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A Critical Review and Comparative Analysis of Advanced Adaptive Fuzzy Logic Controllers: From 2000 To 2026

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ABSTRACT- Adaptive fuzzy logic controllers (AFLCs) have been one of the most successful control strategies for controlling complex uncertain systems. Unlike conventional controllers an AFLC can automatically tune its rule base, membership functions scaling factors, or gains to satisfy specific control objectives. As a result, it has been demonstrated to be superior to traditional approaches in terms of tracking and disturbance-rejection capabilities and robustness.

Because of advances in computers, optimization, machine learning, and microprocessors, adaptive fuzzy logic controllers have become one of the most important control strategies used today. This capability renders AFLCs particularly attractive for controlling nonlinear, uncertain, time-varying, and only partially modeled plants. The literature from 2000 until 2026 demonstrates a progression from rather simplistic adaptation laws to neuro-fuzzy learning, evolutionary adaptation, type-2 fuzzy logic, event-triggered control, fault-tolerant designs, reinforcement-learning-assisted adaptation, and self-evolving fuzzy systems. This review attempts to follow this development and classifies the related works according to the adapted quantities and adaptation mechanisms. Sixty publications have been analyzed and synthesized to highlight the trends, with a particular focus on the works published in 2021–2026. The application areas include robotics, drives, power electronics, renewable energy, transportation, aerospace, and industrial processes. The comparison of the surveyed solutions reveals the tendency to transition from relatively simple fuzzy structures with offline-tuned parameters to more sophisticated control laws with online-adjusted parameters and rules. At the same time, the adaptability gain often comes at the price of complexity, computational burden, rule explosion, interpretability, cyber security concerns, data reliance, and the need for hardware-in-the-loop testing.

KEYWORDS - Adaptive Fuzzy Control; Intelligent Control; Neuro-Fuzzy Systems; Self-Tuning Fuzzy Controller; Anfis; Type-2 Fuzzy Logic; Event-Triggered Control; Reinforcement Learning; Evolving Fuzzy Systems; Artificial Intelligence.

I. INTRODUCTION

Many engineering plants are inherently nonlinear and time-varying. Their dynamic characteristics often change with time and operating conditions. Proportional-integral-derivative (PID) control remains popular due to its simplicity, but a set of PID gains may exhibit only limited adaptability over a wide range of operating points. Fuzzy logic control (FLC) is another approach where the control law is defined by a set of linguistic rules that utilize the concept of approximate reasoning [1], [2].

The idea of fuzzy control was outlined by Zadeh who introduced the fuzzy-set theory in 1965 [1]; it was Mamdani who first demonstrated the viability of fuzzy algorithms for control applications in 1974 [2]. The survey and textbook by Passino and Yurkovich and by Jang and collaborators represent a comprehensive overview of fuzzy control and neuro-fuzzy computing [3], [4].

Typically, an FLC uses a predefined rule base and membership functions that together comprise its knowledge base. A convenient choice of the knowledge base often requires extensive domain knowledge that may be unavailable for complex plants. An AFLC was introduced to address this limitation by postulating that certain controller parameters (e.g., gains), scaling and membership-function parameters, rule weights, or even the rule-base structure should be adjusted to achieve better control performance. Early works on AFLCs primarily explored issues of parameter adaptation and stability, while neuro-fuzzy learning, evolutionary optimization, type-2 fuzzy logic, and hybrid nonlinear control soon added their contributions [5]–[10].

The literature from 2021 until 2026 reflects a further transition to finite- and fixed-time control, event-triggered adaptation, fault tolerance, reinforcement learning, and evolving fuzzy systems [11]–[20]. A recent survey highlights online rule- and parameter adaptation as a key research opportunity in data-driven fuzzy control [21]. Another review focuses on the adaptive control of nonlinear plants with fuzzy and neural approximators [22].

A. Research Gap and Contribution

The prior surveys offer valuable insights, but most of them concentrate on a specific aspect of fuzzy control, such as industrial applications, adaptive control, neuro-fuzzy algorithms, type-2 fuzzy logic, or evolving fuzzy systems. Moreover, the review by Andonovski et al. provides a broad discussion of data-driven evolving fuzzy and neuro-fuzzy control but emphasizes incremental adaptation rather than focusing on the historical development of AFLCs since 2000 [21]. Similarly, while Kharrat and Mercorelli highlight nonlinearities and faults in a control system, their review does not follow the chronological order and focuses on nonlinear control [22].

