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Survey paper

A survey on industrial applications of fuzzy control

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ABSTRACT

Fuzzy control has long been applied to industry with several important theoretical results and successful results. Originally introduced as model-free control design approach, model-based fuzzy control has gained widespread significance in the past decade. This paper presents a survey on recent developments of analysis and design of fuzzy control systems focused on industrial applications reported after 2000.

Contents

1. Introduction

Classical engineering approaches to the characterization of real-world problems are based on essentially qualitative and quantitative technique based on more or less accurate mathematical modelling. In such approaches expressions like "medium temperature", "big humidity", "small pressure", "very big speed",

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related to the variables specific to the behaviour of a controlled process (CP), are subject to relatively difficult interpretations from the quantitative point of view. This interpretation is difficult because classical automation handles variables/information, processed with well-specified numerical values. Therefore the elaboration of the control strategy and its implementation in the control equipment requires an as accurate as possible quantitative modelling of the CP. Advanced control strategies may require the permanent reassessment of the models and of the values of the parameters characterizing the (parametric) models. Process control based on fuzzy set theory or fuzzy logic) – referred to as fuzzy control or fuzzy logic control – is more pragmatically with this regard because use is made of the linguistic characterization of the quality of CP dynamics and of the adaptation of this characterization as function of the concrete conditions of CP operation.

Zadeh set the basics of fuzzy set theory by a paper that seemed to be just mathematical entertainment about four decades ago [1]. The boom in computer science opened in the seventies the first prospects for applications of the meanwhile built theory in various fields ranging from control engineering, qualitative modelling, pattern recognition, signal processing, information processing, machine intelligence, decision making, management, finance, medicine, and so on. In particular, fuzzy control, as one of the earliest branches and applications of fuzzy sets and systems, has become one of the most successful applications. Fuzzy control has proven to be a successful control approach to many complex nonlinear systems or even nonanalytic ones. It has been suggested as an alternative approach to conventional control techniques in many situations. This paper will be focused on industrial applications, and the analysis is dedicated to the period after 2000.

The first fuzzy control application belongs to Mamdani and Assilian [2,3], where control of a small steam engine is considered. The reference applications of fuzzy control, associated by experiments, deal with a warm water plant [4] and with a small scale heat exchanger [5]. Afterwards, during the eighties in Japan, USA, and later, in Europe, a so-called fuzzy boom took place in the field of fuzzy control applications to several domains beginning with electrical household industry and consumer electronics up to other industries like mechanical and robotic systems, power plants and systems, telecommunications, transportation systems, automotive systems, chemical processes and nuclear reactors. This boom was caused partly by the spectacular development of electronic technology and computer systems that enables:

- the manufacturing of circuits with very high speed of information processing, dedicated (by construction and usage) to a certain purpose including fuzzy information processing and resulting in embedded systems,
- the development of computer-aided design programs, which allow the control system designer to use efficiently a large amount of information concerning the CP and the control equipment.

The industrial applications of fuzzy control reported until now emphasize two important aspects related to this control strategy:

- In some situations (for example, the control of processes with functional nonlinearities which subjected to difficult mathematical modelling and the control of ill-defined processes), fuzzy control can be viewed as a viable alternative to classical, crisp control (conventional control),
- Compared to conventional control, fuzzy control can be strongly based and focused on the experience of a human operator, and a fuzzy controller can model more accurately this experience (in linguistic manner) versus a conventional controller.

The main features of fuzzy control can be organised as follows:

- Fuzzy control employs the so-called fuzzy controllers (FCs) or fuzzy logic controllers ensuring a nonlinear input–output static map that can be influenced/modified based on designer's option.
- Fuzzy control can process several variables from the CP, hence it can be considered as belonging to the class of multi-input–multi-output (MIMO) systems with interactions. Therefore the FC can be considered as a multi-input controller (eventually, a multi-output one, too), similar to linear or nonlinear state-feedback controllers.
- FCs do not possess dynamics, but the applications and performance of FCs and fuzzy control systems (FCSs) can be enlarged significantly by inserting dynamics (i.e., derivative and/or integral components) to fuzzy controller structures resulting in the so-called fuzzy controllers with dynamics.
- FCs are flexible with regard to the modification of the transfer features (by input–output static maps). Thus the possibility to develop a large variety of adaptive control system structures is offered.

The control approach based on human experience is acting in FCs by expressing the control requirements and elaborating the control signal in terms of the natural IF–THEN rules which belong to the set of rules

$$\begin{aligned}&\ldots\\ &\text{IF (antecedent) THEN (consequent)},\\ &\ldots\end{aligned} \tag{1}$$

where the antecedent (premise) refers to the found out situation concerning the CP dynamics (compared usually with the desired/imposed dynamics), and the consequent (conclusion) refers to the measures which should be taken – under the form of the control signal u – in order to fulfil the desired dynamics. The set of rules (1) makes up the rule base of the FC.

