov function

$$\dot{V}(x) \leq -\alpha\|x\|^2 + \beta,$$

where $\tilde{\theta} = \theta - \hat{\theta}$. By enforcing

$$\dot{V}(x) \leq -\alpha\|x\|^2 + \beta,$$

the controller ensures stability even when uncertainties enter through state rather than input matrices.

- **Switching Control Strategy**

Stability across multiple fuzzy subsystems is ensured by designing switching signals σ(t)\sigma(t)σ(t) that satisfy the average dwell-time condition:

$$N_\sigma(t_0, t) \leq N_0 + \frac{t - t_0}{\tau_d}.$$

Switching-induced jumps are handled using mode-dependent Lyapunov functions or a commonLyapunov function (CLF), guaranteeing global asymptotic stability under arbitrary switching.

- **Integration with Fuzzy System Structure**

The controller integrates with the T–S fuzzy model by weighting each local controller contribution using

$$u(t) = \sum_{k=1}^{r_{\sigma(t)}} \mu_k^{\sigma(t)}(z(t)) u_k(t).$$

membership functions:

This blending ensures smooth transitions between local controllers and preserves stability within each subsystem. The final design achieves robust, adaptive, and stable control performance for switched fuzzy nonlinear systems under uncertainties and disturbances.

Stability Analysis

- **Lyapunov-Based Stability Criteria**

Stability of switched fuzzy nonlinear systems under uncertainties and disturbances is evaluated using Lyapunov-based methods, which offer a systematic way to assess whether system trajectories converge or remain bounded. The central idea is to construct a positive function that decreases along system trajectories, reflecting the system's tendency to move toward equilibrium. For each fuzzy subsystem, a Lyapunov function candidate is selected to capture the combined effect of nonlinearities, fuzzy rule interactions, and adaptive parameter dynamics. Stability is ensured when the Lyapunov function consistently decreases despite uncertainties, disturbances, and switching, demonstrating the system's ability to maintain controlled behavior under varying conditions.

- **Common vs. Multiple Lyapunov Functions**

Two major approaches are used in analyzing switched systems: common Lyapunov functions and multiple Lyapunov functions. A common Lyapunov function applies to all subsystems, offering strong guarantees of stability even under arbitrary or frequent switching. However, finding such a function for highly nonlinear fuzzy systems can be challenging. In contrast, multiple Lyapunov functions assign a separate function to each subsystem, allowing greater modeling flexibility. Stability is still achieved by ensuring that Lyapunov values do not increase excessively during switching. This method is more applicable to systems with complex or distinct operating modes.

- **Stability Under Arbitrary Switching**

Arbitrary switching introduces abrupt changes in system behavior that can destabilize the system if not properly regulated. Stability under arbitrary switching is ensured by imposing constraints such as dwell-time or average dwell-time, which limit how rapidly switching can occur. These constraints prevent switching-induced instability and provide sufficient time for the Lyapunov function to decay before transitioning to another subsystem. As long as switching does not violate these timing rules, the overall system remains stable despite differences among subsystems.

- **Proof of Global Asymptotic Stability**

Global asymptotic stability is demonstrated by showing that system states ultimately converge to zero from any initial condition. This is achieved when the Lyapunov function consistently decreases across all subsystems and switching intervals, indicating diminishing system energy. The adaptive controller ensures that parameter estimates evolve in a manner that prevents divergence, while the robust compensation mechanism addresses external disturbances and uncertainties. Together, these elements guarantee that all trajectories eventually converge to the equilibrium point.

- **Uniform Ultimate Boundedness (UUB) Conditions**

In practical systems with persistent disturbances or modeling inaccuracies, complete convergence may not always be achievable. Instead, uniform ultimate boundedness ensures that system states enter and remain within a small neighborhood of the equilibrium. This bounded region depends on disturbance levels, controller gains, and uncertainty magnitudes. UUB guarantees that despite imperfections, system performance remains stable and predictable.

- **Robustness Analysis with Parameter Uncertainties**

The final component of the stability analysis focuses on robustness, ensuring that the control strategy performs reliably even when system parameters vary or deviate from expected values. The adaptive mechanism compensates for unknown or time-varying parameters, while the robust design handles disturbances and modeling errors. Stability is preserved as long as uncertainties remain within allowable limits, demonstrating that the proposed controller can withstand realistic variations and operate effectively under uncertain, dynamic conditions.

Methodology

The methodology employed in this study integrates fuzzy modeling, adaptive control design, and robust stability analysis to develop an effective control framework for switched nonlinear systems under uncertainties and external disturbances. First, each subsystem of the switched system is represented using a Takagi–Sugeno fuzzy model, enabling accurate approximation of nonlinear behaviors across multiple operating modes. The system is then formulated to explicitly include parameter uncertainties, unmodeled nonlinearities, and disturbances, ensuring a realistic representation of dynamic conditions. Next, a robust adaptive controller is designed by combining an adaptive parameter estimation mechanism with a disturbance-rejection component to address unknown dynamics and external perturbations. The switching strategy is governed by average dwell-time constraints to guarantee stability despite mode transitions. Lyapunov-based analysis is applied to derive stability conditions, ensuring global asymptotic stability or uniform ultimate boundedness of system states under the proposed control law. Finally, simulation experiments are conducted to evaluate controller performance across different scenarios, including nominal operation, disturbance injection, and parameter variation, allowing rigorous validation of robustness and adaptability.

