

# Survey on the Recent Design and Tuning Approaches for model-free Fuzzy PID/PI Controllers

Kamran Sabahi<sup>1</sup>, Ardashir Mohammadzadeh<sup>2</sup>, Mehdi Tavan<sup>3</sup>, Amir A. Ghavifekr<sup>4</sup>

<sup>1</sup> Department of Engineering Sciences, Faculty of Advanced Technologies, University of Mohaghegh Ardabili, Namin, Iran.

<sup>2</sup>Department of Electrical and Electronic Engineering, Sakarya University, Sakarya, Turkiye.

<sup>3</sup>Department of Electrical Engineering, Nour branch, Islamic Azad University, Nour, Iran.

<sup>4</sup>Faculty of Electrical and Computer engineering, University of Tabriz, Tabriz, Iran.

E-mail addresses

\*[aa.ghavifekr@tabrizu.ac.ir](mailto:aa.ghavifekr@tabrizu.ac.ir)

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## Abstract

Proportional–Integral–Derivative (PID) controllers have been widely used in industrial systems due to their simple structure and ease of implementation. However, because the parameters of classical PID controllers are fixed, uncertainties, nonlinearities, and variations in system dynamics may degrade their control performance. To address these limitations, fuzzy logic systems (FLSs) have been incorporated into PID controllers to enhance adaptability and robustness without requiring an accurate mathematical model of the controlled plant. This paper presents a comprehensive survey of model-free fuzzy PID and PI control approaches. In particular, two widely used architectures, fuzzy gain scheduling PID (FGPID) and fuzzy PID (FPID) controllers, are reviewed and analyzed. Different implementations of these controllers based on type-1 fuzzy logic systems (T1FLS), interval type-2 fuzzy logic systems (IT2FLS), and general type-2 fuzzy logic systems (GT2FLS) are discussed. Furthermore, various tuning strategies for fuzzy parameters, including analytical methods, gradient-based learning, and evolutionary optimization algorithms, are examined. The challenges associated with parameter tuning and closed-loop stability analysis are also highlighted. The survey provides a structured overview of recent developments and identifies open research directions for improving the design, stability, and practical implementation of fuzzy PID controllers in complex nonlinear systems.

## Keywords

Fuzzy systems, Machine learning, Learning algorithms, PID, Survey, Stability

## 1. Introduction

Regarding the simplicity of proportional, integral and derivative (PID) controllers, they are employed in wide practical systems [1, 2]. Since they are linear and some trial-and-error methods are used to tune their gains, uncertainties and variation in the controlled systems' parameters can degrade the closed-loop performance. PID control principle is simple and easy to implement, but its parameterization is exceptionally troublesome. Many industrial practices have shown that although classical PID controllers have presented very good robustness in practical applications, their control of complex nonlinear systems is not good, and many researchers are trying to use fuzzy logic to enhance the control effect of classical PID controllers [3, 4]. Because of the capability of the fuzzy logic systems (FLS)s and artificial neural networks (ANN)s, they are extensively used to ease the problem of PID controllers dealing with the problem of tuning procedures, nonlinearities, and variation in the parameters of the controlled systems. The classical PID/PD controllers are used in combination with intelligent ANN and FLS controllers in which the classical controller handles the transient stability and the intelligent

controllers are designed to tackle the nonlinearities, i.e., feedback error learning (FEL) approaches [5-11]. Alternatively, as discussed in this paper, the FLSs are exploited to improve the PID/PI controller performance. So the fusion of traditional control methods based on fuzzy logic and neural networks provides ideas for dealing with complex uncertain dynamics and nonlinear systems. In 1985 M. Sugeno et al [12]. derived fuzzy control rules and designed fuzzy controllers from operator's control actions to realize simple turning of model carts, but the failure rate was high. In 1993, Li-Xin Wang [13] developed an adaptive fuzzy controller that does not require an accurate mathematical model of the controlled system, integrates fuzzy control rules directly into the controller, and ensures global stability of the closed-loop system. In 1999, Kurt Fischle [14] proposed two methods for stabilizing adaptive fuzzy control of nonlinear systems. The second of these methods is based on a controller structure that has been employed in the neural network domain. In this context, the adaptive fuzzy controller can be viewed as a fuzzy neural network, which combines the knowledge representation of the fuzzy controller with the learning capability of the neural network. In 2000, J Yi

[15] proposed a fuzzy controller based on the SIRM dynamically connected fuzzy inference model for the stabilization control of inverted pendulum systems. The fuzzy controller has a simple structure, and the simulation results show that the fuzzy controller has a high generalization ability. In 1995 R. Ketata [16] proposed a parallel control structure between PID and fuzzy controllers which achieves better control performance during transient and steady state periods. In 2001 K. S. Tang [17] proposed an optimal fuzzy PID controller, which is a discrete time version of the conventional PID controller, which retains the linear structure of the conventional PID controller but with constant coefficients and self-tuning control gains. In 2002 Michail Petrov [18] proposed a method for the design of a nonlinear fuzzy PID controller and applied it to the level control of the controlled object, the authors introduced the structure of the fuzzy neural PID controller, the fuzzy controller was obtained using Sugeno fuzzy technique, and through the simulation, the fuzzy neural network was learned and the output transient response of the system was significantly improved. In 2005, Han-Xiong Li [19] proposed a new fuzzy controller combining optimal fuzzy inference with PID controller. The analysis and simulation results show that the proposed optimal fuzzy inference method is very flexible in rectifying the nonlinear gain of the system, handles complex problems better, and improves the robustness of the control system. In 2012 R. Arulmozhiyal [20] applied an improved fuzzy PID controller to the control of a brushless DC motor and the simulation results showed that the motor speed control using fuzzy PID is better than the conventional PID control. 2017 E Kuantama [21] simulated a conventional PID controller and a fuzzy PID controller applied to a quadcopter moving on a circular trajectory. Fuzzy PID control includes components such as fuzzification, determining fuzzy rules, and defuzzification. Two groups of these controllers are categorized as follows: (i) the PIDs are tuned via FLS. In this structure, which is famous for fuzzy gain scheduling PID (FGPID) controllers, the PID controller generates the actual signal [22-25]. (ii) The rules are used to create the PID, and the controller is extracted directly from the FLS. This scheme is named fuzzy PID (FPID) controller [26, 27]. In the FGPID approaches, the FLS is used to tackle the tuning problems of classical PID controllers, which in most industrial systems are based on trial and error methods [28]. Like the classical linear PID controllers, the structure of the FPID is defined in such a way that this controller's input-output relation is like the classical PID controller which has proportional, integral and derivative terms [29]. Both the FPID and FGPID controllers can be realized using three types of FLSs: type-1 FLSs (T1FLS)s, interval type-2 FLSs (IT2FLS)s [30] and general T2FLSs (GT2FLS)s [31]. T1FLSs are the most basic type of linguistic scheme, and then, they can only describe a limited level of imprecision or ambiguity. Although more computationally demanding than T1FLSs, they enhance the overall fuzzy model by being more resistant to measurement noise when inferred. The second important kind of FLS representation is GT2FLSs, which, like IT2FLSs, handle uncertainty inherently. In essence, this kind of uncertainty representation is substantially more noise-resistant than the IT2FLSs. In both FPID and

FGPID control design approaches, the important matter is how to determine the FLS parameters such as the consequent/antecedent MFs and the input/output scaling factors. In this way, some optimization algorithms such as gradient descent (GD)-based algorithms and evolutionary optimizations methods have been exploited. Another important issue that must be considered in constructing both FPID and FGPID is the closed-loop stability and the boundedness of the adaptive parameters. In these controllers, because the model of the controlled plant is often not involved in the design procedures, proving the closed-loop stability and boundedness adaptive parameters are challenging problems and interesting topics for future researches. In this paper, we have tried to review the different structures that have been introduced to realize the both FPID and FGPID controllers. Moreover, the ways of the adjusting parameters of these controllers and their closed-loop stability problems are discussed carefully.

