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Review Article

Type-3 Fuzzy System-Based Intelligent Control Approaches and Applications

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Type-3 fuzzy logic has been recently used in many control methods. The type-3 fuzzy controller enhances the handling of uncertainty and improves robustness by integrating fuzzy sets with fuzzy membership functions. The latest approaches using type-3 fuzzy logic in the field of control are studied and evaluated. An overview of developments in control methods based on type-3 fuzzy logic is also provided. It is shown that type-3 fuzzy system has many advantages compared to type-1 and type-2 fuzzy. The advantages and challenges of using type-3 fuzzy logic are identified and discussed. The studies are classified according to the type of control approach, as well as by the type of control applications. Finally, the main achievements, open challenges, and future directions and impacts are identified, to provide important guidance for interested researchers.

Keywords: adaptive control; fuzzy system; machine learning; optimization algorithms; type-1 fuzzy system; type-2 fuzzy system; type-3 fuzzy controller; type-3 fuzzy system

1. Introduction

Fuzzy system is a powerful concept for designing control systems that can handle uncertainties inherent in practical systems and environments. Fuzzy systems started with efforts of authors in [1–5], which introduced the type-1 fuzzy (T1F) systems. These T1F systems have seen many practical applications and have been used in various types of fuzzy controllers [6–12]. Later the author in [13] advanced the field by proposing type-2 fuzzy (T2F) set, for better handling uncertainty. The development of T2F systems started by the efforts of authors in [14–17] and has led to many applications [18–21]. Recently, type-3 fuzzy (T3F) systems have appeared, showing promise for addressing various practical problems, as demonstrated by several recent studies [22, 23]. T3F system is a new concept for modeling systems with large uncertainty. T3F controllers were introduced to deal with the restrictions in T1F and T2F controllers by extending the concept of fuzzy logic to include uncertain variability in the membership functions (MFs) themselves. Unlike T1F controllers, which use fixed MF to represent degrees of truth. T3F controllers include fuzzy sets with fuzzy MFs, enabling them to handle larger levels of uncertainty and imprecision. In the last 5 years, many works were presented in the design of T3F controller for different applications. One of the first researches about T3F system is presented in [23], a new interval T3F system is proposed and the efficacy of the presented approach is tested by simulations and experimental work. Some works use T3F system with optimization algorithm to build an optimal controller [24, 25]. Other works is related to the use of machine learning approach with the T3F system [26, 27]. Also some works present model-based control scheme that use the T3F system to build an estimator with adaptive controller, predictive controller and sliding mode control scheme [28, 29]. Other studies demonstrate the use of IT3F systems in other approaches for different complex applications [30, 31]. They show how IT3F systems improve robustness and accuracy in systems that suffer from uncertainty and external disturbances.

In general, researchers are studying the use of T3FS-based control methods in various applications such as robotics, automotive systems, power systems, and industrial control applications. The results were compared with those using T1F and T2F system, and the proposals using T3FS showed better performance especially in cases with high uncertainty. Overall, these works show that T3FS outperforms traditional fuzzy systems (T1F and T2F), providing opportunities for more efficient control. Its ability to incorporate uncertainty into MFs improves performance, robustness, and efficiency. It allows for efficient handling of nonlinear dynamics, noisy sensors, and environmental disturbances. However, issues of increased complexity and large computational requirements must be taken into account when implementing these controllers in practical systems. Finally, one can say T3F-based controllers are suitable for applications with higher complexity, while T1F-based controllers can be used effectively for simpler systems.

To our knowledge, there have not been many papers reviewing T3F applications in control, just the works in [32, 33], but here we are presenting a more extensive overview of the state of the art. Our review focuses on using T3F systems in control approaches. The review will categorize the current state of researches based on both T3F system –based control approaches and the type of control applications.

Although the purpose of this paper is not to discuss the theoretical principles or how to build and use these systems, we briefly provide a simplified idea of T3F systems, so that interested readers can better understand them. We mainly consider the different control approaches, applications, advantages, current challenges, and future trends. The review will highlight the enhanced capabilities of T3F systems in managing complex and uncertain environments and explore its application in various control problems, including robotics, industrial control, automotive systems, and power systems. In order to attain this aim, a search has been made for documents with "Type-3 Fuzzy Control" term was made on Scopus database and Google Scholar for the years (from 2021 to 2025).

The main contributions of this review are:

a. Explore, study, evaluate, and categorize the current state of researches on using T3F logic in control system.
b. The publications are classified according to the type of control applications. In addition, they are classified according to the T3F system–based control approaches into four categories.
c. The main applications in robotics, industrial, automotive systems, and other applications are discussed, illustrating the efficacy of T3F controllers in various domains.
d. Recent advancements and research trends, including improvement methods and real-time implementation strategies, are discussed.
e. Identify the benefits and challenges and propose solutions to address the challenges.
f. Suggest ideas for future trends. Also future impacts are presented.

This research will cover peer-reviewed articles, books, and chapters in the last 5 years. The article is organized into six sections as shown in Figure 1. The remainder of the article is organized as follows: The methodology and statistical analysis is presented in Section 2. The basic concept of T3F sets is presented in Section 3, The literature review is presented in Section 4. In Section 5, a discussion and future trends is presented, and finally, the conclusion is in Section 6.

2. Methodology and Statistical Analysis

The PRISMA systematic review process was followed to identify studies and narrow down the results for this review. The review process consists of three consecutive steps, namely identification, screening, and eligibility testing. In the first step, papers were identified through Google Scholar and Scopus database searches. A search was conducted for all publications containing the string "Type3 Fuzzy control" in the document title, in the years 2021–2025. The number was 84, including 43 from Google Scholar and 41 from Scopus database search. In the second step, duplicate and nonmatching papers were removed, and after this step, 55 papers were selected. Then in the final step, the eligibility testing step, we removed papers that were not relevant to our topic, and the remaining 52 papers were included in the review. The tables and figures in this part were prepared based on the results of the search on Scopus database. The number of published documents up January 7 2025 was 41. Figure 2 shows the number of documents published each year since 2021. Figure 3 shows the citations number. Figure 2 shows that the search terms first appeared in five publications in the year 2021. Notably, the number of related publications remained relatively modest until 2023, at which there was a significant jump, with the number rising from 5 at 2021 and 9 at 2022 to 16 at 2023 so the path of development is promising. Figure 3 shows the number of citations per year. In 2021, the first five publications on the search terms appeared, with the first 11 citations appearing in 2021. The number of citations is increasing year-on-year, with 95 citations in 2022, 268 in 2023, and 296 in 2024. This large jump in the number of citations is likely due to the growing interest in newly developed systems. Since 2023, a significant increase has been observed, likely due to the growing interest in newly developed systems. The total citations in the search date are 721, and the total citations are expected to grow significantly, likely due to the growing interest in newly developed T3F-based control methods. The results indicate that the total citations in 2025 will significantly exceed previous years, indicating an increase in scientific interest in the topic.

The documents are published in high-impact sources, as shown in Table 1, which includes the seven sources that most publish these documents. Most of these sources are leading