Research results obtained in studying the behaviour of the human expert emphasize that the expert has a specific strongly nonlinear behaviour accompanied by anticipative, derivative, integral and predictive effects and by adaptation to the concrete operating conditions. Colouring the linguistic characterization of CP dynamics (and, accordingly, of fuzzy mathematical characterization) based on experience and translating it to the control signal elaboration and the analysis of CP dynamics will be characterized by parameters that enable the modification of FC features. From this point of view the FCSs can be regarded as belonging to the general framework of intelligent control systems.

The block diagram of principle (considered as classical in the literature) of an FCS is presented in Fig. 1. The FCS is considered as a single input system with respect to the reference input r and as a

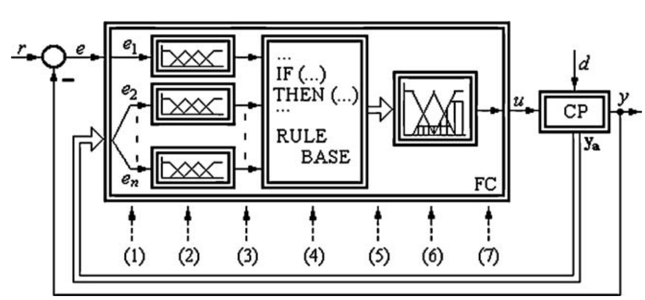

Fig. 1. Basic fuzzy control system structure.

single output system with respect to the controlled output y. The second input fed to the CP/FCS is the disturbance input d.

Fig. 1 highlights also the operation principle of an FC in its classical version, characterizing Mamdani FCs, with the following variables and modules:

(1) the crisp inputs,
(2) the fuzzification module,
(3) the fuzzified inputs,
(4) the inference module,
(5) the fuzzy conclusions,
(6) the defuzzification module,
(7) the crisp output.

The essential, already mentioned, particular feature of FCSs concerns the multiple interactions regarded from the process to the controller by the auxiliary variables $\mathbf{y_a}$, gathered in the input vector $\mathbf{e}'$

$$\mathbf{e}' = [\, e \quad \mathbf{y}_a^T \,] = [\, e_1 \quad e_2 \quad \ldots \quad e_n \,]^T. \tag{2}$$

These variables are direct or indirect inputs to the fuzzy controller. No matter how many inputs to the FC are, the FC should possess at least one input variable e_1 that corresponds to the control error e

$$e_1 = e = r - y. \tag{3}$$

According to Fig. 1, the operation principle of a Mamdani FC involves the sequence of operations (a), (b) and (c):

(a) The crisp input information – the measured variables, the reference input (the set point), the control error – is converted into fuzzy representation. This operation is called fuzzification of crisp information.
(b) The fuzzified information is processed using the rule base, composed of the fuzzy IF-THEN rules referred to as fuzzy control rules of type (1) that must be well defined in order to control the given process. The principles to evaluate and process the rule base represent the inference mechanism/engine and the result is the "fuzzy" form of the control signal u, the fuzzy control signal.
(c) The fuzzy control signal must be converted into a crisp formulation, with well-specified physical nature, directly understandable and usable by the actuator in order to be capable of controlling the process. This operation is known under the name of defuzzification.

The three operations described briefly here characterize the three modules in the structure of an FC (Fig. 1), the fuzzification module (2), the inference module (4) and the defuzzification module (6). All three modules are assisted adequate databases.

In the majority of applications an FC is used for direct feedback control or on the low level in hierarchical control system structures. However, it can be used on the supervisory level, for example in adaptive control system structures. Nowadays fuzzy control is no longer only used to directly express the knowledge on the CP or, in other words, to do model-free fuzzy control. An FC can be calculated from a fuzzy model obtained in terms of system identification techniques, and thus it can be regarded in the framework of model-based fuzzy control. Most often used are:

- Mamdani fuzzy controllers, referred to also as linguistic FCs, with either fuzzy consequents that represent type-I fuzzy systems according to the classifications given in [6] or singleton consequents belonging to the type-II fuzzy systems. These FCs are usually used as direct closed-loop controllers.
- Takagi-Sugeno (T-S) fuzzy controllers, known also as type-III fuzzy systems especially when affine consequents are employed, and typically used as supervisory controllers.