To provide a clearer understanding of the existing research landscape, the reviewed studies in this survey can be broadly categorized according to the controller structure and the tuning strategy employed. From a structural perspective, fuzzy PID/PI controllers are mainly implemented in two forms: fuzzy gain scheduling PID (FGPID) controllers, where a fuzzy logic system is used to adaptively tune the parameters of a conventional PID controller, and fuzzy PID (FPID) controllers, in which the fuzzy inference mechanism directly generates the control signal. From the tuning perspective, the existing approaches can be grouped into analytical design methods, learning-based approaches (e.g., gradient descent and adaptive algorithms), and evolutionary optimization methods such as genetic algorithms, particle swarm optimization, and other metaheuristic techniques. This categorization helps to highlight the relationships among the reviewed works and provides a structured overview of the main research directions in the design of model-free fuzzy PID controllers.

Although several review papers have discussed fuzzy PID controllers, many of them mainly focus on specific aspects such as classical fuzzy PID structures or particular application domains. In addition, recent developments in fuzzy logic system representations, parameter tuning algorithms, and stability analysis techniques have not been comprehensively summarized in a unified framework. Therefore, an updated and structured survey is needed to better understand the current research landscape of model-free fuzzy PID controllers.

In this work, we present a comprehensive review of recent design and tuning approaches for fuzzy PID controllers. The main contributions of this survey are summarized as follows: (i) a clear classification of fuzzy PID controllers into fuzzy gain scheduling PID (FGPID) and fuzzy PID (FPID) architectures; (ii) a systematic review of fuzzy system implementations including type-1, interval type-2, and general type-2 fuzzy logic systems; (iii) a comparative discussion of parameter tuning approaches such as analytical methods, adaptive learning algorithms, and evolutionary optimization techniques; and (iv) a consolidated analysis of closed-loop stability results and

practical applications reported in the literature. These contributions aim to provide a clearer understanding of the design principles, challenges, and research opportunities in fuzzy PID control systems.

To better organize the reviewed literature, this survey proposes a taxonomy for classifying recent design and tuning approaches of fuzzy PID controllers. The existing methods can generally be categorized into four main groups. The first group includes rule-based design methods, in which fuzzy rules and membership functions are manually designed based on expert knowledge and heuristic tuning. The second group consists of self-tuning approaches, where fuzzy inference systems dynamically adjust the PID parameters according to system errors and their derivatives. The third group includes optimization-based approaches, where metaheuristic algorithms such as genetic algorithms (GA), particle swarm optimization (PSO), gravitational search algorithms (GSA), and other evolutionary techniques are used to determine optimal fuzzy system parameters. The fourth group comprises adaptive and learning-based methods, where controller parameters are updated online using techniques such as gradient descent, Kalman filtering, or Lyapunov-based adaptive mechanisms.

Despite the large number of published studies on fuzzy PID control, the novelty of the present survey lies in its structured and gap-oriented synthesis of recent model-free fuzzy PID/PI controller developments. Existing review papers often discuss fuzzy PID controllers in a general way, without clearly separating the main controller architectures, without systematically classifying the tuning methodologies, or without sufficiently covering recent developments in advanced fuzzy system representations. In particular, previous surveys have typically not provided a unified treatment of fuzzy gain scheduling PID (FGPID) and fuzzy PID (FPID) controllers together with their corresponding type-1, interval type-2, and general type-2 fuzzy implementations.

The specific gap addressed by this paper is therefore the absence of a comprehensive and up-to-date taxonomy for recent design and tuning approaches in model-free fuzzy PID control. To fill this gap, the present survey makes four main contributions. First, it clearly distinguishes the literature according to controller architecture, namely FGPID and FPID schemes. Second, it classifies the tuning approaches into rule-based, self-tuning, optimization-based, and adaptive learning categories. Third, it consolidates stability-related results, including Lyapunov-based methods, small-gain analysis, and Lyapunov–Krasovskii techniques, which are often scattered in the literature. Fourth, it highlights practical implementations and recent trends in advanced fuzzy PID design, especially those involving interval type-2 and general type-2 fuzzy systems for uncertain and nonlinear applications. In this way, the survey provides a clearer comparison framework and identifies research directions that are not sufficiently emphasized in earlier reviews.

The remainder of this paper is as follows: In section 2, different types of FLSs are explained. The FGPID and FPID controllers are provided in section 3 and 4, respectively. Finally, the conclusion is in section 5.

## 2. Different Types of FLSs

A FLS is distinctive in that it is capable of handling numerical-linguistic knowledge simultaneously. A fuzzy system is essentially a system that converts human natural language expertise into a series of IF-THEN rules, and then performs fuzzy reasoning on a quantized set of input fuzzy language and then generates corresponding operations on objects. Currently fuzzy logic systems have been widely used in automatic control, pattern recognition, signal processing and other fields [32-35]. The advantage of the fuzzy logic system lies in its ability to deal with fuzzy numerical variables and linguistic knowledge in the real world, and it is able to form a nonlinear mapping of the relationship between things in the real world, i.e., mapping a fuzzy variable to another variable, and the fuzzy set theory and fuzzy logic establish a typical nonlinear mapping [36]. There are two techniques to designing FLSs, according to Lotfi Zadeh: T1FLSs and T2FLSs. The second is presented as a continuation of the first. Expertise and experience are required while developing T1FLSs to choose the MFs and fuzzy rules. Type I fuzzy sets are described by a two-dimensional affiliation function, where each element in the fuzzy set corresponds to an affiliation function value which is any value in [0, 1]. The rule base of the type II fuzzy logic system is also constructed from the same IF-THEN rules as the type I fuzzy logic system, which means that it still relies on expert knowledge. Type II fuzzy logic systems have a similar structure to type I fuzzy logic systems. The input data is first fuzzified to generate a type II fuzzy set, then the fuzzy inference machine will reason the fuzzy output based on the fuzzy rule base, and finally the final result is obtained after defuzzification [37]. T2FLSs can manage the ambiguity inherent in linguistic terms better than T1FLSs. The uncertainties are represented by a fuzzy MF. As a result, T2FLSs are better suited to situations where determining the precise MF for a fuzzy set (FS) is challenging, which is particularly beneficial for incorporating uncertainties [38, 39]. Type-1 FS (T1FS)s have completely certain MFs, whereas type-2 FS (T2FS)s have fuzzy MFs. As a result, the rules are ambiguous at T2FSs. A type-1 membership grade is a crisp integer in [0, 1], but a type-2 membership grade, known as primary membership, maybe any subset in [0, 1] [40, 41].

### 2.1. T1FLS structure

A T1FS,  $A$ , in terms  $x \in X$ , is represented as:

$$A = \int_{x \in X} \mu_A(x) / x \quad (1)$$

where,  $\int$  denotes union. Using a type-1 triangular MF,  $\mu_A(x)$  is represented in Fig. 1.

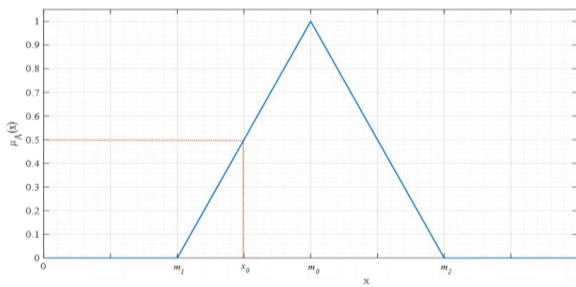


Fig. 1. type-1 triangular MF

From this figure, it can be seen  $\mu_A(x)$  is constrained to be between 0 and 1 for all  $x \in X$ , and is a two-dimensional function and, therefore, there exists an obvious membership for  $x = x_0$  the value of  $\mu_A(x = x_0)$  is 0.5. As can be seen, the triangle MF itself has three tunable parameters  $m_1, m_0$  and  $m_2$ . In this way, the block diagram of T1FLS, which can be constructed using T1FSs, is shown in Fig. 2. This fuzzy logic control system is capable of controlling the reactor water level efficiently and is expected to reduce the burden on the operator to monitor the water level [42]. Not only in industry, Ibrahim Saleh proposed a fuzzy logic system for evaluating students' academic performance, which is represented as a block diagram of three fuzzy logic controllers [43]. Nguyen Hoang Phuong has developed knowledge-based medical diagnostic systems using fuzzy set theory and fuzzy logic systems, including a fuzzy logic lung disease expert system, fuzzy logic-based reasoning for medical cases, and a diagnostic system that combines the dialectic of Chinese and Western medicine, which have been tested in hospitals [44]. Although type-one fuzzy systems have been used in a very large number of applications, they have some disadvantages for complex problems. For example, the accuracy and dynamic characteristics of the system are reduced due to the simplicity of the fuzzy rules, and the one-type fuzzy system cannot deal with the uncertainty caused by the inconsistency in the description of the posterior due to the inherent fuzzy differences of the linguistic variables and the inconsistency in the knowledge of the experts, and so on [32].