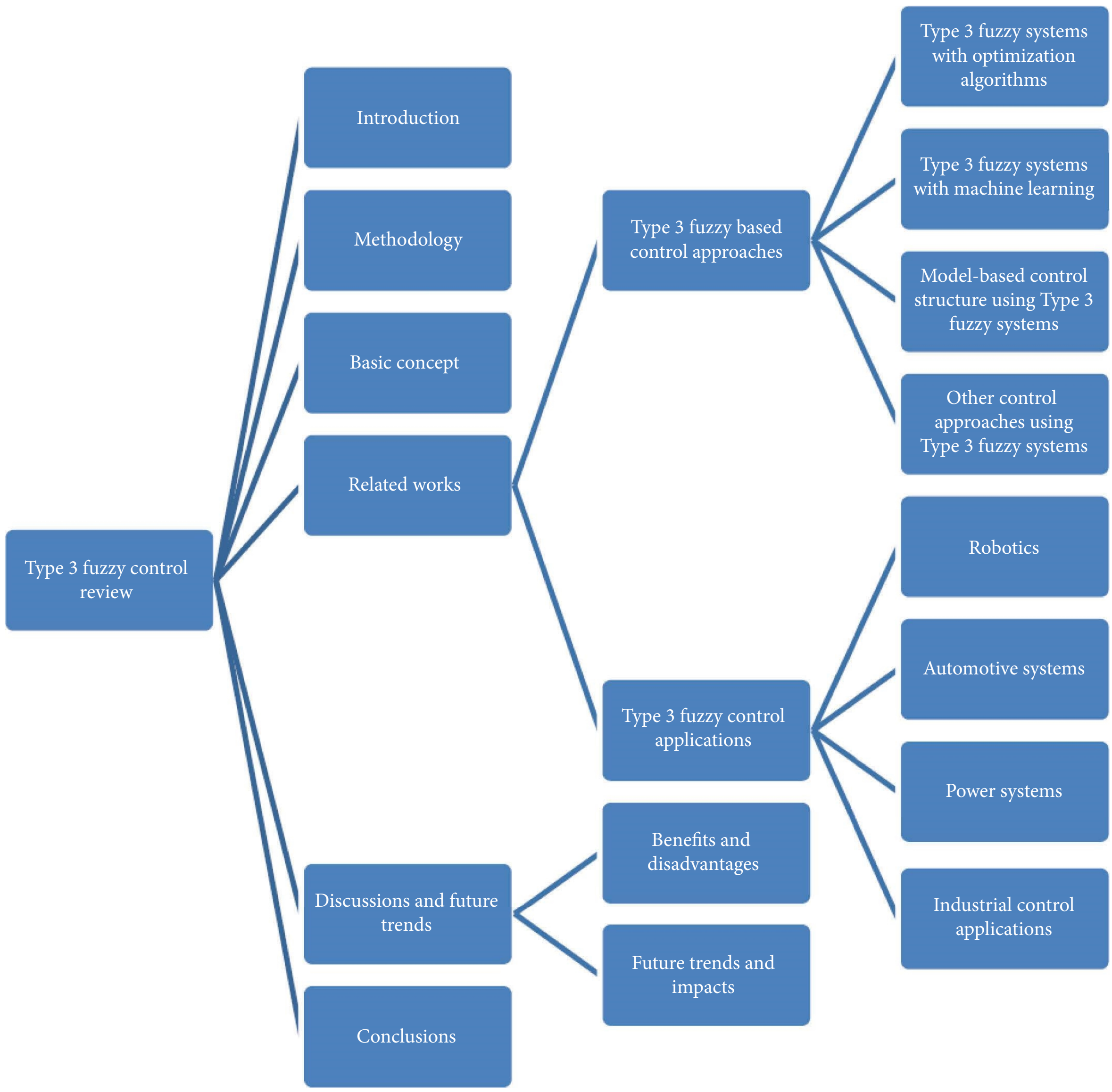

Figure 1: Structure of this review.

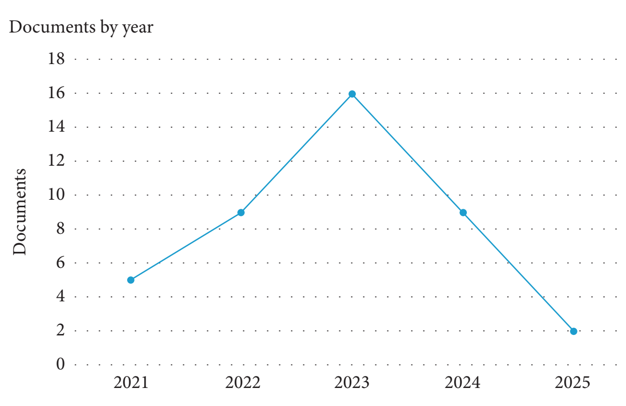

Figure 2: Documents by year.

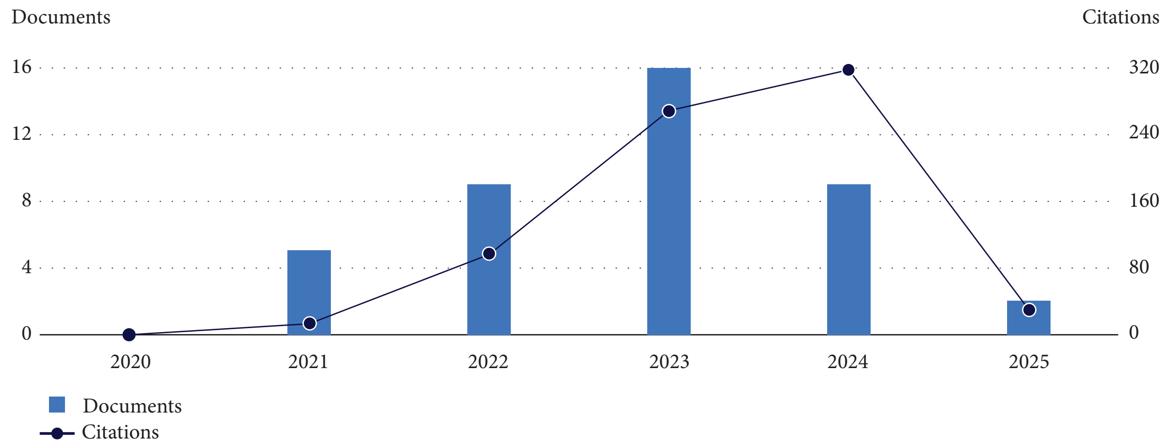

Figure 3: Citation overview.

Table 1: Sources per documents.

Source	Documents
SpringerBriefs in Applied Sciences and Technology	4
Symmetry	4
Complex and Intelligent Systems	3
IEEE Access	3
International Journal of Fuzzy Systems	3
Electronics Switzerland	2
Engineering Applications of Artificial Intelligence	2

first and second quartile sources, published by well-known and reputable publishing houses. Figure 4 shows the list of documents by country. It indicates that the list includes many different countries. Figure 5 shows the names of the scientific institutions and universities of the researchers. It is noted that they are prestigious international institutions, which indicates that this research topic has attracted the attention of many researchers in different countries. Researchers in different parts of the world have become interested in this topic, and we attribute this to the development of science and technology, which necessitates dealing with complex systems in which the presence of T3F logic is necessary and an important solution. Figure 6 shows document by subject area, and Figure 7 shows document types.

3. The Concept of Interval T3F System

A T3F set $B^{(3)}$ is represented by an MF in the Cartesian product $X \times [0, 1] \times [0, 1]$ in $[0, 1]$, where X is the universe of the primary variable of $B^{(3)}$, x. The MF is denoted by $\mu B^{(3)}$ (x, u, v) or simply $(\mu B^{(3)}$ [34].

$$\begin{gathered}\mu_{B^{(3)}} X \times [0,1] \times [0,1] \longrightarrow [0,1],\\ B^{(3)} = \left\{ \left(x, u(x), v(x,u), \mu_{B^{(3)}}(x,u,v)\right) \mid x \in X, u \in U \subseteq [0,1], \quad v \in V \subseteq [0,1] \right\},\end{gathered} \tag{1}$$

where U is the universe for the secondary variable, u, and V is the universe for the tertiary variable v. A T3F set $B^{(3)}$ can be expressed by:

$$\begin{gathered}B^{(3)} = \int_{x\in X}\int_{u\in[0.1]}\int_{v\in[0.1]} \mu_{B^{(3)}}\frac{(x,u,v)}{(x,u,v)},\\ B^{(3)} = \int_{x\in X} \frac{\left[\int_{u\in[0,1]}\left[\int_{v\in[0,1]}\mu_{B^{(3)}}(x,u,v)/v\right]/u\right]}{x},\end{gathered} \tag{2}$$

where $\iiint$ denotes the union over all the admissible x, u, v values.

If $\mu_{B^{(3)}}(x,u,v) = 1$, the set is called an interval T3F set denoted B as in (3).

$$B = \int_{x\in X} \frac{\left[\int_{u\in[0,1]}\left[\int_{v\in\left[\underline{\mu}_B(x,u),\overline{\mu}_B(x,u)\right]}\right]^{1/v}\right]/u}{x}, \tag{3}$$

where

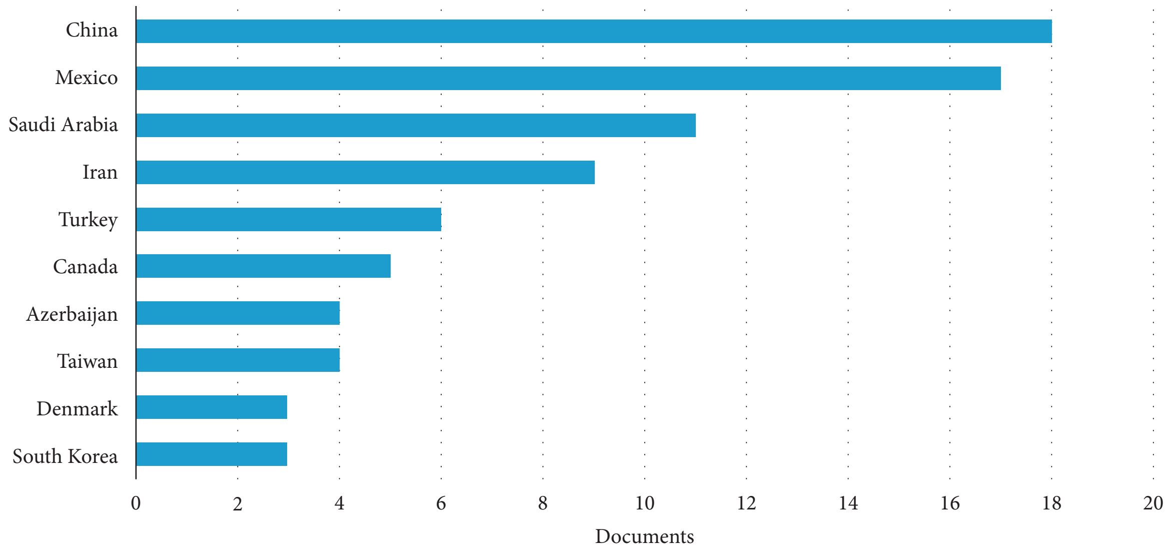

Figure 4: Documents for each country.