Several excellent books and tutorial articles on fuzzy control are well-acknowledged [7–24]. Several survey and position papers highlight specific topics in fuzzy control, make characterizations and present points of view. A good survey on fuzzy modelling for control is done in [25]. The stability analysis methods for type-II fuzzy control systems are analyzed in detail in [6]. A very good survey on neuro-fuzzy rule generation in a rather general setting of soft computation is given in [26]. The fusion of computational intelligent methodologies, including fuzzy logic and sliding mode control, is thoroughly discussed in [27]. Conclusions of great wisdom regarding the perspectives of fuzzy control systems are pointed out in [28]. An excellent survey on analysis and design methods of model based fuzzy control systems is given in [29].

This paper is focused on industrial applications of fuzzy control with application fields that include but are not limited to manufacturing, robotics, automotive and process industry, and control of servo systems and actuators as well. A large part of these applications can be viewed in the framework of mechatronic systems. The authors are aware of the fact that the publications on the topic of fuzzy logic control are so huge that an exhaustive list is impossible. Selected papers are given in the end of this paper. Many excellent works are unfortunately missed. In addition, this survey paper is not able to cover all categories of industrial applications of fuzzy logic control in detail.

The paper addresses the following topics. Industrial applications of control systems with Mamdani fuzzy controllers are discussed in Section 2. Next, Section 3 is focused on control systems with Takagi-Sugeno fuzzy controllers. The stable design of model-based fuzzy control systems and aspects concerning the tensor product (TP) model transformation are considered. Applications of adaptive and predictive fuzzy control dealing with supervision and optimization, i.e., multi-level fuzzy control systems, are presented in Section 4. Section 5 gives concluding remarks, perspectives and challenges of fuzzy control.

2. Control systems with Mamdani fuzzy controllers

The design of FCSs with Mamdani FCs is usually performed by heuristic means incorporating human skills and experience, and it is often carried out by a model-free approach. The immediate shortcoming resulted from the model-free design and FC tuning concerns the lack of general-purpose design methods. Although the performance indices of such control systems are generally satisfactory, a major problem is the analysis of the structural properties possessed by the FCSs including stability, controllability, parametric sensitivity and robustness [19,22–24,28]. In addition, the design of such control systems suffers from the lack of systematic approaches. Therefore much research attention has been devoted to the stability analysis. Actual trends make use of Lyapunov's approach [30], Krasovskii's approach [31], the describing function method [19], Krasovskii-LaSalle's invariant set theorem [32], the small gain theorem [33], algebraic approaches [34] including the vector norms approach [35,36], applicable to Mamdani FCs but also with minor modifications to T-S FCs. The common idea of all these approaches is to regard the FC as a nonlinear controller with Lurie-Postnikov nonlinearity, the CP with crisp model (linear or not) and embed the stability problem of FCSs into the stability theory of conventional nonlinear systems.

Several applications of FCSs with Mamdani FCs are reported in manufacturing. They include control of industrial weigh belt feeders [37], the realization of specific controllers [38,39], control of machining processes [40–43], laser tracking systems [44], plastic injection molding [45] and vibration suppression [46]. The manufacturing area is related to robotics. Mamdani FCs concern control of both manipulators and mobile robots [47–60].

The automotive industry is one special successful area of Mamdani FCs. Problems and practical issues related to suspension control are discussed in [61]. The control of hybrid electric vehicles is treated in [62] and the complexity of all related control strategies is emphasized in [63]. The control of anti-lock braking systems is analyzed in [64,65].

Process industries include Mamdani fuzzy control. The applications reported in this context tackle the control of furnaces [66,67], filtration processes [68], air conditioning [69,70], heat exchangers [71] or forging machines [72].

Control systems should exhibit generally very good steady-state, dynamic performance and robustness as well. Hence they require high quality servo systems that ensure both stabilization and tracking. The same problem is in case of complex control systems where the actuators can be viewed as local control systems with high needs as the performance is concerned. Servo systems are widely used in mechatronics applications characterized by tight coupling of different implementation techniques including hydraulics, mechanics, electro-mechanics, electronics and software [73–75]. Applications of these servo systems can be found in electro-hydraulic systems, actuators in robots or automotive systems, etc., where the CPs can be well characterized in simplified forms by benchmark systems [76–83]. One of the actual trends in control systems for mechatronics is that newer generations shall always be smaller, cheaper and/or provide additional functionality [75]. One difficult and challenging task coming from this is to devise cost-effective solutions that guarantee improved performance of these systems. Fuzzy control has recently been applied to a variety of servo systems and actuators in mechatronics [84–93].

Aircraft, missile autopilot and helicopter control represent also areas where fuzzy control is applied ensure performance improvements. The results outlined in these areas [94–102] can be connected well to those dedicated to servo systems.