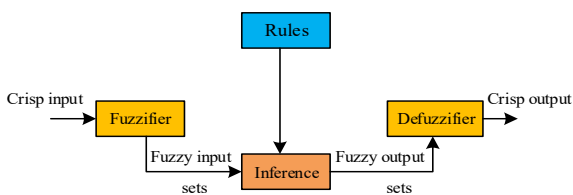


Fig. 2. the block diagram of T1FLS

2.2 T2FLS structure

T2FSs are derived from the expansion of T1FSs, which have been shown to have a better ability to deal with uncertainties. A T2FS,  $\tilde{A}$ , is written as:

$$\tilde{A} = \int_{x \in X} \int_{u \in J_x} \mu_{\tilde{A}}(x, u) / (x, u) \quad (2)$$

Where  $\int$  denotes union. Also,  $J_x$  is MF of  $x$  and  $\mu_{\tilde{A}}(x, u)$  is secondary MF. As given in **Error! Reference source not found.**, in type- 2 FSs all  $\mu_{\tilde{A}}(x, u)$  are equal 1 and in the general one, shown in **Error! Reference source not found.**,  $\mu_{\tilde{A}}(x, u)$  is in the interval of [0, 1]. Like the

T1FSs and for a tringle MF, both  $\bar{\mu}_{\tilde{A}}(x)$  and  $\underline{\mu}_{\tilde{A}}(x)$  have three tunable parameters.

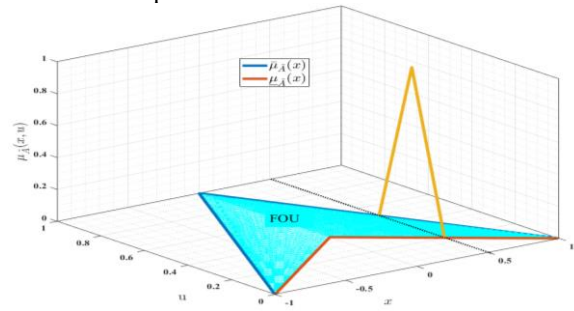


Fig. 3. General type-2 fuzzy set

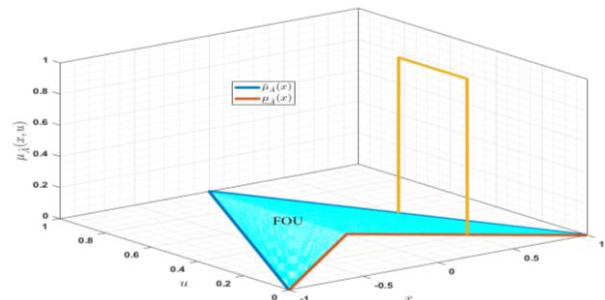


Fig. 4. Interval type-2 fuzzy set

The general and interval T2FLSs can be constructed using T2FSs in which the block diagram of that is similar to T1FLS, except that in the T2FLSs there is an extra unit called type reducer to convert the output into a T1FLS. A block diagram of a T2FLS is depicted in Fig. .

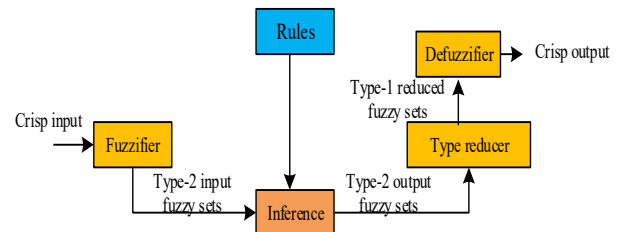


Fig. 5. The block diagram of T2FLS

The T2FLSs rules are similar to the T1FLSs, except T2FSs are used to express the antecedents and/or consequents. Some techniques known as type-reduction approaches may be used to reduce type-2 fuzzy consequences to type-1, as detailed in greater detail in [45]. Using the center-of-set (COS) type-reduction method and after defuzzification, the final output (crisp output) of an IT2FLS can be represented as follow:

$$y = \frac{1}{2}(y_l + y_r) \quad (3)$$

where  $y_l$  and  $y_r$  are the end points and:

$$y_l = \frac{\sum_{i=1}^p \bar{f}^i y_l^i + \sum_{p+1}^M \underline{f}^i y_l^i}{\sum_{i=1}^p \bar{f}^i + \sum_{p+1}^M \underline{f}^i} \quad (4)$$

$$y_r = \frac{\sum_{i=1}^q \bar{f}^i y_r^i + \sum_{q+1}^M \underline{f}^i y_r^i}{\sum_{i=1}^q \bar{f}^i + \sum_{q+1}^M \underline{f}^i}$$

where  $\bar{f}^i$  and  $\underline{f}^i$  are the upper/lower firing levels (for the  $i$ -th rule). Also,  $y_l^i$  and  $y_r^i$ , which are tunable parameters, represent the centroid of the consequent set

(for the  $i - th$  rule) [38] and  $M$  is the number of the fuzzy rules. K. A. Naik compares the effect of type I fuzzy logic system and type II fuzzy logic system in pitch angle control of wind energy system, by comparing the control results of two fuzzy controllers, it is proved that type II fuzzy controller is able to overcome the uncertainty of the rules and the affiliation function well, has lower overshoot and fast rise time compared to type I fuzzy controller [46].

The fundamental structures and inference mechanisms of T1FLS, IT2FLS, and GT2FLS introduced in this section provide the basis for designing fuzzy PID controllers. In the following sections, these fuzzy system types are incorporated into different fuzzy PID controller architectures.

### 3. Fuzzy Gain Scheduling PID (FGPID) Controllers

#### 3.1 Structure of FGPID Controllers

In fuzzy gain scheduling PID (FGPID) controllers, a fuzzy logic system is used to tune the parameters of a conventional PID controller in real time. The classical PID controller generates the final control signal, while the fuzzy inference system determines suitable gain values based on the system error and its derivative. This structure allows the controller to adapt its behavior to varying operating conditions and nonlinear dynamics without requiring an explicit mathematical model of the controlled plant.

The basic structure of the FGPID controller is depicted in Fig.. The linear PID with tunable parameters of  $K_p$ ,  $K_i$  and  $K_D$  generates the final control signal ( $u(t)$ ), and we have:

$$G(s) = K_p + K_i/s + K_D s \tag{5}$$

In the FGPID controller structure, the fuzzy logic controller (FLC) is used to adaptively tune the PID gains based on the system error and its derivative. The fuzzy inference system can be implemented using type-1, interval type-2, or general type-2 fuzzy logic systems. The

basic structures of these fuzzy systems were introduced earlier in Section 2; therefore, the following discussion focuses on their role in PID parameter adjustment.

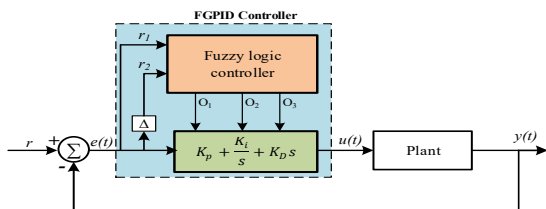


Fig. 6. The basic structure of the FGPID controller

In the FGPID controller, after the MFs are defined for both inputs and outputs, the next step is to define the fuzzy control rule. The FLC rules can be prepared by human experts in the form of linguistic descriptions. These principles are generally derived through trials of the step response. An example of the defined inputs and outputs MFs for FLC for the structure shown in Fig. is illustrated in Fig. [47].