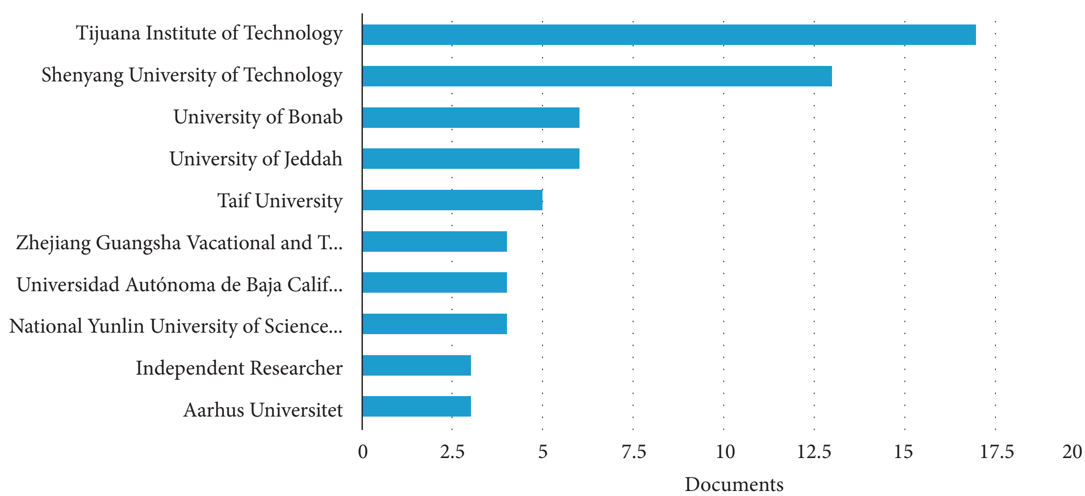

Figure 5: Documents for each institution.

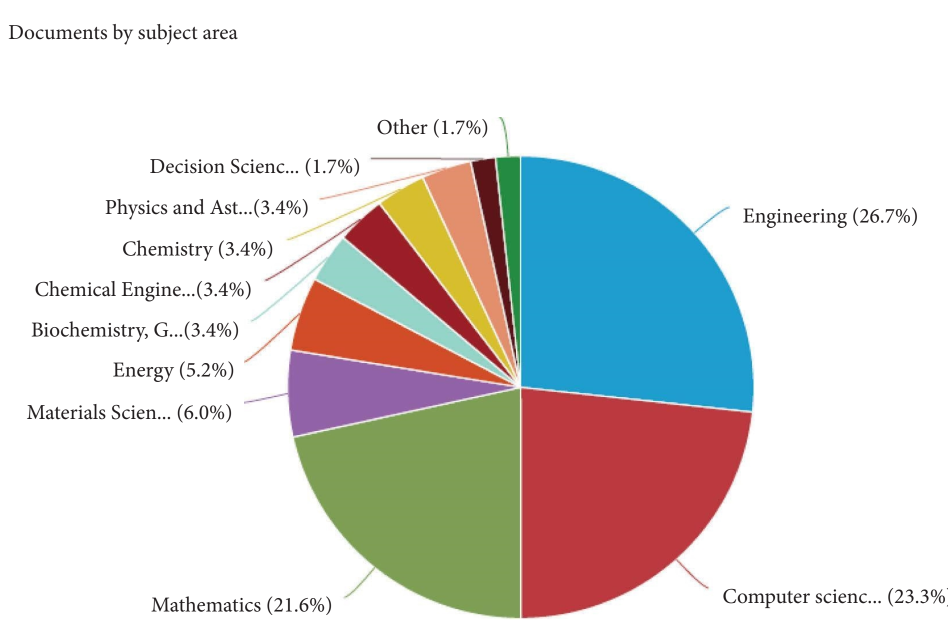

Figure 6: Documents by subject area.

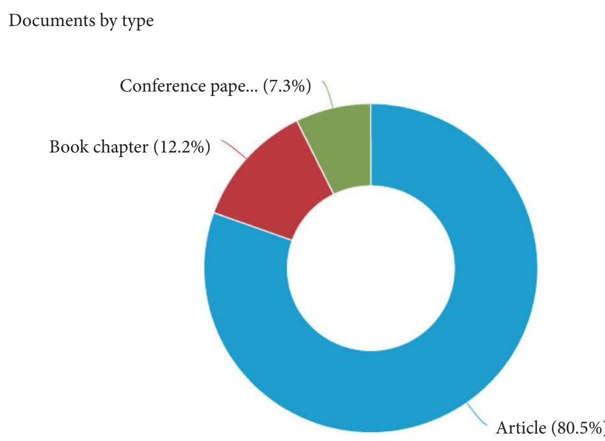

Figure 7: Documents type.

$$\mu_{B_{(x,u)}}(v)\int_{v\in\left[\underline{\mu}_B(x,u),\overline{\mu}_B(x,u)\right]}1/v,$$

$$\mu_{B(x)}(u,v)=\int_{u\in[0,1]}\frac{\left[\int_{v\in\left[\underline{\mu}_B(x,u),\overline{\mu}_B(x,u)\right]}1/v\right]}{u}, \tag{4}$$

$$B=\int_{x\in X}\mu_{B(x)}\frac{(u,v)}{x},$$

Let us assume $v\in[\underline{\mu}_B(x,u),\overline{\mu}_B(x,u)]$

The least and higher MF $\underline{\mu}_B(x,u)$, $\overline{\mu}_B(x,u)$ are general T2 MF in (x, u) coordinates

The interval T3 MF is written as follows:

$$\tilde{\mu}_B(x,u)=\left[\underline{\mu}_B(x,u),\overline{\mu}_B(x,u)\right], \tag{5}$$

and the equation can be written as:

$$B=\int_{x\in X}\int_{u\in[0,1]}\tilde{\mu}_B\frac{(x,u)}{(x,u)}, \tag{6}$$

with $\underline{\mu}_B(x,u)\leq\overline{\mu}_B(x,u)$.

The IT3 fuzzy set described by T2F sets $\underline{B}$ with MF $\underline{\mu}_B(x,u)$ and $\overline{B}$ with MF $\overline{\mu}_B(x,u)$ described by the following equations:

$$\begin{aligned}\underline{B}&=\frac{\int_{x\in X}\int_{u\in[0,1]}\underline{\mu}_B(x,u)/(x,u)=\int_{x\in X}\left[\int_{u\in[0,1]}\left(\underline{f}_x(u)/u\right)\right]}{x},\\ \overline{B}&=\frac{\left(\int_{x\in X}\int_{u\in[0,1]}\left(\overline{\mu}_B(x,u)/(x,u)\right)=\int_{x\in X}\left[\int_{u\in[0,1]}\overline{f}_x(u)/u\right]\right)}{x},\end{aligned} \tag{7}$$

where the secondary MFs of $\underline{B}$ and $\overline{B}$ are T1 MF given by

$$\begin{aligned}\underline{\mu}_{B(x)}(u)&=\int_{u\in J_x}\frac{\underline{f_x}(u)}{u},\\ \overline{\mu}_{B(x)}(u)&=\int_{u\in J_x}\frac{\overline{f}_x(u)}{u}.\end{aligned} \tag{8}$$

In general, the operations and concepts of T3F systems are largely the same as those of T2F systems. The key difference is in the shape of the MF and the corresponding differences in the operations. More information about operations can be found in [27, 32, 35]. The basic stages of the fuzzification process, rule base, inference, type reduction, and defuzzification are largely the same as for a T2F system. The main changes are seen when calculating the firing strengths of the antecedents and consequent parts of the rule base using α-planes. The fuzzification block maps a crisp input vector with multiple inputs into other input T3F sets. These fuzzy sets are also known as input T3F sets. The rule structure of a general T3F system is given by:

$$\text{If } x_1 \text{ is } F_1^i \text{ and} \ldots\ x_n \text{ is } F_n^i \text{ then } y \text{ is } Y^i \text{ where } i=1,\ldots,M. \tag{9}$$

In this rule, x_j is the jth input to the system, F_j^i is the jth input T3F MF, y is the rule output, and Yi is the ith output T3F MF. The inference engine combines rules and considering the calculated firing strengths of the antecedents and consequent parts of the rule base using α-planes, a mapping from input T3F sets to output T3F sets. The output of inference engine is a T3F sets. In addition, vertical-slice representation is used for type reduction of the fuzzy sets. Finally, any defuzzification method results in the crisp output [5, 32, 33, 35–37]. The structure of an interval T3F system in two different forms is shown in Figure 8 [37].

Interested researchers can find more information on concepts, operations, inference, type reduction, and other information related to T3F logic in [19, 34, 36]. MATLAB programs with many examples are also available in [36, 38].

4. Related Works

Several control approaches and applications have been proposed that integrate T3F logic with other techniques. In this section, a review of different control approaches and various applications based on the use of T3F logic is presented. The publications will be classified according to the type of control approach as well as the type of control applications. The most recent innovative techniques are considered in this study. The contribution will be highlighted by discussing the limitations of the related works. This work aims to illustrate the advantages and challenges of T3F logic in different control methods and control applications.