2.1. PI-, PD- and PID-fuzzy control

PI, PD and PID controllers are still the most widely used in industrial control loops worldwide because they have simple structures, can be designed easily and offer good control system performance at acceptable cost [103]. The CS performance indices provided by these PID controllers depend not only on the tuning parameters, but also on the necessary implementation of additional functionalities including anti-windup, feedforward action, and set point filtering [104]. However, PI, PD and PID controllers might not ensure satisfactory control system performance if the mathematical model of the CP is highly nonlinear, subjected to parameter variance, and/or uncertainties. On the other hand, conventional fuzzy control is known for its ability to cope with nonlinearities and uncertainties. Introduction of dynamic fuzzy controller structures with the aim of control system performance improvement leads to PI-, PD- or PID-fuzzy controllers [105–108]. Several Mamdani PI-fuzzy controllers (PI-FCs), PD-fuzzy controllers (PD-FCs) and PID-fuzzy controllers (PID-FCs) [109–111] as well as Takagi-Sugeno PI-FCs, PD-FCs and PID-FCs [17,90,100,111] are developed.

PI-FCs, PD-FCs, and PID-FCs can be designed and tuned using two approaches:

- the first is based on the fact that under some well-stated conditions, the approximate equivalence between linear and fuzzy controllers is generally acknowledged [37,112–114],
- the second relies on the consideration of these fuzzy controllers (FCs) as nonlinear PD, PI, or PID controllers with variable gains [115–118].

The first approach is considered as the direct action type of PI-FCs, PD-FCs and PID-FCs [110] since the inference module calculates the control signal (action) directly to control a system. The second approach is viewed as gain scheduling [119,120].

Industrial implementations of PI-, PD- or PID-fuzzy controllers involve both approaches although the gain scheduling was first accepted from industry [121]. Applications of PI-FCs, PD-FCs and PID-FCs were classified and pointed out at the beginning of this section. Other applications are reported in [118,122–128]. Several topics of interest regarding PI-FCs, PD-FCs or PID-FCs, which are well identified in [29], concern the industrial applications FC tuning [117], optimal FCs by inserting genetic algorithms [122,124,129–134] or neural networks [29,135–137], and robust FCs [29,93,138–140].

2.2. Sliding mode fuzzy control

It is well acknowledged that sliding mode control exhibits robustness properties [141]. So a natural direction is to embed this property in fuzzy control. This will lead to the alleviation of the negative effects due to the chattering phenomenon specific to sliding mode control systems and the combination between the two techniques, sliding mode and fuzzy control, leads to complementing the advantages of both ones.

Usual approaches to sliding mode control are:

- The sliding mode controller handles linguistic information modelled by means of fuzzy processing with the elimination of the chattering phenomenon by the creation of fuzzy boundary layers [142–145].
- Supervisory sliding mode controller is inserted to fuzzy controller structures leading to the guarantee of stability and improvement of robustness [146–150].

These approaches ensure the convenient treatment of FCS stability analysis and design in the framework of the well developed methods dedicated to sliding mode control. Symmetrical FCs (as to their definition in an input–output matrix) can be regarded as sliding mode controllers with multiple sliding lines.

2.3. 2-DOF fuzzy control

Since the main tasks in control, the achievement of high performance in set-point tracking and the regulation in the presence of disturbance inputs are difficult to be accomplished by means of PI and PID controllers, one typical approach is to design two-degree-of-freedom (2-DOF) controllers which have advantages over the one-degree-of-freedom ones [151–153]. But, the main drawback of 2-DOF controllers is that although they ensure the regulation, the reduction of overshoot is paid by slower set-point responses because the 2-DOF structures can be reduced to feedforward controllers with set-point weighting.

The control performance enhancement with respect to the modifications of set-point and of load disturbance inputs ensured by the FCs in connection with the overcome of the above mentioned drawback of 2-DOF controllers leads to the idea of 2-DOF fuzzy controllers [154–158]. Very good control system performance with respect to the set-point and disturbance input

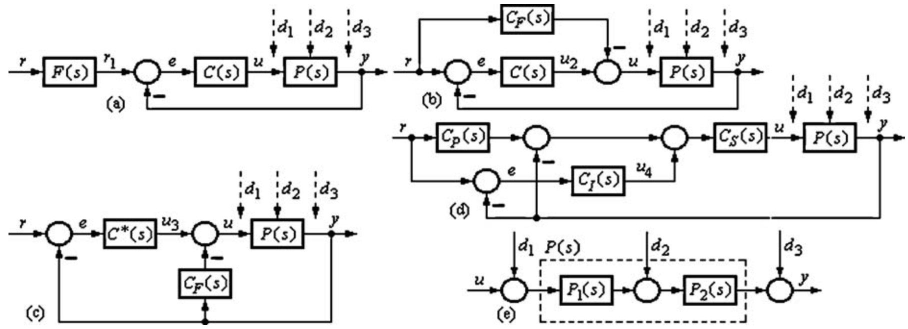

Fig. 2. Set-point filter 2-DOF control system structure (a), feedforward 2-DOF control system structure (b), feedback 2-DOF control system structure (c), component-separated 2-DOF PI control system structure (d), definition of load disturbance input scenarios (e).