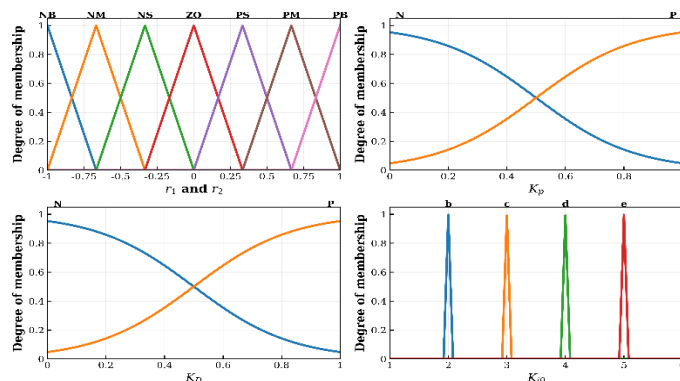


Fig. 7. MFs for  $r_1$ ,  $r_2$ ,  $K_p$ ,  $K_D$  and  $K_{i0}$

Based on the defined MFs, the general form of the fuzzy rules was given as follow:

*IF  $r_1$  is  $A_1$  and  $r_2$  is  $A_2$  THEN  $K_p$  is  $B_1$  and  $K_{i0}$  is  $B_2$  and  $K_D$  is  $B_3$*  (6)

where  $A_1$  and  $A_2$  are the antecedent MFs and  $B_1$ ,  $B_2$  and  $B_3$  represent the consequent MFs. In this FGPID controller, the proportional and derivative gains are directly deduced from the related fuzzy outputs i.e.,  $K_p = O_1$  and  $K_D = O_3$ , and the integral gain is indirectly determined by the fuzzy-logic controller (FLC) output, i.e.,  $K_i = K_p^2 / (K_{i0} \times K_D)$  where  $K_{i0} = O_2$ . According to Table which demonstrates the effects of changes in the closed loop performance with changes in the PID gains, the FLC rules can be constructed to better adjust the PID.

**Table I.** Effects of gains in the amount of rise time, overshoot, and settling time

Gains	Effects		
	Rise time	Overshoot	Settling Time
$K_p$	reduce	amplify	Small change
$K_i$	reduce	amplify	amplify
$K_D$	reduce	reduce	reduce

According to the general rule of thumb between changes in the PID controller parameters and closed loop system performance, the complete rule bases for the three outputs FLC,  $K_p$ ,  $K_D$ , and  $K_{i0}$  are given in Table , Table , and **Error! Reference source not found.**, respectively.

**Table II.** Fuzzy rule base used to determine the proportional gain  $K_p$  in the FGPID controller as a function of the two fuzzy inputs  $r_1$  and  $r_2$ .

$r_1 \downarrow r_2 \rightarrow$	NR	NM	NL	ZO	PL	PM	PR
NR	P	P	P	P	P	P	P
NM	N	P	P	P	P	P	S
NL	N	N	P	P	P	N	N
ZO	N	N	N	P	N	N	N
PL	N	N	P	P	P	N	N
PM	N	P	P	P	P	P	N
PR	P	P	P	P	P	P	P

**Table III.** Fuzzy rule base used to determine derivative gain  $K_D$  in the FGPID controller based on fuzzy inputs  $r_1$  and  $r_2$ .

$r_1 \downarrow r_2 \rightarrow$	NR	NM	NL	ZO	PL	PM	PR
NR	N1	N1	N1	N1	N1	N1	N1
NM	P1	P1	N1	N1	N1	P1	P1
NL	P1	P1	P1	N1	P1	P1	P1
ZO	P1	P1	P1	P1	P1	P1	P1
PL	P1	P1	P1	P1	P1	P1	P1
PM	P1	P1	N1	N1	N1	P1	P1
PR	N1	N1	N1	N1	N1	N1	N1

**Table IV.** Fuzzy rule base used to determine the auxiliary integral-related parameter  $K_{i0}$  in the FGPID controller from the fuzzy inputs  $r_1$  and  $r_2$ .

$r_1 \downarrow r_2 \rightarrow$	NR	NM	NL	ZO	PL	PM	PR
NR	b	b	b	b	b	b	b
NM	c	c	b	b	b	c	c
NL	d	c	c	b	c	c	d
ZO	e	d	c	c	c	d	e
PL	d	c	c	b	c	c	d
PM	c	c	b	b	b	c	c
PR	b	b	b	b	b	b	b

The MF shapes are important in some problems when designing a FLC because they affect the fuzzy inference system. They may be triangular, trapezoidal, Gaussian, and other forms. Each of these MFs has a number of parameters, as mentioned earlier, in the triangular MFs the tunable parameters are  $m_1$ ,  $m_0$  and  $m_2$ , whose proper adjustment of them can defiantly improve the performance of FLC. In this way, in [23, 48, 49] FGPI controllers were designed for frequency regulation in which it was shown that the intervals and shape of fuzzy MFs (MF)s have a severe effect on the performance. For example, the FLC in [23] consists of seven MFs for inputs (error and its derivative) and outputs ( $K_p$  and  $K_i$ ) defined in the range of [-1,1]. While the number and shape of MFs in [48] are similar to defined one in [23], the first input (error) range for the FLC is [-0.0171, +0.0171], the second input range is [-0.0283,+0.0283], and the outputs ( $K_p$  and  $K_i$ ) range are [-1,1].

### 3.2 Parameter Tuning Methods for FGPID Controllers

A critical step in the design of FGPID controllers is determining the parameters of the fuzzy logic system, including membership functions, rule bases, and scaling factors. Several tuning approaches have been proposed in the literature. These approaches can generally be classified into analytical design methods, adaptive learning algorithms, and evolutionary optimization techniques.

For this reason, and to improve the efficiency of the FGPIDs, in [50] an online tuning algorithm based on the extended Kalman filter (EKF) was designed to adjust the centre of triangle MFs and the weight of the control output.

With this online tuning method, the FGPID controller is able to deal with variation in the operating points and the external disturbances. The EKF optimized FGPID controller was applied for a force control problem and the simulation evaluation and experimental results illustrated that the designed controller could achieve good tracking in the case of variation of disturbances. One of the major disadvantages of the proposed method is the large number of parameters that must be adjusted. To avoid this high computational time the online tuning methods, the offline tuning methods such as genetic algorithm (GA) optimization and particle swarm optimization (PSO) are the solution. For this, the PSO was employed to determine the fuzzy MFs parameters in [51]. Cheng Liu designed and optimized a fuzzy PID controller using genetic algorithm. The fuzzy logic controller is used in the fuzzy control strategy to extend the finite PID gain to the possible combinations in the stable region and the genetic algorithm is used to improve the extension accuracy by quadratic optimization of the subordinate function (MF) of the FLC [52]. In [53], the gravitational search algorithm (GSA) based on Cauchy mutation and mass weighing (GSA-CW) was exploited to optimize the FLS's parameters of the FGPID controller that applied to regulate the frequency/power of generating unit. Juing-Shian Chiou proposed a particle swarm optimization enhanced evolutionary algorithm for tuning the fuzzy PID controller parameters of an active automotive suspension system. The authors demonstrate how to help the PSO to search the fuzzy PID controller parameters efficiently, and the gain and fuzzy affiliation function of the fuzzy PID can be obtained through the use of the PSO characteristics, and the fuzzy PID controller significantly improves the driving performance and the stability of the vehicle in comparison with the traditional linear feedback control method [54]. K.K. Ahn proposed a new method for online optimization of fuzzy PID controllers using Robust Extended Kalman Filtering (REKF) for automatic tuning of the controller parameters to reduce the control error. The method adapts conventional PID control with self-tuning fuzzy sets and uses the REKF algorithm to adjust the shape of the affiliation function online, obtaining better control performance and accuracy compared to conventional controllers [55]. To decrease the impact of uncertainties and time-delay in the performance of the FPID controller, a predictive functional control (PFC) was designed in the feedback path to predict of the future process behavior ( $p$ -step ahead of the output) [56]. This structure is shown in Fig. . Using the coke furnace as a case study system, it was shown that the combination of PFC and FPID controller has considerably improved the performance regarding the impact of uncertainty and disturbance.