4.1. T3F Systems–Based Control Approaches. The publications are classified into four categories: T3F system with optimization algorithm, T3F system with machine learning approach, model-based control scheme using T3F system, and other control methods using T3F system.

4.1.1. T3F Systems With Optimization Algorithms. The study in [24] presents a hybrid approach using T3F system for the tuning of the parameters of bee colony optimization (BCO) algorithm and using the developed T3F—BCO scheme, to locate the best segmentation of the MF of the T3F Controller for path following in an autonomous mobile robot. Results demonstrate that the proposed control scheme give better performance. The study presents a new hybrid approach combining Interval T3F Logic with BCO for dynamic parameter adaptation and trajectory tracking in autonomous robots. It shows that the developed scheme outperforms other fuzzy systems (T1FS, interval T2FS, and general T2FS) under uncertainty. The use of multiple performance metrics strengthens the analysis, though more details on disturbance modeling would enhance clarity.

The authors in [25] develop a new parameter tuning method for the differential evolution (DE) algorithm. The developed T3F DE algorithm is used in finding an optimal T3F controller for the mobile robot. Results show that the developed controller performs better. The methodology effectively enhances DE through the dynamic adaptation of parameters using interval T3F logic and shows strong promise in improving controller performance in noisy environments. The study in [39] explores using T3F system for parameter tuning in harmony search (HS) algorithms to solve of local minima problem. By employing T3F system, which uses vertical slices for MFs, the approach manages uncertainty more effectively. Experiments demonstrate that this T3F HS enhances solution quality and robustness, especially under disturbance.

In [40], a T3F system is proposed to improve the HS algorithm. T3F system is used for the optimization of parameters in HS algorithms. The research highlights the novelty of applying T3F system with HS in optimizing ball-and-beam fuzzy controllers. This study introduces T3F logic to enhance parameter optimization in the HS algorithm for control problems. Through experiments and statistical comparisons, the research demonstrates the potential advantages of T3F logic over traditional T1 and T2 systems. Further experimentation could strengthen the findings.

The study in [41] presents a hybrid interval T3F system with the DE algorithm to enhance the convergence of DE algorithm. By changing the least Scale (λ) parameter of interval T3F sets, the study aims to enhance DE convergence. Testing with benchmark functions and control of motor shows an improved performance. This article introduces interval T3F sets in the DE algorithm, a new approach in the field. By varying the lower scale (λ) parameter, the study explores how this influences DE's parameter adjustment, aiming to improve convergence. Experiments on benchmark functions and motor control optimization demonstrate that T3F logic enhances DE's performance, outperforming T1F and T2F DE variants, presenting a significant advancement in optimization techniques. Table 2 shows a comparison of methods and techniques used T3F system with optimization algorithm.

These studies highlight the increasing importance of T3F logic in improving the performance of optimization algorithms and control systems. Using interval T3F sets, these studies address uncertainty and dynamic adaptation, and improve algorithms such as DE and HS. Many studies focus on real-world applications, such as robot trajectory tracking and motor control, where T3F logic provides robust performance in noisy and uncertain environments. New ideas such as using Boltzmann machines (BMs) to model errors or dynamically changing parameters further improve accuracy and convergence. In some of these works, Mamdani-type FLS rules are used. Other works use Takagi–Sugeno-type rules. The results are compared with those using T1F, IT2F, and GT2F system, and the proposal using IT3F system shows better performance especially in cases with large uncertainty. Overall, these works demonstrate that T3F logic outperforms traditional fuzzy systems (T1F and T2F), providing opportunities for more efficient control and optimization.

4.1.2. T3F Systems With Machine Learning. The study in [26] presents an interval T3F neural network with an adaptive reinforcement learning (RL) method to enhance the path following of quadrotor unmanned aerial vehicles (UAVs). The combination of an adaptive robust controller with the suggested RL method is proposed to enhance the robustness Stability is achieved by the Lyapunov method. Results show good performance. The presented adaptive RL control method with interval T3F neural networks enhances trajectory tracking for quadrotors in various conditions. It shows robust performance, independent of system dynamics, by using measurable signals. The design ensures stability, accurate tracking, and improved robustness through a high-gain observer and Lyapunov analysis. Simulations show superior performance over conventional methods.

In [27], the authors propose a novel interval T3F neural network–based model predictive control to improve the

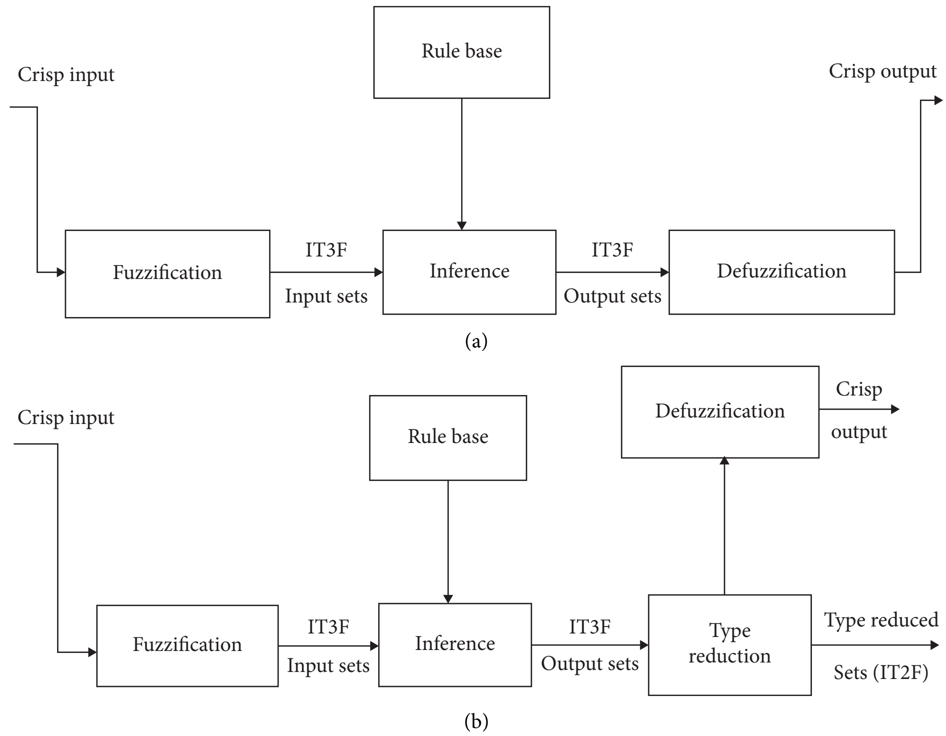

FIGURE 8: The structure of interval T3F system. (a) Direct defuzzification. (b) Type reduction and defuzzification [37].

boost converters implemented in the micro grid and power system distribution. The controller is designed to achieve a fast-transient response of system voltage. The operation of the designed controller is validated by hardware. The proposed controller is designed as a constrained control problem, and its operation is verified by real-time hardware simulations, indicating its practical applicability and effectiveness in power system distribution. The study in [42] presents a path-following scheme for mobile robots using T3F system with BM. The BM is trained with contrastive divergence, and adaptive rules based on a stability theorem train the T3F system. Simulations and real-world tests show the good performance. This study presents an innovative path-following scheme for mobile robots using an intelligent T3F system. The system is particularly designed to handle disturbances and uncertainties. Results demonstrate that the proposed scheme is accurate and robust.

In [43], frequency regulation in power systems is considered. A new dynamic model based on restricted BM and deep learning algorithm is introduced for online identification. The controller is designed by the dynamic estimated model, error feedback controller, and interval T3F compensator. The gains of feedback controller tuning rules are extracted using a fractional-order stability analysis by the linear matrix inequality. This study presents a dynamic fractional-order model for frequency regulation in multiarea power systems. The controller, incorporating an error feedback and interval T3F logic compensator, outperforms T1F and T2f logic under varying conditions, and ensuring stability despite load changes. In [44], a new T3F-based control scheme is developed for micro grids. A learning method is proposed for the online optimization of the controller. The suggested fuzzy-based compensator keeps the robustness in current sharing and voltage balancing. To enhance the accuracy of approximation, a learning method is designed using unscented Kalman filter (UKF). Simulation results show good transient response. The proposed distributed control algorithm uses an interval T3F system and a special learning strategy to improve accuracy. The method ensures voltage convergence and system robustness against uncertainties. Simulation results confirm effective transient response and stability.

In [45], the study introduces a deep-learned T3F system for modeling CO_2 solubility based on temperature, NaCl molality, and pressure. It employs a hybrid learning method and UKF to optimize and adapt the model. The approach, tested with real-world data and compared to conventional fuzzy neural networks, shows high reliability and performance. Sensitivity analysis of input variables is conducted using the Sobol method. The study in [46] proposes a novel data-driven control scheme for micro-electro-mechanical-system (MEMS) gyroscopes using a T3F system with nonsingleton fuzzification to address dynamics uncertainties and input measurement errors. The rules are online tuned to compensate for disturbances. Stability is ensured through a new linear matrix inequalities set, and simulations show the superiority of the proposed scheme compared to others. The proposed data-driven control scheme offers an innovative solution to manage dynamics uncertainties and input errors. Online tuning of fuzzy rules improves disturbance compensation, and the stability is achieved. Simulations show the scheme's effectiveness, demonstrating its

Table 2: T3F system with optimization algorithm.