can be obtained if the process with the transfer function of the controlled process $P(s)$ is included to the generic 2-DOF control system structures presented in Fig. 2, referred to as the set-point filter structure (Fig. 2(a)), the feedforward structure (Fig. 2(b)), the feedback structure (Fig. 2(c)) and the component-separated structure exemplified for the 2-DOF PI controller (Fig. 2(d)), where: r – the set-point, y – controlled output, $e = r - y$ or $e = r_1 - y$ – the control error, u – the control signal, r_1, u_2, u_2 and u_4 – the outputs of the blocks $F(s)$, $C(s)$ (in Fig. 2(b)), $C^*(s)$ and $C_I(s)$, respectively, and d_1, d_2 and d_3 – several load disturbance inputs defined in Fig. 2(e).

Some of the controller blocks in Fig. 2 can be fuzzified in order to improve the control system performance [158]. Similar structures can be formulated under the form of state-feedback control systems to be treated in the following sections.

3. Control systems with Takagi-Sugeno fuzzy controllers

T-S fuzzy models represent fuzzy dynamic models or fuzzy systems [25,28,159,160]. This brings a twofold advantage. First, any model-based technique (including a nonlinear one) can be applied to the fuzzy dynamic models. Second, the controller itself can be considered as a fuzzy system. Since the fuzzy model of the nonlinear process is usually based on a set of local linear models which are smoothly merged by the fuzzy model structure, a natural and straightforward approach is to design one local controller for each local model of the process. This idea is known as parallel distributed compensation [18]. In parallel distributed compensation (PDC) the structure of the FC model matches the structure of the fuzzy model of the CP.

The identification of T-S fuzzy models is of great importance generally for T-S FC designs and strictly necessary for PDC. Many good results and applications with this respect are reported in [16,18,29,161–166] where use is made of two approaches. The first one is to linearize the nonlinear model of the process in the vicinity of important operating points assuming that the model of the process is known for example in its first principle form. The second one, applied when the model of the process is unknown, is to make use of the data generated (analytically or experimentally) from the original nonlinear process. The second approach consists of two steps, the structure identification and the parameter estimation, and it employs various techniques to solve the optimization problem with the aim in fitting the models to the pairs of input–output data.

The industrial applications of T-S FCs were presented in the previous section in close connection to those of Mamdani FCs. However, due to the model-based design, most references offer results concerning the stabilization of T-S fuzzy models.

3.1. Stable design of model-based fuzzy control systems

The following continuous Takago-Sugeno fuzzy model of the process is considered in the state-space form

$$\begin{aligned} \dot{\mathbf{x}}(t) &= \sum_{i=1}^{r_B} h_i(\mathbf{z}(t))(\mathbf{A}_i\mathbf{x}(t) + \mathbf{B}_i\mathbf{u}(t)), \\ \mathbf{y}(t) &= \sum_{i=1}^{r_B} h_i(\mathbf{z}(t))\mathbf{C}_i\mathbf{x}(t), \end{aligned} \tag{4}$$

where r_B is the number of rules, $\mathbf{z}(t)$ is the vector of measurable variables of the process, $\mathbf{x}(t)$ is the state vector, $\mathbf{u}(t)$ is the control signal (input) vector, $\mathbf{y}(t)$ is the output vector, and

$$h_i(\mathbf{z}(t)) \geq 0, \quad i = \overline{1, r_B}, \tag{5}$$

are the degrees of fulfilment of the rules satisfying the convex sum property

$$\sum_{i=1}^{r_B} h_i(\mathbf{z}(t)) = 1. \tag{6}$$

The local linear models of the process

$$\begin{aligned} \dot{\mathbf{x}}(t) &= \mathbf{A}_i\mathbf{x}(t) + \mathbf{B}_i\mathbf{u}(t), \\ \mathbf{y}(t) &= \mathbf{C}_i\mathbf{x}(t), \quad i = \overline{1, r_B}, \end{aligned} \tag{7}$$

are supposed to be observable and controllable. In discrete T-S fuzzy models, $\dot{\mathbf{x}}(t)$ is replaced by $\mathbf{x}(t+1)$ in the models (4) and (7).