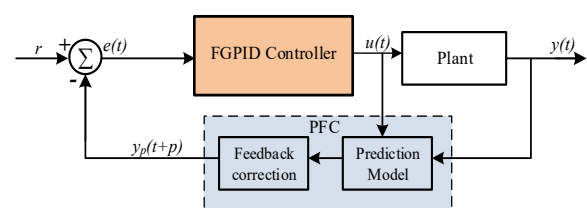


Fig. 8. The predictive functional control FPID controller

To tackle the effects of structure uncertainties and measurement noise in a pendulum on a cart, an IT2FPID controller was designed in [57]. The inputs and outputs MFs for the interval type-2 FLC are defined as follows: Five triangular MFs in the range of [-3,3] and [-1.5,1.5] for (error) and (derivative of error), respectively, four triangular MFs in the range of [0,100] and [0,50] for the first (to generate  $K_p$ ) and second (to generate  $K_i$ ) outputs, respectively, and three triangular MFs in the range of [0,10] for the third (to generate  $K_D$ ) output. Also, In [58] and using the hardware-in-the-loop (HIL) simulation, the IT2FGPID was applied to control of a nonlinear pendulum. It was shown that the proposed type-2 FLC outperforms the type-1 one in some closed loop criteria.

In [59] an interval type-2 FGPID (IT2FGPID) was presented for frequency tuning of an interconnected system in which just the consequent MFs was optimized using PSO algorithm. The modified harmony search algorithm (MHSA) and PSO algorithm were exploited to optimize the structures of the general type-2 FPI (GT2FGPI) controllers to frequency regulation of micro-grid power system and power-line inspection (PLI) robot in [60] and [61], respectively. In [61], as the controlled system owns four states, to reduce the input dimension for the general type-2 FLC, using a fusion information and quadratic optimal control theory, fuzzy inputs were reduced to 2. In that work, using three triangular MFs for each output, the first output (to generate  $K_p$ ) is in the range of [40,120], the second one (to generate  $K_i$ ) is in the range of [5,20], and the third one (to generate  $K_D$ ) is in the range of [10,25]. Peyman Razmi proposed a fuzzy gain scheduling proportional, integral, differential controller (FGPID) with an adaptive structure to deal with the variation of power system parameters [62].

Based on the fact that in the most of real-world control design problems, the PID controller design matters can be considered as a multi-objective (MO) problem, a multi-objective GA (MOGA) was utilized to optimize two conflicting objectives (overshoot and settling time) for the FGPID controller applied to control of inverted pendulum fourth order nonlinear systems [63]. Unlike the single objective optimization method, in the MO design approaches and according to the importance of the objectives, different PID gains can be obtained. In [64] and [65], the structures of FGPID controllers were optimized using mine blast (MB) and PSO algorithms to regulate the frequency in power system and to control of mold level, respectively. The FGPID controller tuning methods based on evolutionary optimization algorithms are offline methods and the problem of closed loop stability has not been investigated.

### 3.3 Stability Analysis of FGPID Controllers

Although numerous tuning approaches have been proposed for FGPID controllers, analyzing their closed-loop stability remains a challenging problem, especially in model-free settings. Only a limited number of studies have addressed stability using theoretical tools such as Lyapunov-based analysis. The following works represent some of the efforts that explicitly investigate stability properties of fuzzy gain scheduling PID controllers.

In [24] a gradient descent based learning algorithm combined with the Lyapunov theory was used to update the FLS consequent parameters in the FGPID controller.

In this online tuning method, PID controller gains according to the FLS output can be given as follow:

$$K_{PID} = [K_p, K_i, K_D]^T = W^T c \tag{7}$$

where  $W$  is the normalized firing strength and  $c$  is the consequent tunable parameters. Using a Lyapunov function, the adaptation algorithm for  $c$  was derived as

$$\dot{c} = \gamma W^T E (\dot{s} + ks) \tag{8}$$

where  $\gamma$  is learning rate,  $E = [e, \int e, \dot{e}]^T$ , and  $s$  is error surface. In Table a summary of contributions to design of the FGPID controllers has been illustrate. The following criteria were used to make the comparison in this table: authors (publication, year), FLS's parameters tuning approach(s) and if the closed loop stability is studied.

**Table V.** Some presented contributions to design of the FGPID controllers

Author(s)(pub.year)	FLS's parameters tuning approach(s)	Closed-loop stability analysis?
[47]	Analytical design	NO
[23]	Analytical design	NO
[50]	Extended Kalman filter	NO
[51]	PSO	NO
[53]	gravitational search algorithm	NO
[56]	Analytical design	NO
[57]	Analytical design	NO
[59]	PSO	NO
[61]	PSO	NO
[63]	MOGA	NO
[64]	mine blast algorithm	NO
[65]	PSO	NO
[24]	Lyapunov based gradient descent	YES

Recent studies have also focused on improving fuzzy PID controllers using advanced intelligent optimization and data-driven techniques. In particular, several works published in recent years have explored hybrid approaches combining fuzzy control with machine learning algorithms, adaptive learning strategies, and metaheuristic optimization techniques. These developments demonstrate the continuing research interest in enhancing the adaptability, robustness, and practical applicability of fuzzy PID controllers for complex nonlinear systems.

## 4. FPID Controller

### 4.1 Structure of FPID Controllers

In contrast to the FGPID architecture, FPID controllers employ the fuzzy logic system as the main controller. The fuzzy inference mechanism directly generates the control signal based on the system error and its derivative, while

scaling factors are used to adjust the influence of proportional, integral, and derivative components. This structure enables the controller to capture nonlinear control behavior through fuzzy rules.

As previously stated, the traditional linear PID controllers produce the final signal in the FGPID controller, which is susceptible to uncertainties and nonlinearities. Using a FLS as a direct controller is one solution to these issues. The FPID controller is the name for this approach. The well-known construction of an FPID controller type is seen in Fig. [26]. Unlike the FGPID, the fuzzy inference generates the main control signal  $u(t)$  to the plant.

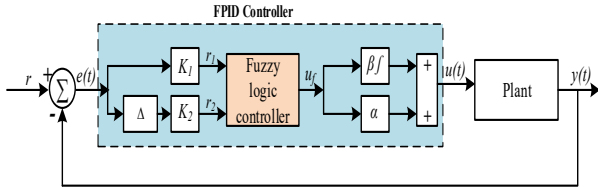


Fig. 9. The structure of FPID

In this controller,  $u$  is the final signal (output of FPID controller),  $e(t)$  represents the error (the input of the FPID controller),  $u_f$  denotes the output of FLS,  $\alpha$  and  $\beta$  are scaling factors, and  $K_1$  and  $K_2$  are input scaling gains. The scaling factor has a crucial role in the efficiency of the FPID [66]. For a FPID we have:

$$u(t) = \alpha u_f(t) + \beta \int_0^t u_f(t) dt \quad (9)$$

Then the controller is:

$$u_f(t) = A + Pr_1 + Dr_2 \quad (10)$$

where  $A$ ,  $P$ , and  $D$  are fixed values and  $r_1 = K_1 e$  and  $r_2 = K_2 \dot{e}$  are inputs of FLS. From **Error! Reference source not found.** and **Error! Reference source not found.**, the output of FPID is as:

$$u(t) = \alpha A + \beta A t + \alpha K_1 P e + \beta K_2 D \dot{e} + \beta K_1 P \int e(t) dt + \alpha K_2 D \dot{e} \quad (11)$$

To control of nonlinear time-delay system, a fuzzy PI type controller was proposed in [67]. This structure which is illustrated in Fig. , has three output-input scaling factor parameters  $ke$ ,  $kde$  and  $ko$ . According to the defined MFs, the symmetrical rule base, which is in the general and frequently used form, for the delay-free case is given in Table . In that work, to deal with the time-delay, the idea of “shifting the rules to the appropriate reign” is used.