References	Application	Methods/techniques	Comments
[24]	Mobile control	BCO is adapted by interval T3F to optimize the fuzzy controller	T3F give best results compared with T1F and T2F systems
[25]	Mobile robot	Parameter adaptation of DE to optimize the T3F controller	Good results
[39]	Experiments	T3F system for parameter tuning in HS algorithms	Manages uncertainty more effectively
[40]	Ball-and-beam	T3F for parameter tuning HS algorithms	T3F for parameter tuning HS algorithms
[25]	Experiments with benchmark functions and motor control	Interval T3F system with DE algorithm.	Improves performance compared to T1F and IT2F variants.

superior performance compared to traditional methods in handling real-world uncertainties and measurement errors.

The authors in [47] present an adaptive interval T3F system with deep RL for stabilizing the voltage in 5G base transceiver stations supplying constant power loads. The system addresses the challenges of negative impedance instabilities. Hardware-in-the-loop tests demonstrate the effectiveness of the adaptive interval T3F system for reliable 5G telecom power system operation. The adaptive interval T3F system with deep RL offers a good solution for voltage stabilization in 5G base transceiver stations supplying constant power loads, addressing negative impedance instabilities. This approach ensures reliable operation of 5G telecom power systems, making it a robust and scalable solution for modern telecom infrastructure.

The paper in [48] presents a T3F neural network for dynamic system control, utilizing interval T3F systems and TSK-type fuzzy rules. The T3F neural network employs three-dimensional MFs and Gaussian functions with uncertain centers to handle high uncertainty. The system's design integrates T3F logic with neural networks, and learning is performed using genetic algorithms and gradient descent. Simulations on nonlinear, time-varying dynamic systems demonstrate the effectiveness of the developed scheme in dynamic system control. The proposed system offers a robust solution for dynamic system control, effectively handling high uncertainty with three-dimensional MFs and Gaussian functions. By combining T3F logic with neural networks and using genetic algorithms and gradient descent for learning, the system achieves accurate modeling and control. Simulation results for validate its effectiveness, demonstrating its potential for managing complex, uncertain dynamic systems. Table 3 shows a comparison of methods and techniques used T3F system with machine learning.

These studies highlight the increasing use of T3F logic with machine learning control approaches to solve complex control problems in systems with uncertainty and nonlinearity. These papers demonstrate the superior ability of T3F systems combined with machine learning algorithms to handle high levels of uncertainty compared to traditional T1F and T2F systems. In applications ranging from quad-rotor UAV trajectory tracking, mobile robot path planning, micro grid and power system control to frequency regulation in power systems, CO_2 solubility modeling, gyroscope control, and power system operation control for 5G communications, T3F systems demonstrate improved performance through improved approximation accuracy and robustness. Several papers present advanced control strategies, including T3F logic–based neural network with adaptive RL, T3F logic–based predictive model control, T3F system with BM, T3F system with BM and deep learning algorithm, T3F system with UKF, and online tuning rules for T3F system with linear matrix inequality. These techniques allow to efficiently handle nonlinear dynamics, noisy sensors, and environmental disturbances. Simulations confirm the feasibility and performance of T3F logic–based systems in various applications. Overall, these studies demonstrate the potential of T3F systems in advancing control system design, providing a new direction for future research and practical applications.

4.1.3. Model-Based Control Structure Using T3F Systems. The study in [28] presents a new T3F system–based controller for nonholonomic mobile robot. The T3F systems are used for modeling, and errors in modeling are adopted in stability analysis based on Lyapunov function. A terminal Sliding Mode Controller (SMC) is used to eliminate the effects of error detected by an observer. It is used for mobile robot with good accuracy. The study presents a T3F controller for nonholonomic wheeled robots, addressing control challenges like modeling complexity and disturbances. By integrating an observer and terminal SMC, the method enhances robustness. The results show good accuracy under constraints and nonholonomic uncertainty. However, more detailed performance metrics may be needed to validate this approach.

In [29], the authors introduce a control scheme for autonomous car for path-tracking. It employs an adaptive control system combining fractional-order terminal SMC and a Gaussian nonsingleton T3F system for approximating dynamics. The Lyapunov stability and Barbalat's lemma are adopted to make sure the uniform ultimate boundedness and the convergence of tracking errors. The work presents a robust nonlinear adaptive control framework for high-speed autonomous car path tracking, using a fractional-order terminal sliding mode system and Gaussian T3F system. It ensures robustness against measurement errors and sensor faults. Simulations show good performance in path tracking under uncertainties.

The work in [49] presents a system identification and parameter estimation approach based on T3F logic system to form an online model for the mobile robot dynamics. The model is used to design a model-based control system. A Lyapunov analysis is adopted for stability analysis. Simulations show that the developed control scheme gives good results. This study deals with the control of wheeled mobile robots with nonlinear dynamics and constraints, which is challenging due to system uncertainty. A new T3F system is used to identify the system and estimate the parameters, which leads to the establishment of an online model of the robot dynamics. The optimal supervisor compensates for model errors and dynamics, ensuring stability under constraints. Simulations confirm the effectiveness, providing a promising solution under complex conditions. The study in [50] presents a new control approach for uncertain nonlinear systems with unmodeled dynamics, using interval T3F systems for dynamic fractional-order modeling. The best model is selected, and control signals are designed accordingly.

Stability analysis via linear matrix inequalities guides adaptation laws for interval T3F system parameters. The approach is tested through simulations on hyper chaotic systems, real-time tests on brushless DC motors, and experimental validation on a heat transfer system. The developed control approach effectively handles uncertain

Table 3: T3F system with machine learning algorithm.

References	Application	Methods/techniques	Comments
[26]	Quadrotor unmanned aerial vehicles.	Interval T3F neural network with an adaptive method. Stability is achieved by a Lyapunov method.	Good performance, enhance the path following and robustness.
[27]	Stabilizing power electronic devices.	Interval T3F neural network–based model predictive control.	Effectiveness is confirmed by hardware and simulations
[42]	Path-following scheme for mobile robots.	T3F system with BM. The BM is trained with contrastive divergence, and adaptive rules.	Good performance.
[43]	Frequency regulation in multiarea power systems	Boltzmann machines and deep learning, online identification. Error feedback controller and interval T3F compensator.	Outperforms T1 and T2F controller.
[44]	Current sharing and voltage balancing in direct current micro grids.	Interval T3F system and a learning strategy with a correntropy unscented Kalman filter (CUKF)	Ensures voltage balance, accurate transient response, and robustness
[45]	A modeling CO2 solubility based on temperature, NaCl molality, and pressure	A deep learned T3F system model. Hybrid learning method and unscented Kalman filter.	Shows high reliability and performance.
[46]	Data-driven control scheme for MEMS gyroscopes.	Rules are online tuned to compensate for disturbances. Stability is ensured by new linear matrix inequalities.	Offers an innovative solution to manage dynamics uncertainties and input errors
[47]	Stabilizing the voltage in 5G base transceiver stations	Interval T3F system with deep reinforcement learning	A robust and scalable solution for modern telecom infrastructure.
[48]	T3F neural network TSK-type fuzzy rules.	Integrates T3F logic with neural networks, and learning is performed using genetic algorithms and gradient descent	Offers a robust solution for dynamic system control, effectively handling high uncertainty with three-dimensional membership functions and Gaussian functions

nonlinear systems with unmolded dynamics. Its robustness is demonstrated through simulations on complex systems like the Lorenz and brushless DC motor models, as well as experimental tests on a heat transfer system. The method shows promise for real-world applications, offering adaptability and stability in difficult, dynamic environments.

The study in [51] introduces a new control idea based on T3F system. The T3F system is adopted for the estimation of the dynamics of robot manipulator and the perturbations. The online learning law is used to improve the stability. Results show good performance. The work investigates the control of robotic manipulators, focusing on their nonlinear dynamics, multi-input-multi-output nature, and uncertainties like friction and disturbances. To address these challenges, the authors propose using T3F systems, which improve accuracy in noisy environments. The T3F system estimates the dynamics and perturbations, with online learning to enhance stability. A compensator is introduced to address estimation errors. In [52], a T3F system compensates for dynamic identification errors and is tuned using a sliding mode control strategy. The approach enhances modeling accuracy and robustness, with simulations showing that the optimized T3F system and the SMC maintain stability and accurate trajectory following for the UAV despite uncertainties and perturbations. The work addresses limitations in ensuring stable flight and precise control of UAV in adverse conditions. It proposes an adaptive model identified from input/output data, with new adaptation laws for dynamic parameters. A T3F system compensates for dynamic identification errors and is tuned using SMC approach. Simulations demonstrate that the system ensures robustness, accuracy, and stability, even under uncertainties and perturbations.