The PDC controller for the system (4) is

$$\mathbf{u}(t) = -\sum_{i=1}^{r_B} h_i(\mathbf{z}(t))\mathbf{F}_i\mathbf{x}(t). \tag{8}$$

The goal of the control design problem is to obtain the gain matrices $\mathbf{F}_i$, $i = \overline{1, r_B}$, of the nonlinear state-feedback control law (8) such that the closed-loop system modelled by Eqs. (2) and (8) is stable and eventually robust. Many design problems derive the least conservative conditions [28] that fulfil the condition

$$\sum_{i=1}^{r_B}\sum_{j=1}^{r_B} h_i(\mathbf{z}(t))h_j(\mathbf{z}(t))\boldsymbol{\Gamma}_{ij} < 0, \quad \boldsymbol{\Gamma}_{ij} = \boldsymbol{\Gamma}_{ij}^T. \tag{9}$$

The first results consider the quadratic Lyapunov function candidate [167]

$$V(\mathbf{x}) = \mathbf{x}^T(t)\mathbf{P}\mathbf{x}(t), \quad \mathbf{P} = \mathbf{P}^T > 0. \tag{10}$$

The calculation of the derivative of the function defined in (10) along the trajectories of the FCS characterized by Eqs. (2) and (8) leads to the result

$$\Gamma_{ij} = (\mathbf{A}_i - \mathbf{B}_i\mathbf{F}_j)^T\mathbf{P} + \mathbf{P}(\mathbf{A}_i - \mathbf{B}_i\mathbf{F}_j) < 0, \quad i, j = \overline{1, r_B}, \tag{11}$$

for continuous T-S models or

$$\Gamma_{ij} = (\mathbf{A}_i - \mathbf{B}_i\mathbf{F}_j)^T\mathbf{P}(\mathbf{A}_i - \mathbf{B}_i\mathbf{F}_j) - \mathbf{P} < 0, \quad i, j = \overline{1, r_B}. \tag{12}$$

for discrete T-S fuzzy models:

The main approach to solve the system of Eqs. (9) and (11) makes use of linear matrix inequality (LMI)-based techniques [168]. Popular approaches employ quadratic, piecewise quadratic, non-quadratic, parameter-dependent, polynomial and fuzzy Lyapunov functions [169–182], and they show the constant effort to reduce the conservativeness of the stability conditions. Although the LMIs are computationally solvable they require numerical algorithms embedded in well acknowledged software tools.

The LMIs can be applied to other control system structures with T-S FCs and models. They include the cascade control systems [183] eventually with fuzzy observers [184] which are validated by experiments and/or simulations.

3.2. Tensor product model transformation and fuzzy control systems

One of the current trends in fuzzy control is to derive less conservative conditions to prove the stability and the performance of FCSs [19,28,185]. The fuzzy partitions are the combinations of the products of rather simple arguments expressed as membership functions. In real-world applications one particular case concerns fuzzy modelling of nonlinear systems under the form of TP fuzzy systems. The expression of TP fuzzy systems can be understood in terms of operations on multi-dimensional arrays [185].

The TP model transformation is capable of transforming a dynamic system model, given over a bounded domain, into the TP model form, including polytopic or T-S fuzzy model forms. The TP model transformation may be defined as one numerical method capable of transforming the linear parameter-varying (LPV) dynamic models into parameter-varying weighted combination of parameter independent (constant) system models under the form of linear time-invariant (LTI) systems. This transformation of LPV models is uniform in both theoretical and algorithmic execution and it considers different optimization constraints. The main advantage of TP model transformation in modifying the given LPV models to varying convex combinations of LTI models is that the LMI-based control design frameworks can be applied immediately to the resulting affine models in order to get a tractable and improved performance of the FCSs.

The widely applied transfer function of the product decision operator-based T-S fuzzy models and the function of the TP model is the same from the analytical point of view in widely general cases. The main philosophical difference between them is that the T-S fuzzy model originally means a fuzzy combination of locally linearized LTI models, where the locality is expressed by the shape of the antecedent fuzzy sets, for instance, by triangular fuzzy sets where the location of the fuzzy set is readily determinable. However in case of TP model the weighting functions (which correspond to the membership functions in the fuzzy models) may not have locality, they spread in the whole interval of interest, so as the LTI components of the model cannot readily be assigned to a definite operation point. They are mostly vertexes of a polytopic structure. In conclusion, the T-S fuzzy model originally is a fuzzy combination of linearized operation points (LTI systems are close to local models), while the TP model is originally a polytopic structure (LTI systems are the vertex models of a convex hull of the model, they may be relatively far from any linearized operation points). In other words, an LTI system affects a fuzzy local area in case of T-S models. In the case of TP models an LTI system affects the whole operation domain, but according to the weighting functions. As a matter of fact, in today systems these two original ideas are combined in both T-S and TP models, therefore the difference is not important.