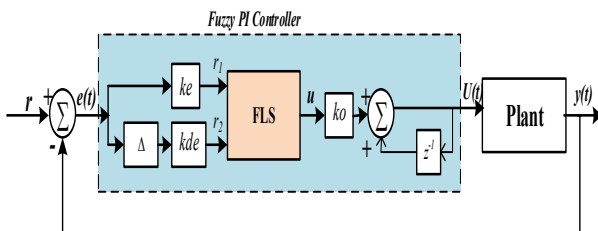


Fig. 10. The structure of fuzzy PI type controller proposed in [67]

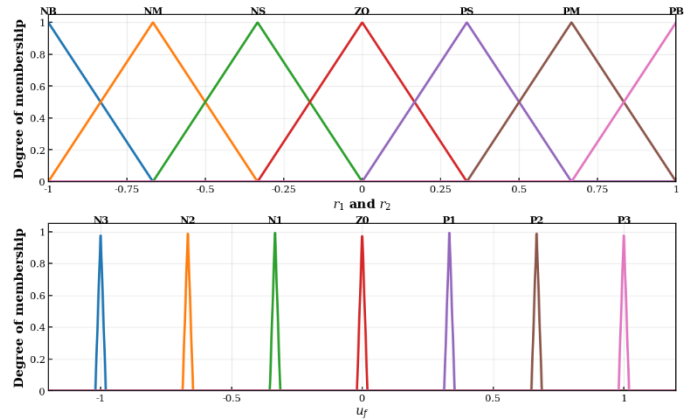


Fig. 11. Inputs and output MFs for fuzzy PI type controller

Table VI. Fuzzy tuning rules for  $u$

$r_1$ ↓	$r_2$ →	NB	NM	N S	Z O	PS	P M	P B
NB		Z0	P1	P2	P3	P3	P3	P3
NM		N1	Z0	P1	P2	P3	P3	P3
NS		N2	N1	Z0	P1	P2	P3	P3
ZO		N3	N2	N 1	Z0	P1	P2	P3
PS		N3	N3	N 2	N 1	Z0	P1	P2
PM		N3	N3	N 3	N 2	N1	Z0	P2
PB		N3	N3	N 3	N 3	N2	N1	Z0

An adaptive mechanism based on the peak observer idea was designed for online tuning of the output scaling factor  $\beta$  and input coefficient  $K_2$  of the FPID for frequency regulation in [26]. The online tuning algorithm (for the strategy given in Fig.) is as follows:

$$\beta = \delta \beta_0, \quad K_2 = \frac{K_0}{\delta} \quad (12)$$

where  $\delta$  is the peak value for step response, and  $\beta_0$  and  $K_0$  are the initial values for  $\beta$  and  $K_2$ , respectively. In that observer-based FPID controller, as given in Fig., the FLS rule base was constructed using two MFs and four rules. The related rule bases are given in Table .

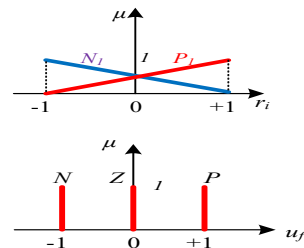


Fig. 12. The antecedent and consequent MFs

Table VII. Fuzzy tuning rules for  $u$

$r_1$ ↓	$r_2$ →	N1	P1
N1		N	Z
P1		Z	P

In [68], the  $k$ th rule of the FPID controller in Fig. was defined as follow:

if  $r_1$  is  $N_k$  and  $r_2$  is  $M_k$  Then  $u_f$  is  $C_k$  with  $\theta_k$  (13)

where  $N_k$  and  $M_k$  are the input MFs,  $C_k$  is the output MF, and  $\theta_k$  is the weighting vector. In the case of singleton MFs for output, the output of FLC can be written as follow:

$$u_f = \frac{\sum_{i=1}^m f_k c_k \theta_k}{\sum_{i=1}^m f_k \theta_k} \quad (14)$$

where  $f_k$ ,  $c_k$ , and  $w_k$  are the firing degree, parameter and the output for  $k$ th rule. In this work, the weights are used to apply the high or low importance of a rule. Considering the regionalized step response of a controlled system shown in Fig. (a), the defined MFs in Fig. (b), and the complete rule base in table, at the region 1, as the error decreases, the significance of the rules  $R_8 / R_7$  decreases, while the effect of rules  $R_5 / R_4$  increases. Thus, the weights are adjusted as  $\theta_5 = 1 - Abs(e)$ ,  $\theta_4 = 1 - Abs(e)$ ,  $\theta_7 = Abs(e)$ , and  $\theta_8 = Abs(e)$ .

Table VIII. FPID rules

$r_1 \downarrow r_2 \rightarrow$	N	Z	P
N	$N(\theta_1)$	$N(\theta_2)$	$Z(\theta_3)$
Z	$N(\theta_4)$	$Z(\theta_5)$	$P(\theta_6)$
P	$Z(\theta_7)$	$P(\theta_8)$	$P(\theta_9)$

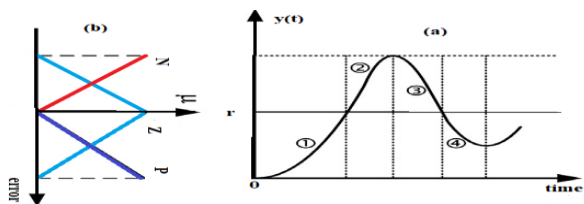


Fig. 13. The regionalized step response (a) and the error input MFs (b) [68]

Using two MFs for inputs and four for outputs (as shown in Fig. (a) and (b)), a bounded-input/bounded-output (BIBO) stable T1FPID controller was designed for some linear and nonlinear control system in [69]. This controller has three inputs that in the discrete time  $Ep = Kp(e(nT) - e(nT - T))$ ,  $Ei = Ki(e(nT))$ , and  $Ed = Kd(\dot{e}(nT) - \dot{e}(nT - T))$ , in which  $T$  is sampling time and  $n$  represents the sample.

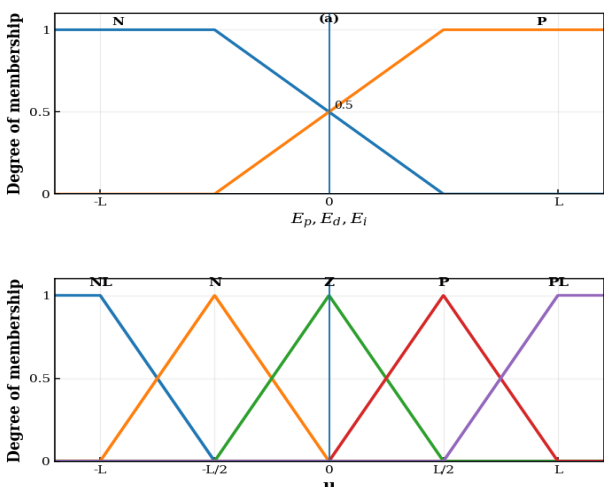


Fig. 14. Input MFs (a) and output MFs (b) According to the input/output MFs, the rules of FPID controller were written as follows:

If  $Ep$  is  $N$  and  $Ei$  is  $N$   $Ed$  is  $N$  then  $u$  is  $NL$   
 If  $Ep$  is  $N$  and  $Ei$  is  $N$   $Ed$  is  $P$  then  $u$  is  $N$

If  $Ep$  is  $P$  and  $Ei$  is  $N$   $Ed$  is  $N$  then  $u$  is  $N$   
 If  $Ep$  is  $N$  and  $Ei$  is  $P$   $Ed$  is  $N$  then  $u$  is  $NL$   
 If  $Ep$  is  $P$  and  $Ei$  is  $N$   $Ed$  is  $P$  then  $u$  is  $P$   
 If  $Ep$  is  $N$  and  $Ei$  is  $P$   $Ed$  is  $N$  then  $u$  is  $N$   
 If  $Ep$  is  $N$  and  $Ei$  is  $P$   $Ed$  is  $P$  then  $u$  is  $P$   
 If  $Ep$  is  $P$  and  $Ei$  is  $P$   $Ed$  is  $N$  then  $u$  is  $P$   
 If  $Ep$  is  $P$  and  $Ei$  is  $P$   $Ed$  is  $P$  then  $u$  is  $PL$

Using the small gain theorem and according to the response of the control system, the BIBO stability of the designed FPID controller has been illustrated.