In [53], the study introduces a model-based predictive control approach for MEMS gyroscopes utilizing fractional-order operations and interval T3F systems. It addresses unknown dynamics, faults, and disturbances with two interval T3F systems for online modeling and error prediction, optimized by Lyapunov rules. The scheme demonstrates superior tracking accuracy, performance, and robustness compared to other controllers, even under dynamic perturbations and actuator nonlinearities. The work proposes a nonlinear model–based predictive control scheme for MEMS gyroscopes using fractional-order arithmetic and T3F interval systems. The method effectively models uncertainty, compensates motor errors, and ensures stability. Simulation results demonstrate strong tracking accuracy, outperforming other controllers in dealing with dynamic disturbances and motor nonlinearity.

In [54], the study presents a new observer-based control approach with interval T3F systems to improve approximation of uncertainties and complex nonlinear systems. An adaptive compensator enhances robustness and reduces errors in approximation. Lyapunov function and Barbalat's lemma are adopted for stability analysis. Simulations and experiments show the approach provides accurate model approximation and robust performance against uncertainties and parameter variations. The study in [38] explores interval T2F, generalized T2F, and interval T3F systems. It highlights differences among these fuzzy sets. The research includes examples like online identification and robotic control, with simplified computations and derivative equations for adaptation. Simulation results demonstrate that the Matlab tools offer simplified computations and perform well, enhancing interval T3F logic applications.

The study in [55] enhances synchronization and management of chaotic systems for mobile robots in secure path-tracking applications. The main innovations include a robust fractional-order predictive controller with T3F systems error compensation, and online tuning for stability. Practical implementation and simulations demonstrate the controller's effectiveness, accuracy, and robustness in real world, addressing uncertainties and dynamic perturbations.

The study in [56] presents a robust T3F controller designed to enhance path-tracking and lane-keeping efficiency for driverless cars under critical conditions and disturbances. The proposed controller operates independently of parameter information, addressing unknown and nonlinear system dynamics. It improves robustness by eliminating error bounds and ensures stability through Lyapunov stability theorem and Barbalat's lemma. Additionally, a nonlinear predictive control technique enhances lateral displacement. Results show the effectiveness in various road conditions and uncertainties, demonstrating good performance in path-tracking tasks. The study in [57] addresses the path-following of an under-actuated surface vehicle using an interval T3F system. The interval T3F system improves upon singleton fuzzy controllers by better handling uncertainties and disturbances. It employs surge-guided line of sight for surge and heading control, and uses predictive compensators to reduce approximation errors. Stability is analyzed with Lyapunov theory and Barbalat's lemma. Simulations confirm the effectiveness of the proposed strategy in solving path-following problems.

The article in [58] explores stability in fuzzy control by extending the fuzzy Lyapunov approach, initially used for T1F control, to T2 and then to T3F controllers. The proposed method ensures stability in T3F systems. As a case study, a robotic manipulator is used to illustrate the approach. The results highlight the potential of the T3F Lyapunov extension for advancing stability in fuzzy control applications. The article effectively advances stability in fuzzy control by extending the fuzzy Lyapunov approach from T1 to T2 and ultimately to T3F controllers. The method maintains stability while enhancing control flexibility. The case study on a robotic manipulator demonstrates the approach's practical applicability, offering valuable insights into the potential of T3F systems for more robust and stable control solutions in complex systems. The study in [59] presents a new interval T3F fuzzy system combined with an online learning for power control and battery management in photovoltaic/battery systems. It addresses fully unknown dynamics and variable conditions like temperature and load. Using Lyapunov/LaSalle's theorems, the method ensures robustness and stability, with new tuning rules and compensators for approximation errors. Comparisons show superior performance under challenging conditions, outperforming established methods. The proposed method provides a robust solution for power control and battery management, addressing unknown dynamics and environmental variations. The performance of this method outperforms existing methods, especially under severe conditions such as temperature and load variations. Table 4 shows a comparison of methods and techniques used T3F system with model-based approaches.

These studies highlight the increasing use of advanced model–based control technique using T3F logic to solve complex control problems in systems with uncertainty, nonlinearity, and time delays. These papers illustrate the good ability of T3F systems to handle high levels of uncertainty compared to traditional T1F and T2F systems. In applications ranging from financial system modeling and chaotic mobile robot path planning, UAV control to autonomous car path tracking, robot manipulator control, and automation control, T3F systems show improved performance through enhanced approximation accuracy, robustness, and adaptability. Several papers present advanced control strategies, including inverse adaptive controllers, sliding mode control, hybrid controllers, and predictive control laws, along with T3F systems for real-time tuning and error compensation. These techniques allow for effective handling of nonlinear dynamics, noisy sensors, and environmental disturbances. Also Lyapunov function and Barbalat's lemma are adopted for stability analysis in several works. Simulations and real-world applications confirm the feasibility and performance of T3F logic–based systems in various applications. Overall, these studies demonstrate the potential of T3F systems in advancing control system design, providing a new direction for future research and practical applications.

4.1.4. Other Control Approaches Using T3F Systems. In [30], the paper introduces a T3F system–based controller for chaotic financial systems, employing Riccati equation solutions for optimality and robustness. New learning rules enhance error minimization and system stabilization. The proposed approach shows superior performance in various financial benchmarks.

In [31], the paper introduces a new fuzzy control strategy using interval T3F system to generate limit cycles for nonlinear systems with unknown uncertainties. The strategy improves closed-loop response quality and robustness through adaptive backstepping control. The study in [60] introduces a new control scheme for economic efficient autonomous road vehicles using interval T3F systems to tackle uncertainties and perturbations in lateral path-tracking. Key innovations include handling uncertainty with fuzzy sets, compensating errors with advanced compensators, and estimating uncertain error bounds with adaptation laws. The controller ensures stability under dynamic conditions and outperforms traditional fuzzy approaches in maneuvering performance.

In [61], the authors introduce an interval T3F PID controller, using a type reduction algorithm from general T2F sets. Tested on nonlinear plants, this controller outperforms traditional PID and other fuzzy PID controllers in terms of control performance. It also shows promising results in controlling the output c, demonstrating its robustness and effectiveness in handling complex, nonlinear systems. In [62], the authors introduce a new T3F system for maximum power point following in photovoltaic system for enhancing tracking efficiency. The T3F controller is applied to a PV module with a DC–DC buck converter to efficiently extract maximum power while protecting battery lifespan. Compared to T1 and T2F controllers, T3F controller shows superior performance in simulations and experiments under various weather conditions, demonstrating better stability and robustness.

The study in [63] introduces a method for constructing interval T3F system which involves constructing an interval T3F system with uncertain T2F nonsingleton set and training using gradient descent. It is applied to predict surface temperature in a hot strip mill. The method demonstrated superior stability and performance compared to similar approaches. The aim of the study in [64] is to show the advantages of T3F system in a quality control. The authors develop a new approach that combine T3F system with fractal theory and use it for sound speaker quality control. A quality control application in speaker manufacturing is used to demonstrate the potential of T3F sets combined with fractal theory, outperforming previous methods. Simulation results show good performance.

This study in [65] proposes using meditative fuzzy logic (MFL) in control problems where contradictory expert knowledge exists. MFL integrates multiple experts' insights into fuzzy controller design, aiming to enhance control outcomes. The study introduces an MF control architecture for T1F logic and extends it to T2 and T3F logic. The analysis shows that T3 MFL outperforms T2 and T1 MFL in managing uncertainties and noise in control processes. The study in [66] addresses the consensus problem in multiagent systems (MASs) with time delays. It develops a T3F logic system to manage these uncertainties and design a new control scheme. The control scheme uses signals to stabilize approximation and consensus errors, with constrained control laws updated at each time step based on model predictive control. Simulations demonstrate the convergence, and effective transient response.

This study in [67] evaluates interval T3F systems for stabilizing nonlinear plants under perturbations. Interval T3F systems are compared with T1, interval T2, and generalized T2F systems using vertical slices for result approximation. Simulations demonstrate that interval T3F systems deliver superior performance in control problems.

The paper [68] presents a predictive controller using T3F system to regulate blood glucose levels in type 1 diabetic patients. The system estimates the unknown glucose dynamics online, enhancing accuracy in uncertain conditions. It includes a predictive controller and adaptive compensator, with stability ensured through Lyapunov analysis. The method is tested under various uncertainties and compared with other established approaches, showing superior performance in managing glucose regulation. The proposed control scheme offers a robust solution for regulating blood glucose, effectively handling uncertainty in glucose dynamics. By integrating online estimation, adaptive compensation, and Lyapunov stability analysis, the system

Table 4: Model-based control structure using T3F systems.