The TP model transformation generates two kinds of polytopic models. Initially, it reconstructs the high order singular value decomposition (HOSVD)-based canonical form of the LPV models. The major outcome of the recently developed HOSVD comes from its ability in decomposing a given N-dimensional tensor into a full orthonormal system in a special ordering of higher order singular values.

Regarding the variety of well acknowledged and implemented identification techniques, it is difficult to derive the uniform representation of the designed LPV model forms and the forms resulted from the identification. Hence the TP model transformation might be a possible solution for that situation, and an immediate link between the model transformation and the LMIs should be determined.

A key advantage of the TP model transformation is that it allows the modification of the parameter varying convex combination according to the designer's option. The type of the convex combination considerably influences the further LMI design and resulting control performance. Therefore the design can be based on the manipulation of the convex hull beside the manipulation of the LMIs.

Based on the core theory of the TP model transformation that is coming from the singular value decomposition (SVD) methods [186] the TP model transformation is capable of reducing the complexity of TP structured functions like T-S fuzzy models or B-spline models and so on. The multilinear generalizations of the SVD and the investigation on how the tensor symmetries affect the decomposition are discussed in [187]. The HOSVD has been developed since the existing framework of vector and matrix algebra; it appeared to be insufficient as increasing number of signal processing problems involved the manipulation of quantities of which the elements are addressed by more than two indices, i.e., higher-order tensors. Use is made of higher-order tensors to describe the transformations in the same way as the matrices describe linear transformations between vector spaces.

Making use of the TP model transformation, different optimization and convexity constraints can be considered and the transformations can be executed as well without any analytical interactions within less time. Thus, the transformation replaces the usual analytical conversions.

Accepting an N-dimensional bounded parameter vector $\mathbf{p}(t)$ and considering the LPV model

$$\begin{aligned} \dot{\mathbf{x}}(t) &= \mathbf{A}(\mathbf{p}(t))\mathbf{x}(t) + \mathbf{B}(\mathbf{p}(t))\mathbf{u}(t), \\ \mathbf{y}(t) &= \mathbf{C}(\mathbf{p}(t))\mathbf{x}(t) + \mathbf{D}(\mathbf{p}(t))\mathbf{u}(t), \end{aligned} \tag{13}$$

the system matrix

$$\mathbf{S}(\mathbf{p}(t)) = \begin{pmatrix} \mathbf{A}(\mathbf{p}(t)) & \mathbf{B}(\mathbf{p}(t)) \\ \mathbf{C}(\mathbf{p}(t)) & \mathbf{D}(\mathbf{p}(t)) \end{pmatrix} \in \Re^{O\times I} \tag{14}$$

is a parameter-varying object. The convex state-space TP model describes the LPV state-space model for any parameter vector $\mathbf{p}(t)$ as the convex combination of LTI system matrices

$$\begin{pmatrix} \dot{\mathbf{x}}(t) \\ \mathbf{y}(t) \end{pmatrix} = S\otimes_{n=1}^{N}\mathbf{w}_n(\mathbf{p}_n(t))\begin{pmatrix} \mathbf{x}(t) \\ \mathbf{u}(t) \end{pmatrix}, \tag{15}$$

where the row matrix $\mathbf{w}_n(\mathbf{p}_n(t))$ contains one bounded variable and its continuous weighting functions, and N indicates the tensor's dimension. The (finite element) TP model defined in (15) is convex only if the weighting functions fulfil the condition

$$w_{n,i}(\mathbf{p}_n(t)) \in [0,1], \quad \forall n, i, \mathbf{p}_n(t),$$
$$\sum_{i=1}^{I_n} w_{n,i}(\mathbf{p}_n(t)) = 1, \quad \forall n, \mathbf{p}_n(t). \tag{16}$$

The LMI-based controller design methods can immediately be applied after the transformation of the LPV model (14) given in HOSVD-based canonical form to the TP model form expressed in (15) and (16). In other words, the TP model transformation is to be used and executed before utilizing the LMI design, i.e., when the LMI design is started the global weighting functions are already defined.

A short presentation of the applications of TP model transformation, well connected to T-S FCSs, is presented in [188] and accompanied by a temperature control application. An attractive control design method accompanied by application is given [189,190] to stabilize parameter varying nonlinear state-space models. It is based on two numerical steps. In the first step the TP model transformation is executed. In the second step LMIs are solved under the PDC framework. The first step consists in transforming a given model into a TP, so that the design techniques of the PDC framework can be employed. The operations associated to the second step produce a controller according to various control specifications. The advantages of this method are twofold. First, the controller can be derived automatically, regardless of analytic derivations. Second, the identified model can be defined either by analytical equations or by other soft computing techniques.