In [70], to handle the uncertainty and measurement noise, the peak observer based self-tuning FPID controller in [26] was developed using IT2FLS with three triangle fuzzy MFs and five rules. In this case, the number of rules of the T2FLS is nine. It was shown that interval T2FPID (IT2FPID) outperforms the T1FPID, because of its MFs and the more degree of freedom. The big bang–big crunch (BB–BC) approach was employed to adjust MFs of IT2FPID, to stabilize a power system and a path tracking problem in [71], [72] and [73], respectively. Fractional order GT2FPID and IT2FPID controllers were designed to control of the inverted pendulum and to speed control of a nonlinear DC motor in [74] and [75], respectively. In [75], a multi-objective stochastic tuning algorithm was developed for the online tuning of IT2FPID. An bee colony-GA (ABC-GA) has been exploited to tune a fractional ordered IT2FPID controller in [76]. The designed controller was implemented on MIMO two-link robot under uncertainties, and it was illustrated that the performance of the fractional ordered IT2FPID is better. PSO and GA approaches were utilized to tune the parameters of T1FPID and IT2FPID controllers applied to frequency regulation in power system and 5-DOF redundant robot manipulators in [77] and [78], respectively. In [79] a single input IT2FPID controller was proposed to enhance the efficiency. This control structure is depicted in Fig. The single input IT2FPID includes all three parts of classical PID. Using an input for the FLC, the  $i$ th rule can be written as follow:

$$\text{if } e \text{ is } \tilde{A}_i \text{ Then } u_f \text{ is } u_f \text{ is } B_i \quad (15)$$

And the final output is:

$$u_f = \frac{u_f^l + u_f^r}{2} \quad (16)$$

Using fully overlapping triangular FSSs,  $u_f^l$  and  $u_f^r$  can be simply written as:

$$u_f^l = \frac{\bar{\mu}_{\tilde{A}_i}(e) \cdot B_i + \underline{\mu}_{\tilde{A}_{i+1}}(e) \cdot B_{i+1}}{\bar{\mu}_{\tilde{A}_i}(e) + \underline{\mu}_{\tilde{A}_{i+1}}(e)} \quad (17)$$

$$u_f^r = \frac{\underline{\mu}_{\tilde{A}_i}(e) \cdot B_i + \bar{\mu}_{\tilde{A}_{i+1}}(e) \cdot B_{i+1}}{\underline{\mu}_{\tilde{A}_i}(e) + \bar{\mu}_{\tilde{A}_{i+1}}(e)}$$

where  $\bar{\mu}_{\tilde{A}_i}(e)$  and  $\underline{\mu}_{\tilde{A}_i}(e)$  are an upper/lower MFs.

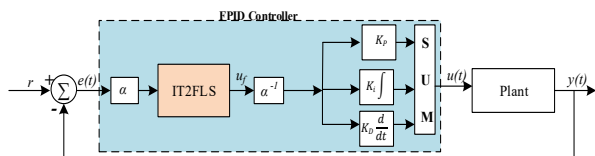


Fig. 15. The structure of single input IT2FPID controller

By Lyapunov-Krasovskii (L-K) approach a stable IT2FPID controller was schemed to steer the frequency

variation to zero under time delay and uncertainties in [80]. In that model free method, the adaptation laws were extracted using the following L-K functional:

$$V(t) = \frac{1}{2}e(t)^2 + \frac{1}{2} \int_{t-\tau(t)}^t e(s)^2 ds + \int_{-\tau_{max}}^0 \int_{t+\theta}^t e(\theta)^2 d\theta ds \quad (18)$$

where  $e(t)$  is closed loop error and  $\tau_{max}$  is the maximum amount of the delay. As can be seen from the L-K functional, despite the convergence of error to zero, the boundedness of  $\alpha$  and  $\beta$  cannot be concluded.

The adaptation laws for ( $\alpha$  and  $\beta$ ) were derived as:

$$\begin{aligned} \dot{\beta} &= -0.5(1 + \tau_{max})e \left( \int u_f \right)^{-1} \\ \dot{\alpha} &= -0.5(1 + \tau_{max})e (J u_f)^{-1} \end{aligned} \quad (19)$$

In [81] a Lyapunov based adaptive IT2FPID was suggested for the frequency adjustment of a micro-grid. In this approach, it was shown that adaptive gains remain bounded and the error approaches to zero properly. To evaluate the close-loop stability and to derive the adaptive scheme for IT2FPID, the following Lyapunov function was used:

$$V(t) = \frac{1}{2}e(t)^2 + \frac{1}{2\gamma_1}\tilde{\alpha}^2 + \frac{1}{2\gamma_2}\tilde{\beta}^2 \quad (20)$$

where

$$e(t) = y_d(t) - y(t) \quad (21)$$

and  $y$  is the power system frequency,  $y_d$  is the reference signal,  $\tilde{\beta} = \beta^* - \beta$ ,  $\tilde{\alpha} = \alpha^* - \alpha$ .  $\beta^*$  and  $\alpha^*$  are the optimal parameters. The adaptation of ( $\alpha$  and  $\beta$ ) were written as:

$$\begin{aligned} \dot{\alpha}(t) &= \gamma_1(e) \dot{u}_f \\ \dot{\beta}(t) &= \gamma_1(e) u_f \end{aligned} \quad (22)$$

In [82], the suggested controller in [81] was developed for a frequency control that suffers from nonlinearities and measurement noise. Using center of gravity defuzzification (COG) method, FPID controller was experimentally used to control of a magnetic system which suffers from nonlinearities, uncertainties and time-delay in [83].

## 4.2 Closed-Loop Stability Analysis of Fuzzy PID Controllers

Closed-loop stability is a critical issue in the design of fuzzy PID controllers, particularly because many of these controllers are developed in a model-free framework. While numerous studies focus on improving control performance through optimization and heuristic tuning, only a limited number of works provide rigorous theoretical guarantees regarding stability and convergence.

One commonly adopted approach is the use of Lyapunov stability theory to derive adaptive laws for controller parameters. In these methods, a Lyapunov candidate function is constructed based on the tracking error and the controller parameter estimation error. By ensuring that the derivative of the Lyapunov function is negative semi-definite, the stability of the closed-loop system and boundedness of the adaptive parameters can be established. For example, gradient-descent-based adaptation combined with Lyapunov analysis has been

used to update the consequent parameters of fuzzy gain scheduling PID controllers.

Another important analytical framework is the small-gain theorem, which has been applied to analyze the bounded-input bounded-output (BIBO) stability of fuzzy PID control systems. In this approach, the fuzzy controller and the plant are interpreted as interconnected subsystems, and stability conditions are derived based on the gain properties of the interconnected system. This method provides a systematic way to verify stability for both linear and nonlinear plants.

For systems with time delays and uncertainties, Lyapunov–Krasovskii (L–K) functional methods have been employed. In these approaches, delay-dependent Lyapunov functionals are constructed to account for the influence of time-delay dynamics in the closed-loop system. Using this framework, adaptation laws for scaling factors and controller parameters can be derived while ensuring convergence of the tracking error.

Although these analytical techniques provide valuable theoretical insights, the survey indicates that rigorous stability analysis is still limited in many fuzzy PID studies. A large portion of the literature focuses on optimization-based parameter tuning without providing formal stability guarantees. Therefore, developing systematic stability analysis tools for model-free fuzzy PID controllers remains an important research direction.

## 4.3 Practical Applications and Experimental Implementations of Fuzzy PID Controllers

Although many studies on fuzzy PID controllers focus on theoretical analysis and simulation-based validation, several works have demonstrated their effectiveness in real-world control applications. These practical implementations highlight the capability of fuzzy PID controllers to handle nonlinearities, uncertainties, and varying operating conditions in complex systems [84-89]. In robotics and mechatronic systems, fuzzy PID controllers have been widely applied for motion control and trajectory tracking. For example, fuzzy PID-based strategies have been implemented in robotic manipulators and mobile robots to improve tracking accuracy and robustness against disturbances. In redundant robotic systems and multi-link manipulators, optimized fuzzy PID controllers have shown improved performance compared with classical PID controllers, particularly in the presence of nonlinear dynamics and parameter uncertainties.

In power and energy systems, fuzzy PID controllers have been extensively employed for load frequency control (LFC), microgrid regulation, and renewable energy applications. Several studies have reported successful experimental or hardware-in-the-loop implementations of interval type-2 fuzzy PID controllers for frequency stabilization in interconnected power systems and AC microgrids. These controllers demonstrate enhanced disturbance rejection and improved robustness compared to conventional control methods.

Fuzzy PID controllers have also been implemented in motor drive systems, including DC motors, permanent magnet synchronous motors (PMSM), and brushless DC

motors. Experimental results in these systems indicate that fuzzy PID controllers can significantly improve transient response characteristics, reduce overshoot, and enhance steady-state accuracy under varying load conditions.

In addition, industrial process control applications such as temperature regulation, level control, and chemical process control have benefited from fuzzy PID-based strategies. In many of these systems, fuzzy PID controllers are implemented in programmable logic controllers (PLCs) or embedded control platforms due to their relatively simple structure and robustness.