References	Application	Methods/techniques	Comments
[28]	NH wheeled robot	T3F system for modeling, an observer is designed to detect the error, and its effect is eliminated by a developed terminal SMC.	Good accuracy
[29]	Autonomous cars	Nonlinear adaptive control system combining (fractional-order terminal sliding mode and a Gaussian T3F system)	Strong performance
[49]	Mobile robot	T3F is used to form an online model for the mobile robot dynamics. Lyapunov is adopted for stability analysis.	Good results.
[50]	Brushless DC motor	Interval T3F systems for dynamic fractional-order modeling. Stability analysis via linear matrix inequalities. Tested through simulations and real-time tests on brushless DC motor	Shows promise for real-world applications.
[51]	Robot manipulator	Model-based T3F systems to estimate dynamics and perturbations.	Enhanced performance
[52]	Trajectory following for the unmanned aerial vehicles.	T3F system compensates for dynamic identification errors and is tuned using a SMC strategy.	Enhances accuracy and robustness.
[53]	For micro-electro-mechanical-system gyroscopes	A nonlinear model–based predictive control scheme using fractional-order and interval T3F systems	Superior tracking accuracy, and robustness
[54]	Complex nonlinear systems.	Observer-based control approach with interval T3F systems. Lyapunov function and Barbalat's lemma are adopted for stability analysis.	Accurate model approximation and robust performance.
[38]	The research includes examples like online identification and robotic control.	Explores interval T2F, generalized T2F and interval T3F systems. With simplified computations and derivative equations for adaptation.	Simulation results show that the MATLAB tools perform well, enhancing.
[55]	Synchronization and management of chaotic systems for mobile robots in secure path-tracking applications	Good accuracy, and robustness in real world, addressing uncertainties and dynamic perturbations	Good accuracy, and robustness in real world, addressing uncertainties and dynamic perturbations
[56]	Driverless cars	Robust T3F controller to enhance path-tracking and lane-keeping efficiency. Lyapunov stability theorem and Barbalat's lemma. Predictive control	Strong performance
[57]	Under-actuated surface vehicle, interval T3F system	Predictive compensator to reduce approximation errors. Stability is analyzed with Lyapunov theory and Barbalat's lemma.	Simulations confirm the effectiveness of the proposed strategy in solving path-following problems.
[58]	Robotic manipulator. Extending the fuzzy Lyapunov approach from T1 to T2 and ultimately to T3 fuzzy controllers.	The article effectively advances stability in fuzzy control by extending the fuzzy Lyapunov approach from T1 to T2 and ultimately to T3 fuzzy controllers. The method maintains stability while enhancing control flexibility.	The case study demonstrates the approach's practical applicability, offering valuable insights into the potential of T3F systems for more robust and stable control solutions.
[59]	Photovoltaic/battery hybrid systems	Interval T3F system with an online learning approach and Lyapunov/LaSalle's theorems	Superior performance

ensures reliable control. The study in [69] introduces a novel approach for MASs using T3F systems to approximate agent dynamics. It provides event-triggered conditions to ensure stability with minimal actuator use and develops new tuning rules for T3-FLSs. Adaptive compensators address perturbations, actuator failures, and errors. Simulations show effective convergence to the leader agent and highlight the event-triggered scheme's efficiency, updating actuators 20%–40% of the time.

The study in [70] develops a new T3F control for the chaotic systems. The uncertainty and perturbation are approximated by an online method and using adaptive compensator. The rules of T3F system are optimized by the Lyapunov theorem. This article presents a robust T3F control scheme for chaotic systems, addressing issues like dynamic uncertainties, and unknown perturbations. The T3F controller uses online estimation and Lyapunov optimization to handle approximation errors and actuator nonlinearities. Simulation results show good performance.

The work in [71] presents a method that uses interval T3F system to automate quality control in manufacturing. The paper explores T3F logic for surface quality control in material manufacturing. The method, using surface roughness and porosity, demonstrates that T3F systems can outperform T1 and T2F in automating surface quality control. In [72], the authors introduce an intelligent system using T3F logic for automating image quality tuning in televisions. By applying interval T3F fuzzy logic, the system aims to achieve production quality standards efficiently. The approach optimizes image quality and automates the tuning process on production lines. Simulation results are promising, and validation against human experts confirms the efficacy of this T3F method for image tuning.

In [73], the authors introduce the T3F system for the control of dynamic plants, considering the limitations of deterministic models in handling uncertainties. Through adopting T3 MF, T3F system enhances uncertainty modeling. The inference mechanism of T3F system is developed using α slices and interval T3F MFs. The developed T3F system is utilized for controlling nonlinear dynamic plants. Simulation result shows efficient performance. The article in [74] presents a design method for an artificial pancreas for the regulation of blood glucose in type 1 diabetes and addressing sensor faults. It uses a T3F predictive controller with fuzzy identifier, adaptive compensator, and a virtual dynamic to identify sensor faults. Lyapunov stability ensures system stability. Evaluation is done using Bergman's minimum model under various uncertainties. The proposed design method effectively addresses blood glucose regulation in type 1 diabetes by incorporating a T3F predictive controller, adaptive compensator, and sensor fault detection. The use of Lyapunov stability ensures system robustness. Evaluation with Bergman's model demonstrates the effectiveness for real-time glucose control. Table 5 shows a comparison of methods and techniques used T3F system with other control approaches.

These studies explore the use of interval T3F systems in various complex applications. They demonstrate how interval T3F improves robustness and accuracy in systems that suffer from uncertainty and external disturbances. The studies cover areas such as trajectory tracking of autonomous vehicles, control of under-actuated surface vehicle voltage balancing in micro-DC networks, mobile robotics, material manufacturing for surface quality control, sound speaker quality control, consensus problem in MASs, blood glucose regulation in type 1 diabetes patients, automation of quality control in manufacturing, and in the design of artificial pancreas for the regulation of blood glucose. By outperforming T1F and T2F systems, IT3F proves to be highly effective in handling dynamic, nonlinear, and uncertain environments. These works highlight the growing potential of interval T3F systems in various engineering fields that require precise and reliable control.

4.2. Applications of T3F Systems–Based Control Approaches. Publications will be categorized into four categories: robotics, automotive systems, power systems, and industrial control applications.

4.2.1. Robotics. T3F controllers are increasingly utilized in robotics to manage the uncertainties associated with dynamic environments and complex tasks. The study in [24] develops a method to improve the BCO algorithm for trajectory tracking in mobile robots by using an interval T3F system. In [25], the authors develop a new parameter adaptation method for the DE algorithm. The developed T3F DE algorithm is used in finding an optimal T3F controller for the mobile robot. In [28], the authors develop a T3F system–based control scheme with observer and SMC for nonholonomic wheeled robots. The authors in [42] introduce an advanced T3F system for path following of mobile robots. It integrates error measurement signals to handle disturbances and uncertainties with a BM predicting compensatory actions. Simulations and real-world tests illustrate good robustness and high accuracy.

The work in [49] presents a system identification and parameter estimation approach based on T3F system to form an online model for the mobile robot dynamics. Simulations demonstrate that the developed control scheme yields good results. The study in [51] introduces a new control scheme based on T3F system for the robot manipulator. Results show good performance. The study in [38] includes examples like online identification and robotic control, using interval T3F system. Simulation results demonstrate that the Matlab tools perform well, enhancing IT3F logic applications. The study in [55] enhances synchronization and management of chaotic systems for mobile robots in secure path-tracking applications a robust fractional-order predictive controller with T3F systems.

4.2.2. Automotive Systems. The automotive industry benefits greatly from T3F controllers, particularly in systems that require adaptive and precise control in dynamic environments. The study in [26] presents a novel control method combining adaptive RL with interval T3F neural networks for quadrotor UAV trajectory tracking. In [29], the authors introduce a control scheme for autonomous car for path-tracking. It employs an adaptive control system combining with fractional-order terminal SMC and a Gaussian non-singleton T3F system for approximating dynamics.

The study in [56] presents a robust T3F controller designed to enhance path-tracking and lane-keeping efficiency for driverless cars under critical conditions and disturbances. The study in [57] addresses the path-following of an under-actuated surface vehicle using an interval T3F system. Simulations confirm the effectiveness of the proposed control strategy. The study in [60] introduces a new control scheme for economic efficient autonomous road vehicles using interval T3F systems to tackle uncertainties and perturbations in lateral path-tracking.

4.2.3. Power Systems. The study in [27] proposes a novel interval T3F neural network–based model predictive control to improve the boost converters implemented in the micro grid and power system distribution. The study in [43] addresses frequency regulation in power systems incorporating demand response, and renewable energy sources, with unknown dynamics. A new dynamic fractional-order model with restricted BMs and deep learning for online identification is proposed. The controller combines this model with an error feedback and an interval T3F. The presented optimized control scheme outperforms T1 and T2F systems under various conditions. The study in [59] presents a new interval T3F system combined with an online learning for power control and battery management in photovoltaic/battery systems. In [61], the authors introduce an interval T3F-PID controller, using a type reduction algorithm from general T2F sets. Tested on nonlinear plants, it also shows promising results in controlling the output voltage of solid oxide fuel cells. In [62], the authors introduce a new T3F system for maximum power point following in photovoltaic system for enhancing tracking efficiency.

4.2.4. Industrial Control Applications. In [45], the study introduces a deep-learned T3F system for modeling CO_2 solubility based on temperature, NaCl molality, and pressure. In [53], the study introduces a model-based predictive control approach for MEMS gyroscopes utilizing fractional-order operations and interval T3F systems. The study in [62] introduces a method for constructing an interval T3F system with uncertain T2F nonsingleton set and training using gradient descent. It is applied to predict surface temperature in a hot strip mill. The work in [63] develops a new approach that combines T3F system with fractal theory and uses it for sound speaker quality control. In [71], the authors introduce an intelligent system using T3F system for automating image quality tuning in televisions. By applying interval T3F fuzzy logic, the system aims to achieve production quality standards efficiently.