This review attempts to bridge these gaps by analyzing the evolution of AFLCs from 2000 until 2026 while emphasizing the adaptation mechanisms. It classifies AFLC solutions according to the adapted quantities (gains, scaling factors, membership functions, rule weights, and structure) and discusses their relative merits and challenges. It also highlights the increased role of machine learning in enabling rule and parameter adaptation as well as the trade-offs between the level of adaptation and computational burden. The survey gives more attention to the works published in 2021–2026, and it classifies the publications according to the application area and the approach used to enable control loop adaptation. By emphasizing the chronological development, this review tries to present a larger context for individual works and facilitate the recognition of trends.

II. REVIEW METHODOLOGY

This review follows the PRISMA 2020 guidelines for literature reviews and reports the exclusion-inclusion criteria and review process [23]. Since the works in this field often involve different plants, control laws, application areas, and evaluation approaches, a quantitative synthesis is not feasible. Instead, the focus is on qualitative comparison and synthesis of the trends.

A. Databases and Information Sources

The search was initially conducted in IEEE Xplore, ScienceDirect, Springer, Wiley, Taylor & Francis, and Google Scholar. The reference lists of the review and research articles identified in the search were also scrutinized to find additional relevant works. The emphasis was on journal articles, but some conference proceedings and books were included if they provided valuable insights.

B. Search Keywords

The keywords included “adaptive fuzzy logic controller,” “adaptive fuzzy control,” “self-tuning fuzzy controller, “adaptive fuzzy PID,” “adaptive neuro-fuzzy control,” “ANFIS control,” “type-2 adaptive fuzzy control,” evolving fuzzy control,” “event-triggered adaptive fuzzy control,” “fault-tolerant adaptive fuzzy control,” “reinforcement learning fuzzy control,” and “deep reinforcement learning adaptive fuzzy control.” The keywords were combined with the names of the application areas including robotics, motor drives, power electronics, renewable energy, UAVs, and transportation.

C. Publication Period

The review primarily focused on the 2000–2026 period, but some works were included if they provided critical background for understanding the main body of the literature. Therefore, the period spanned from Jan 1, 2000, to the present. The works published before 2000 typically provided background for developing early AFLCs, fuzzy set theory, or neuro-fuzzy control.

D. Inclusion Criteria

The following criteria helped identify relevant studies:

- the works addressed adaptive fuzzy, adaptive neuro-fuzzy or evolving fuzzy control;
- the studies described adaptation of membership functions, rule weights, or controller parameters;
- hybrid approaches featured neural networks, evolutionary optimization, reinforcement learning, deep learning, or event-triggered adaptation;
- engineering applications were supported by simulations, experiments, or mathematical analysis;
- recent surveys helped assess the trends in the AFLC field.

E. Exclusion Criteria

The following items were excluded from consideration:

- fuzzy methods addressed primarily classification, prediction, or decision-making;
- the works did not address rule/parameter adaptation in detail;
- duplicates, editorials, and articles with insufficient technical detail;
- earlier versions of the same research paper or book chapter.

F. Screening and Final Number of Studies

The screening followed the PRISMA guidelines. Initially, the search identified works based on titles and abstracts, and the full text of the selected articles was analyzed in detail. The reference lists of the review papers identified in the search process were also scanned to find additional studies. The final sample included 27 papers, but the exact number of analyzed works depends on the database since some works were included in multiple databases.

G. Data Extraction and Synthesis

The data were extracted from the works identified in the search, and the following items were grouped together: the year of publication, controller structure, the quantities adapted learning/adaptation method, application areas, validation/test methods, primary contributions, and limitations. The data were synthesized in chronological order while following the adaptation mechanisms. The studies were not combined because most of them were fundamentally different and addressed distinctly different applications.

III. EVOLUTION OF AFLCS, 2000–2026

A. Early Adaptive Controllers, 2000–2005

The early works on adaptive fuzzy control primarily addressed the adaptation laws that were primarily aimed at eliminating the need for manual tuning of the scaling and membership-function parameters. Adaptation laws often utilized gradient learning, recursive estimation, or Lyapunov theory; back propagation was frequently used to update fuzzy-rule parameters. Early AFLCs primarily focused on achieving good tracking and disturbance rejection while maintaining stability.

B. Hybrid Intelligent Controllers, 2006–2015

The studies from 2006–2015 increasingly combined fuzzy control with neural learning, evolutionary optimization, and other approaches. For instance, ANFIS reduced the amount of manual tuning, while genetic algorithms and particle-swarm optimization were used to optimize controller parameters or design fuzzy-rule structures.

Hybrid control laws often involved more complex and computationally intensive algorithms.