These practical implementations demonstrate that fuzzy PID controllers are not only theoretically attractive but also suitable for real-world applications where accurate mathematical models are difficult to obtain. However, despite these promising results, large-scale industrial adoption remains limited, and further experimental validation and benchmarking studies are still needed.

### 5. Discussion and Critical Analysis of Fuzzy PID Approaches

Although fuzzy PID controllers have been widely studied and successfully applied in many nonlinear control problems, the reviewed literature reveals several important strengths and limitations that should be carefully considered when designing such controllers.

One of the main advantages of fuzzy PID controllers is their model-free nature. Unlike classical model-based control methods, fuzzy PID controllers can be designed without requiring an accurate mathematical model of the plant. This characteristic makes them particularly attractive for complex nonlinear systems with uncertainties, parameter variations, and unknown dynamics. In addition, the integration of fuzzy logic with PID control enables the controller to adapt its behavior based on linguistic knowledge or heuristic rules, which improves robustness under varying operating conditions. However, the survey also shows that the performance of fuzzy PID controllers strongly depends on the proper selection of membership functions, rule bases, and scaling factors. In many studies, these parameters are determined through trial-and-error procedures or heuristic design methods. As a result, the controller design process may lack systematic guidelines, which limits reproducibility and scalability to different systems.

Another important observation is related to the parameter tuning strategies. Evolutionary optimization algorithms such as genetic algorithms (GA), particle swarm optimization (PSO), and gravitational search algorithms (GSA) have been widely used for tuning fuzzy PID parameters. These methods are effective in finding suitable parameter sets but typically operate in an offline manner and may require significant computational effort. Consequently, their applicability to real-time adaptive control scenarios can be limited.

Adaptive and learning-based tuning approaches, including gradient descent methods, extended Kalman filtering, and observer-based adaptation schemes, provide an alternative solution for online parameter adjustment. These approaches allow the controller to adapt to changing system dynamics during operation.

Nevertheless, their stability properties are often difficult to guarantee, particularly in model-free control frameworks.

From a structural perspective, fuzzy gain scheduling PID (FGPID) controllers maintain the classical PID structure while adjusting the gains using fuzzy inference. This structure benefits from the well-understood behavior of conventional PID controllers and can be easier to implement in industrial applications. In contrast, fuzzy PID (FPID) controllers rely entirely on fuzzy inference to generate the control signal. While this approach can better capture nonlinear control behavior, it may increase design complexity and sensitivity to rule-base design.

Another critical issue identified in the reviewed studies is the lack of rigorous stability analysis. Although some works employ Lyapunov-based methods or small-gain theorems to prove closed-loop stability, many optimization-based fuzzy PID designs focus primarily on performance improvement without providing theoretical guarantees. This remains one of the key research gaps in the literature.

Finally, it should be noted that most existing studies evaluate fuzzy PID controllers through simulation experiments or limited laboratory setups. Large-scale real-world implementations and systematic benchmarking across different control scenarios remain relatively scarce. Therefore, future research should focus on developing more systematic design methodologies, improving stability analysis techniques, and validating fuzzy PID controllers in practical industrial environments. Table IX presents a structured comparison of different fuzzy PID controller design approaches based on several practical criteria, including computational complexity, robustness to system uncertainties, implementation difficulty, and typical control performance improvements.

**Table IX.** Comparative Analysis of Fuzzy PID Design and Tuning Approaches

Approach	Computational Complexity	Robustness to Uncertainty	Ease of Implementation	Typical Performance Improvement	Example Techniques
Rule-Based Design	Low	Moderate	High	Moderate improvement in rise time and overshoot	Expert-designed fuzzy rules
Self-Tuning Fuzzy PID	Medium	High	Moderate	Improved transient response and disturbance rejection	Fuzzy gain scheduling
Optimization-Based Methods	High	High	Moderate	Significant reduction in overshoot and	GA, PSO, GSA

				settling time	
Adaptive / Learning Methods	Medium –High	Very High	Moderate –Low	Improved adaptability and steady-state accuracy	Gradient descent, EKF, Lyapunov-based tuning

Despite the significant progress in the design and application of fuzzy PID controllers, several important challenges remain open in the field of model-free fuzzy control. One of the main challenges is the control of systems with time delays and high-order nonlinear dynamics. Many fuzzy PID designs assume relatively simple system structures, whereas practical systems such as power networks, robotic manipulators, and industrial processes often involve time delays, actuator constraints, and complex nonlinear behaviors. Developing fuzzy PID controllers that can effectively handle such complexities remains an important research topic.

Another challenge concerns the systematic design and tuning of fuzzy logic system parameters. In many existing works, membership functions, rule bases, and scaling factors are determined using heuristic procedures or offline optimization algorithms. Although these methods may achieve good performance in specific cases, they often lack general design guidelines and may require significant computational effort. Therefore, developing efficient and systematic parameter tuning methods remains an important research direction.

Closed-loop stability analysis also remains a key issue in model-free fuzzy control. While some studies employ Lyapunov-based approaches, small-gain theory, or Lyapunov–Krasovskii functionals, many fuzzy PID controller designs still rely primarily on simulation-based validation. Establishing stronger theoretical guarantees for stability and robustness in model-free control frameworks is therefore an important topic for future work.

Another promising direction is the integration of fuzzy PID control with modern data-driven and intelligent control techniques. Recent advances in machine learning, reinforcement learning, and data-driven system identification offer new opportunities for improving the adaptability and performance of fuzzy controllers. Hybrid approaches that combine fuzzy inference with learning-based algorithms may provide more efficient solutions for controlling complex uncertain systems.

Finally, further experimental validation and real-world implementations are needed to fully demonstrate the practical effectiveness of fuzzy PID controllers. Future studies should focus on large-scale applications such as smart grids, autonomous robotic systems, renewable energy systems, and advanced industrial process control, where robust and adaptive control strategies are essential.

**6. Conclusion**

This paper presented a comprehensive survey on model-free fuzzy PID/PI controllers, focusing on two widely

used structures, namely fuzzy gain scheduling PID (FGPID) controllers and fuzzy PID (FPID) controllers. The survey reviewed different fuzzy system representations used in these controllers, including type-1 fuzzy logic systems (T1FLS), interval type-2 fuzzy logic systems (IT2FLS), and general type-2 fuzzy logic systems (GT2FLS). In addition, various parameter tuning approaches such as analytical design methods, gradient-based learning algorithms, and evolutionary optimization techniques were discussed.

From the reviewed studies, it can be observed that fuzzy PID controllers offer several advantages compared with classical PID controllers, particularly in handling nonlinearities, uncertainties, and time-varying system dynamics. The integration of fuzzy logic allows the controller parameters to adapt according to system behavior, which improves robustness and control performance. FGPID controllers retain the classical PID structure while adjusting the controller gains through fuzzy inference, making them relatively simple to implement in many industrial applications. In contrast, FPID controllers use fuzzy inference to directly generate the control signal, enabling a more flexible representation of nonlinear control behavior.

Despite these advantages, several challenges remain in the design and application of fuzzy PID controllers. One of the main issues is the determination of appropriate membership functions, rule bases, and scaling factors. In many studies, these parameters are selected using heuristic methods or offline optimization algorithms, which may not guarantee optimal performance under varying operating conditions. Another important challenge is the analysis of closed-loop stability, especially in model-free control frameworks where the system dynamics are not explicitly known. Although some works employ Lyapunov-based approaches, small-gain theorems, or Lyapunov–Krasovskii functional methods, rigorous stability guarantees are still limited in the literature.

Future research on fuzzy PID controllers may focus on several promising directions. First, the development of systematic and computationally efficient parameter tuning methods remains an important topic, particularly for online adaptive control applications. Second, more rigorous theoretical frameworks are needed to analyze stability and robustness of fuzzy PID controllers in uncertain and nonlinear systems. Third, integrating fuzzy PID control with emerging intelligent techniques such as machine learning, reinforcement learning, and data-driven system identification may further enhance controller adaptability and performance. Finally, more experimental studies and real-world implementations are required to validate these controllers in practical engineering systems such as robotics, renewable energy systems, and industrial process control.

Finally, fuzzy PID controllers continue to be an active and promising research area due to their simplicity, flexibility, and capability to handle complex control problems. Continued research in controller design methodologies, stability analysis, and practical implementation will further expand their applicability in modern intelligent control systems.

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