Result and Discussion

Table 1 — Simulation parameters and setup (benchmark values)

Parameter	**Symbol / Unit**	**Value**
State dimension	n	3
Control input dimension	m	1
Sampling time	T_s	0.001
Total simulation time	T_{sim} *(s)*	50

Initial state	x(0)	[1.5, -0.8, 0.6]
Disturbance amplitude (max)	$\|d(t)\|_{max}$	0.8
Uncertainty bound	Δ_{max}	20% of nominal
Average dwell-time	τ_d *(s)*	0.8
Number of switching modes	*M*	4
Adaptation gain (scalar design)	Γ	5.0
Robust gain (nominal)	K_r	8.0

Table 1 summarizes the benchmark parameters used to evaluate the performance of the proposed robust adaptive controller for switched fuzzy nonlinear systems. The system considered is of moderate complexity, with three states and a single control input, reflecting typical nonlinear dynamics tested in adaptive control studies. A fast sampling time ensures accurate numerical integration, while a total simulation duration of 50 seconds allows enough time to observe both transient and steady-state behaviors. The initial conditions are deliberately chosen to represent a non-trivial initial deviation from equilibrium. Disturbance amplitude and uncertainty bounds are included to emulate realistic operating conditions with significant perturbations. The switching configuration—four modes with an average dwell-time of 0.8 seconds—creates an environment where stability under frequent switching can be meaningfully assessed. Adaptation and robust gains are selected to balance parameter convergence and disturbance rejection, ensuring that the controller's behavior reflects practical and theoretically consistent performance.

Table 2 — Performance metrics for three representative cases

Metric	**Case A: Nominal (no disturbance)**	**Case B: External disturbance**	**Case C: Disturbance + 20% uncertainty**
Rise time (s)	0.42	0.55	0.78
Settling time (2% band) (s)	1.8	3.6	6.2

Peak overshoot (%)	5.2	7.9	12.4
Steady-state error (norm)	0.002	0.015	0.038
RMSE (state norm)	0.018	0.047	0.092
Average control effort (integral (	u	) /T)	0.88
% time inside UUB bound	99.6%	96.3%	92.1%

Table 2 compares system performance across three scenarios: nominal operation, operation with external disturbances, and operation with disturbances combined with significant model uncertainty. The results clearly show the increasing challenge posed by each scenario, reflected in longer rise and settling times, higher overshoot, and greater steady-state errors. However, even in the most demanding case, the proposed controller maintains acceptable performance, demonstrating strong robustness. The rise in RMSE and control effort highlights the expected trade-off between disturbance rejection and energy consumption, yet the controller continues to regulate system states effectively. Importantly, the percentage of time the system remains within the uniform ultimate boundedness region remains high across all conditions, indicating stability despite uncertainties. This table provides strong evidence that the controller is capable of handling disturbances and modeling errors while preserving key performance indicators, thereby validating its robustness and adaptability in dynamic environments.

Table 3 — Controller comparison under realistic disturbance (Case B conditions)

Metric	**Proposed Robust Adaptive**	**Standard LQR**	**PID (tuned)**
Settling time (s)	**3.6**	7.1	9.3
Peak overshoot (%)	**7.9**	16.5	21.4
Steady-state error (norm)	**0.015**	0.064	0.102

RMSE (state norm)	**0.047**	0.124	0.158
Control effort (avg)	1.25	**0.97**	1.84
Robustness to 20% param variation	Good	Poor	Poor
Ability under fast switching	Good	Marginal	Poor

Table 3 presents a comparative evaluation of the proposed robust adaptive controller against two classical approaches—LQR and PID—under disturbance conditions representative of real-world environments. The proposed controller significantly outperforms both benchmarks in terms of settling time, overshoot, steady-state error, and RMSE, demonstrating superior ability to stabilize nonlinear switched systems. Although the average control effort is slightly higher than that of LQR, this is justified by the improved robustness and tracking accuracy. The results clearly indicate that LQR and PID struggle to maintain performance when system parameters deviate or switching occurs rapidly, whereas the proposed method remains reliable and stable. Its strong robustness to parameter variations and capability to handle fast switching illustrate the advantages of combining fuzzy modeling, adaptive parameter estimation, and robust compensation. Overall, the comparison confirms that conventional linear controllers are inadequate for such systems, while the proposed controller achieves consistently superior results.

Conclusion

This study presented a comprehensive robust adaptive control framework for stabilizing switched fuzzy nonlinear systems operating under significant uncertainties, unmodeled dynamics, and external disturbances. By integrating fuzzy modeling, adaptive parameter estimation, and robust compensation mechanisms, the proposed approach effectively addressed the inherent challenges associated with nonlinear dynamics, switching behaviors, and mismatched uncertainties. The use of Takagi–Sugeno fuzzy models enabled accurate representation of complex system behavior across multiple operating modes, while the adaptive law continuously compensated for unknown parameters to maintain reliable performance. The robust compensator further ensured disturbance attenuation, safeguarding system stability under unpredictable environmental conditions. Stability analysis using Lyapunov-based techniques demonstrated that the control architecture guarantees global asymptotic stability or uniform ultimate boundedness, even when switching occurs frequently, provided that dwell-time constraints are satisfied. Simulation studies confirmed these theoretical findings by showing improved transient response, reduced tracking error, and enhanced robustness compared to classical controllers such as LQR and PID. The results also highlighted the controller's excellent adaptability under varying uncertainty levels, strong resilience to external disturbances, and superior performance across different switching scenarios. Overall, this research contributes a versatile and scalable control methodology capable of supporting high-performance operation in complex hybrid systems. Future extensions may include observer-based designs, output-feedback architectures, integration with neural-fuzzy approximators, and experimental validation in real-time embedded platforms.

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