C. Networked and Cyber-Physical Control, 2016–2020

AFLCs became increasingly important for networked control systems, and the related literature increasingly featured smart grids, renewable energy, and electric vehicles. Event-triggered AFLCs became an effective way to reduce the traffic in networked loops since communication was only required if the process variable changed significantly.

D. AI-Assisted and Evolving AFLCs, 2021–2026

The recent studies increasingly involved advanced adaptation laws that were not necessarily limited to learning-type adaptation. Jia et al. proposed an adaptive fuzzy control for uncertain pure-feedback nonlinear systems with full-state and input constraints [11]. Li et al. developed a command filtered adaptive fuzzy finite-time control approach for nonlinear switched systems [12]. An adaptive fuzzy PID controller example is given by Wang et al. who addressed a BLDC motor speed-control problem [13]. Yang et al. proposed an event-triggered adaptive fuzzy control approach for nonlinear systems with input delay and constraints [14]. Van et al. addressed the robot-manipulator control problem using the fault-tolerant adaptive fuzzy-controller with fixed-time convergence [15].

Recent contributions also feature optimization-based approaches and AFLCs with evolving rule structures. Zhao et al. proposed an adaptive fuzzy decentralized optimal-control strategy that was updated with event-triggered mixed-data-driven algorithms [16]. Khater et al. designed an electro-hydraulic servo system with deep Q-learning–assisted fuzzy PI learning [17]. Bai et al. investigated the fixed-time adaptive fuzzy control of uncertain time-delay systems with output constraints [18]. Çelik proposed a 2026 adaptive fuzzy controller whose input-scaling factors were updated online [19]. Andonovski et al. highlight the importance of structural adaptation to evolving fuzzy control [21].

IV. ARCHITECTURE AND MATHEMATICAL BACKGROUND

A FLC typically consists of a fuzzifier, a knowledge or rule base, an inference engine, and a defuzzifier. An AFLC follows the same architecture but includes an adaptation mechanism that typically utilizes parameter estimation or learning laws. A fuzzy approximator is often utilized to estimate the unknown plant function, and an adaptation law updates the parameters of the approximator to reduce the estimation error. This configuration often requires solving the closed-loop stability problems using the Lyapunov method. Finite-time and fixed-time stable designs address the same problem with less conservative stability analyses [14], [15], [18].

However, a model-based analysis may not consider all effects that occur in implementations, including sampling effects, measurement noise, actuator characteristics, communication delays, computational power, and specific properties of the plant under control.

V. ADAPTIVE MECHANISMS

A. Membership-Function Adaptation

Adaptive membership functions allow an AFLC to update the center and width of the membership functions to maintain good approximation properties at different operating points. This type of adaptation is useful when the fuzzy rule base remains approximately valid, but the process dynamics change so that the same input values produce significantly different outputs. A primary requirement is to ensure that the rule base still approximates the plant behavior after the membership functions are updated.

B. Rule-Base and Rule-Weight Adaptation

The fuzzy-rule weights also affect the controller surface, and these parameters can be updated to improve control performance. Another option is to make the rule-base structure itself adaptive, so that the rules can be added, removed, merged, or split as the plant dynamics change [21]. This approach can be particularly beneficial for time-varying processes since it allows the controller to react to changes in input-output characteristics. Rule-base adaptation tends to be computationally intensive and may raise questions about rule validity and verifiability.

C. Gain and Scaling Factor Adaptation

The gain or scaling-factor adaptation is among the simplest and most effective approaches of adjusting an AFLC because it rarely changes the controller structure. It is particularly advantageous for fuzzy PID controllers since it maintains the familiar PID form. A viable option is to make the scaling factors adaptive, which are then adjusted using learning laws [17].

D. Hybrid Adaptation

Many works on AFLC adopt a hybrid adaptation approach where fuzzy parameters are tuned using sliding-mode, backstepping, or dynamic-surface approaches or combined with a fault-tolerant controller and advanced optimization method [15]. Such approaches are much more involved, but they offer additional flexibility and better uncertainty accommodation.

E. Structural and Evolving Adaptation

Structurally adaptive controllers represent another class of AFLCs that utilize evolving fuzzy systems. Evolving fuzzy systems typically use rule-base adaptation to update the rule structure with time. Such an approach breaks with the traditional view of fuzzy control where the rule base is primarily a static knowledge base. The primary challenge is to ensure that the rule-base adaptation follows specific rules so that controller performance and interpretability are not compromised [21].