5. Discussions and Future Trends

From the results of studying the related works, one can notice that the performance of T3F controller is better than that of T1F and T2F controllers. In general, T3F controllers come up with several advantages in handling complex, uncertain environments in many applications. Their ability in managing uncertainties in MFs results in an improved performance, robustness, and efficiency. However, the increased complexity and computational needs should be considered when implementing these controllers in practical systems. T3F controllers are best suited for applications with higher complexity, and T1F controllers remain effective for simpler systems. The field of T3F controller is growing rapidly, with big advancements in the development of new algorithms, in addition to the integration with machine learning and optimization algorithms in new applications. Regardless of the challenges in computational efficiency, current development is opening the way for more sophisticated control systems. Future directions indicate a good horizon for T3F controllers in the near future.

5.1. Benefits and Disadvantages of T3F Controller. T3F logic offers significant advantages in dealing with uncertainty and complexity in control systems, but these benefits come at the cost of increased complexity and computational demands. The choice to use T3F logic should be carefully considered based on the specific requirements of the application. T3F logic can be particularly useful in control systems, but it comes with both benefits and disadvantages.

In fact, if the problem of the large computational requirements of T3F controllers can be solved using improved algorithms or better computational tools, the use of these controllers in systems with large uncertainties is promising. As technology develops, it is natural to see an increase in the applications of these advanced controllers.

5.1.1. Benefits of T3F Controller

1. Efficient handling of uncertainty: T3F logic can model more complex uncertainties than T1F logic. It allows for better representation of imprecision and ambiguity in the system.
2. Improved decision making: T3F logic can lead to more robust decision making in uncertain environments.
3. Better performance in complex systems: In complex systems with highly variable inputs or dynamic behaviors, T3F logic can provide a more flexible and adaptive control strategy.
4. Robustness: T3F systems can maintain performance in the presence of noise and disturbances, making them suitable for real-world applications where conditions may change unexpectedly

Table 5: Other control approaches using T3F systems.

References	Application	Methods/techniques	Comments
[57]	Under-actuated surface vehicle	Interval type-3 fuzzy logic controller predictive compensators, Lyapunov theory and Barbalat's lemma	Effective results
[30]	Financial benchmarks	T3F system–based controller for chaotic financial systems, employing Riccati equation.	Shows superior performance
[31]	Generate limit cycles	Interval T3F system to generate limit cycles for nonlinear systems with unknown uncertainties. The strategy.	Improves response quality and robustness through adaptive backstepping control.
[60]	Autonomous road vehicles	Interval T3F controller	Outperforms traditional fuzzy approaches.
[61]	Output voltage of solid oxide fuel cells	Interval T3F PID controller	Outperforms traditional PID and other fuzzy PID.
[62]	Maximum power point tracking	T3F logic algorithm	Superior performance
[63]	Surface temperature in a hot strip mill	Constructing IT3 systems using level-alpha-0 and Gaussian modeling for rule base.	Superior stability and performance
[64]	Sound speaker quality control	Interval T3F system with fractal theory.	Superior performance over T1F and T2F.
[65]	Introduce MFL in control problems.	MFL integrates multiple experts' insights into fuzzy controller design, aiming to enhance control outcomes.	It shows that T3 MFL outperforms T2 and T1 MFL in managing uncertainty and noise in control processes.
[66]	Consensus problem in multiagent systems with time delays	Design a new control scheme using T3Flogic to stabilize approximation and consensus errors, based on model predictive control.	Simulations demonstrate the convergence, and effective transient response.
[67]	Interval T3F systems for stabilizing nonlinear plants	Stabilizing nonlinear plants under perturbations. Interval T3F systems are compared with T1F, interval T2F, and generalized T2F systems.	Simulations demonstrate that interval T3F systems, deliver superior performance in control problems.
[68]	Predictive controller using T3F system to regulate blood glucose levels in type 1 diabetic patients.	The system estimates the unknown glucose dynamics online. It includes a predictive controller and adaptive compensator, with stability ensured through Lyapunov method.	Superior performance offers a robust estimation, adaptive compensation and ensures reliable control.
[69]	Using T3F systems to approximate agent dynamics in MAS.	It provides event-triggered conditions to ensure stability with minimal actuator use and develops new tuning rules for T3F systems.	Simulations show effective convergence to the leader agent and highlight the event-triggered scheme's efficiency.
[70]	T3F control for the chaotic systems.	The uncertainty and perturbation are approximated by an online method. The rules of T3F system are optimized by the Lyapunov theorem.	Simulation results show good performance.
[71]	Automate surface quality control in manufacturing.	Uses interval T3F system to automate surface quality control.	Interval T3F approach outperforms T2F and T1F in surface quality control.
[72]	Automating image quality tuning in televisions.	Using T3F logic for automating image quality tuning in televisions. The approach optimizes image quality and automates the tuning process.	Simulation results are promising, and validation against human experts confirms the efficacy.
[73]	T3F system for the control of dynamic plants.	Using α slices and interval T3F membership functions. The developed T3F system is utilized for controlling nonlinear dynamic plants.	Simulation result shows efficient performance.
[74]	Design of an artificial pancreas for the regulation of blood glucose in type 1 diabetes.	Use T3F predictive controller with fuzzy identifier, adaptive compensator and a virtual dynamic. Lyapunov stability ensures system stability.	Effectively addresses blood glucose regulation. Evaluation with Bergman's model shows the effectiveness for real-time, glucose control.

5.1.2. Disadvantages of T3F Controller

1. Increased complexity: T3F controllers are more complex to design and implement than T1F controllers, requiring more sophisticated algorithms and computational resources.
2. Higher computational load: The calculations involved in T3f systems can be more intensive, resulting in longer processing times, which can be critical in real-time applications.
3. Real-time implementation difficulty: The computational burden may limit the practical real-time implementation of T3F controllers, especially in systems that require fast responses.

5.2. Future Trends and Impacts. The field of T3F control is open for further research and development and here are many potential areas for future directions that have the potential to impact various areas of modern life.

5.2.1. Development of More Efficient Algorithms. The development of more efficient algorithms for T3F controllers reduces computational complexity and improves real-time performance. This includes advancements in inference mechanisms, type reduction methods, and defuzzification methods.

5.2.2. Optimization of T3F Controller. The automation of the selection process of MFs, number of rules, and defuzzification method through optimization is a good future work. The optimization of all parameters (rule parameters and MF parameters) of T3F controller must be considered in alignment with [23, 73].

5.2.3. Fuzzy Hierarchical Systems. The main objective of fuzzy hierarchical systems is to use several interconnected low-dimensional fuzzy systems to form a high-dimensional system, thereby reducing complexity and computational load, in alignment with [75].

5.2.4. Integrating T3F Controllers With Modern Techniques. Study of the idea of the integration of T3F controllers with quantum computing, artificial intelligence, and advanced machine learning algorithms enhances their capabilities.

1. T3F control can take advantage of quantum fuzzy logic, allowing for faster computing.
2. Better handling of uncertainty in T3F systems can help address incomplete or noisy data in modeling and learning process, leading to more efficient modeling and learning in autonomous systems.

5.2.5. Increase Computation Speed. To increase the speed of computation, field programmable gate arrays (FPGAs) have been increasingly utilized. They are considered as an effective tool for real-time hardware method. It can solve the computation time problem. Modern efficient FPGAs can be used for the implementation of T3F controller in the near future. The ability of T3F control to handle more complex uncertainty indicates great potential for future impact in various fields.

T3F control technology has the potential to impact a variety of areas of modern life by offering a more robust and adaptive approach to managing uncertainty in complex systems. As the technology advances, it could play a critical role in areas ranging from Internet of Things (IoT), smart cities to healthcare, autonomous systems, and more, providing control systems with the ability to deal with the uncertainty and variability of real-world conditions. However, it will require overcoming the complexity problem and improving computational efficiency to ensure simplicity for widespread application. For example, in medical diagnosis, T3F systems can be used to interpret medical data that is often noisy, inaccurate, or incomplete, and can then enhance the accuracy of medical predictions. Data ambiguity from IoT devices for different applications can also be effectively handled using T3F systems, leading to improved performance [11].

6. Conclusion

The use of T3F logic–based controller is rapidly increasing in different applications. T3F logic extends the traditional fuzzy logic concept by incorporating an additional layer of fuzziness in MFs, which allows for more accurate handling of uncertainties and imprecisions. The purpose of this review is to explore, study, evaluate, and categorize the current state of researches on T3F logic–based control methods. The researches are classified first based on the type of control approach used, and then on the type of control applications. Finally, the review considers future directions for research and development. We presented the concept of T3F controllers, including their applications in various fields such as robotics, automotive systems, industrial control, and power system. T3F system–based control schemes show better results when compared with T1F- and T2F-based controllers in terms of accuracy and robustness. The development of more efficient algorithms for T3F controllers to reduce computation time may solve the computational complexity problem in T3F–based control system and improve real-time performance. The latest innovative technologies developed in this context have been demonstrated and discussed, and some emerging trends for future works are suggested.

Data Availability Statement

The authors have nothing to report.

Conflicts of Interest

The authors declare no conflicts of interest.

Author Contributions

The authors declare that the study was realized in collaboration with equal responsibility. All authors read and approved the final manuscript.

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