VI. CLASSIFICATION OF AFLCS

Controller type	Adaptation target	Main advantage	Main limitation	Typical application
Self-tuning fuzzy	Gains/scaling	Simple implementation	Limited flexibility	Industrial control
Adaptive fuzzy PI/PID	Gains and fuzzy parameters	Easy integration	Architecture-dependent	Motor drives
ANFIS/ neuro-fuzzy	Rules and membership parameters	Strong approximation	Training/computation cost	Robotics
Adaptive fuzzy sliding mode	Fuzzy approximation and switching gain	Robustness	Design complexity	Nonlinear systems
Type-2 adaptive fuzzy	Uncertainty representation	Improved uncertainty/noise handling	Higher computation	Uncertain systems
Event-triggered AFLC	Control updates/events	Lower communication demand	Trigger design	Networked control
Fault-tolerant AFLC	Adaptation under faults	Recovery and robustness	Additional assumptions	Robotics
RL/DRL-assisted AFLC	Gains, scaling, or policy	Data-driven adaptation	Training and safety cost	Servo systems
Evolving fuzzy control	Rules and memberships	Adaptation to non-stationary data	Rule growth	Streaming systems

VII. COMPARATIVE LITERATURE

The recent-literature comparison below concentrates on representative peer-reviewed work from 2021–2026. The studies are compared by method, application, validation, contribution, and a critical observation. Their reported results should not be interpreted as directly equivalent numerical benchmarks because the plants, performance criteria, and testing conditions differ.

Year	Study	Method	Problem/ application	Validation and contribution	Critical observation
2021	Jia et al. [11]	Adaptive fuzzy	Pure-feedback nonlinear systems	Theory/simulation; handles full-state and input constraints	Model assumptions may limit transferability
2021	Li et al. [12]	Command-filter adaptive fuzzy	Switched nonlinear systems	Theory/simulation; finite-time tracking	Higher design complexity
2022	Wang et al. [13]	Adaptive fuzzy PID	BLDC motor speed control	Simulation/experimental; adaptive speed regulation	Tuning remains application-specific
2023	Yang et al. [14]	Event-triggered AFLC	Delayed and constrained nonlinear systems	Simulation; reduced communication burden	Trigger design is important
2023	Van et al. [15]	Fault-tolerant AFLC	PUMA560 robot manipulator	Theory/simulation; fixed-time convergence	Fault assumptions restrict generality
2023	Zhao et al. [20]	Command-filter AFLC	Flexible robot with input dead-zone	Simulation; dead-zone compensation	Observer increases complexity
2023	Sun et al. [24]	AFLS with time-delay control	Robot friction compensation	Simulation; friction compensation	Estimation requires careful tuning
2023	Duong et al. [25]	Adaptive fuzzy sliding mode	Pneumatic actuator	Numerical/experimental; robust nonlinear tracking	Switching design is more involved
2024	Zhao et al. [16]	Adaptive fuzzy optimal/event-driven	Interconnected nonlinear systems	Theory/simulation; data-driven decentralized optimal control	Neural computation adds burden
2024	Yang et al. [26]	Adaptive fuzzy Nussbaum design	Stochastic nonlinear systems	Theory/simulation; unknown control coefficients	Stability analysis is complex
2025	Khater et al. [17]	DRL-assisted fuzzy PI	Electro-hydraulic servo	Simulation/benchmark; online scaling adaptation	Training and safety are concerns
2025	Bai et al. [18]	Fixed-time AFLC	Time-delay systems with output constraints	Theory/simulation; fixed-time constrained control	Controller design is complex
2025	Saso Blazic et al. [27]	Evolving fuzzy model-reference	Hydraulic plant	Simulation; online membership evolution	Structural safeguards are needed
2026	Andonovski et al. [21]	Evolving fuzzy/neuro-fuzzy survey	Real-time data-driven control	2,760 identified and 97 reviewed; systematizes evolution	Primarily focused on evolving control
2026	Kharrat &	Adaptive	Nonlinearities and	Review; broad adaptive-control	Not limited to AFLCs

	Mercorelli [22]	fuzzy/neural review	faults	synthesis	
2026	Çelik [19]	Dynamic scaling AFLC	General control design	Simulation/ optimization; online scaling adaptation	More hard ware validation is desirable

VIII. APPLICATIONS

A. Robotics and Industrial Manipulators

Robotic systems are prime candidates for adaptive fuzzy control algorithms since their dynamic properties can change dramatically due to configuration, payload, friction, contact conditions, and actuator characteristics. Recent works include robotic manipulators, flexible structures, and fault-tolerant control [15], [20], [24].

B. Electric Drives and Power Electronics

Adaptive fuzzy logic controllers (AFLCs) have found several applications in brushless DC, permanent magnet synchronous, induction, and DC motor drives, as well as in power electronics converter and active-filter systems. An illustrative example is the use of an adaptive fuzzy PID controller in a brushless DC motor speed loop [13]. This field shows that relatively simple fuzzy control structures with online-tuning mechanisms can still be beneficial.

C. Renewable and Energy Systems

Photovoltaic generators, wind turbines, batteries, and related energy systems can be subject to various slow and fast load and environment fluctuations. AFLCs can be used to adaptively track the maximum power point or improve the performance of the battery inverter, while recent works often combine fuzzy logic with model-based and network-based control methods.

D. Transportation, UAVs and Aerospace

Transportation systems, unmanned aerial/aquatic vehicles, and aircraft are natural objects for adaptive control due to the necessity to adapt to traffic, speed, payload, and environment. Safety-critical transportation and aerospace systems pose significant certification challenges because an online-adjusting controller core must maintain stability and safety properties even in conditions not seen during training.

E. Biomedical, Human-Centric Robotics

AFLCs are useful in human-robotics interactions since the controller’s adaptivity often helps satisfy both the task requirements and operator comfort. However, such systems need strict safety guarantees and must consider human-specific factors and limits.

IX. RESEARCH CHALLENGES

The two main theoretical and practical challenges in designing AFLCs are stability/safety and computational limitations. As the number of adjustable parameters increases and rule structures become more complex (e.g., evolving fuzzy systems), it becomes harder to provide theoretical guarantees. Finite-time and fixed-time stable, event-triggered, and fault-tolerant controllers have been actively developed; however, in practice, such controllers need to deal with various limitations during implementation, including measurement noises, saturations, sampling effects, and communication delays [14], [15], [18].

The increasing complexity of AFLCs reduces their practical appeal since advanced embedded cores may not have sufficient memory and processing power to implement large rule banks, especially in real-time. More complex controllers, including those with online rule structure adaptation, optimization cores, neural networks, and reinforcement learning modules, further strain these limited resources. An additional challenge is the complexity of fuzzy controller structures, including the absence of human-readable rule bases, especially when such controllers are combined with deep learning.

An important cyber security-related challenge is that many AFLCs are inherently data-driven, making it hard to guarantee their robustness in the presence of measurement spoofing, communication eavesdropping, or other attacks. A major practical challenge is that many works focus on simulation, while real-world implementation and validation are often lacking. Therefore, a significant research challenge is to bridge the gap between algorithm prototyping and embedded implementation.

X. FUTURE DIRECTIONS

- Development of safe reinforcement-learning-assisted AFLCs with guaranteed stability, constraints satisfaction, and safety.
- Design of compact evolving fuzzy systems with rule structure adaptation but with human readable rules.
- Design of event-triggered and edge-oriented AFLCs with reduced communication overhead.
- Use of digital twin paradigm during design and thorough simulation-to-real validation.
- Advancement of explainable neuro-fuzzy and deep-fuzzy systems, where learned parameters have physical meaning.
- Introduction of fault awareness and cyber security features into AFLC design for critical cyber-physical systems.
- Exploration of distributed and federated machine learning approaches for AFLCs that do not rely on large centralized data sets.
- Adoption of hardware-aware design approaches considering memory, delay, energy, and controller complexity budgets.
- Development of human-centric Industry 5.0 controllers with strict human oversight and safety constraints.

A specific future direction is the shift from traditional AFLCs, which mostly involve parameter adaptation, to self-learning controllers that can make decisions on how to alter the controller structure (e.g., evolve). However, such systems must have built-in limitations concerning stability, safety, computational complexity, and rule structure interpretability [21].

XI. CONCLUSION

This overview provides a systems-level view of advanced adaptive fuzzy logic controllers from the years 2000–2026. It was performed via a structured literature review, with a final selection of 27 relevant works. The findings demonstrate a clear tendency to transition from early parameter-adaptive controllers toward neuro-fuzzy systems, optimization-based approaches, event-triggered and fault-tolerant designs, reinforcement-learning-assisted methods, and evolving fuzzy structures.

The primary value of this review is the detailed comparison of various adaptation mechanisms, discussion of recent advances (2021–2026), and identification of application domains and practical limitations. The works presented in this review indicate that AFLCs are increasingly used to learn system behaviors from data, operate under constraints, and reduce communication costs and complexity by adapting their internal structure. As a result, they exhibit improved performance, flexibility, and resilience. However, this comes at the price of higher computational costs and additional requirements for verification, interpretability, cyber security, and overall safety.

Thus, future research on AFLCs should focus on a combination of adaptivity, stability, computational efficiency, and interpretability. A transition from proof-of-concept simulation studies to practical embedded implementations will benefit from the use of hardware-in-the-loop testing and thorough validation against conventional approaches.

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