A popular TP model application deals with controlling the TORA system [191] where a nonlinear controller has been designed making use of the TP model transformation and a LMI-based controller design technique. The results show that both numerical methods, the TP model transformation and the LMIs, can be accomplished numerically without analytical derivations, leading to fast controller designs.

A case study regarding the TP model transformation behaviour in real-world applications is discussed in [192] with focus on the single pendulum gantry system. A generalization of the double fuzzy summation results to multiple summations with a TP structure is emphasized in [185]. This is meant to replace the well accepted common structure in many fuzzy models. A simulated application concerning the inverted pendulum system is included.

A Matlab toolbox for TP model transformation, the TP Tool, is implemented and described in [193]. The toolbox is applied to several benchmark systems and to the real-time control of the liquid levels in a three tank system [194].

An excellent application of the TP model transformation deals with offering a control solution for the aeroelastic wing section problem that was considered as unsolved previously [195,196]. This is the first convincing well detailed example of applying TP model transformation with PDC design framework. It shows the observer design as well.

4. Adaptive fuzzy control, supervision and optimization

There are many formations for the FC in FCSs similarly to the different control schemes focused on PI controllers presented in Fig. 2. An adaptive FC has one extra component, a supervisory module, as shown in Fig. 3. The supervisory module has

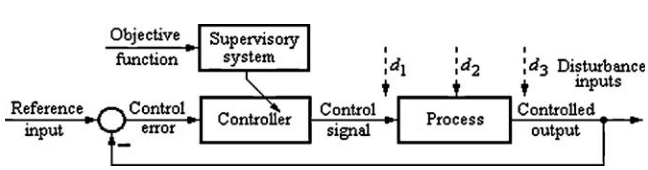

Fig. 3. An adaptive fuzzy controller with a supervisory system.

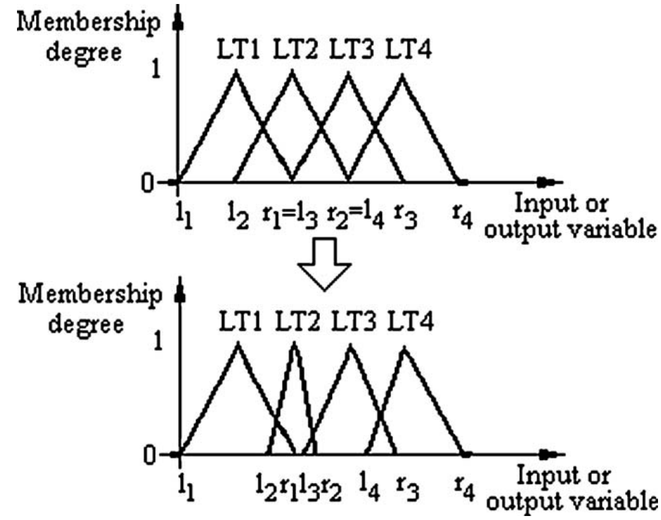

Fig. 4. Changing the side slopes of a group of membership functions. The modal values (centres) stay at the same position.

understanding of the process and of the controller, and has access to all input and usually also to all output signals. The supervisory module can modify several components of the fuzzy controller like the size of the membership functions of the fuzzy sets, the position of the membership functions, the rule weights and/or the link values. These four items will be discussed below. A predictive FC will be also described. That controller does not change the parameters of the underlying FC, but it chooses every time the best control signal based on a performance measure expressed in terms of an objective function. The goal is to minimize the objective function.

4.1. Adaptation of the size of the membership functions

The supervisor can change the size of the membership functions of the fuzzy sets corresponding to the linguistic terms of the FC, e.g., increase or decrease the support (width) of an individual membership functions or change the width to the left-hand or right-hand side, like in Fig. 4, applicable to both input and output linguistic variables of the fuzzy controller. The triangular membership functions of the linguistic terms LT1, Lt2, LT3 and LT4 were chosen in Fig. 4, with the parameters $l_i, r_i, i = \overline{1,4}$. Likewise, the spread σ of Gaussian fuzzy sets can be adapted.

Actually, the adaptation means that the supervisor can change the partitioning of the membership functions on the universe of discourse. An example of this is a controller for the cruise control of a car [197]. With cruise control the driver fixes the speed of the car. If the car goes uphill or downhill the cruise system controls the throttle in such a way that the car keeps its velocity, if the driver touches the break pedal or the "coach button" the cruise system will stop working until the "resume button" is touched. By then, the car will accelerate until it returns to the desired speed. Depending on the load of the car and the weather conditions this can lead to too fast or too slow acceleration and overshoot. The supervisor should "learn" the load of the car and adapt the cruise control to the current situation.

In [197] the system is described as in Fig. 5. The error in the velocity is calculated from the vehicle and the reference speed, the same holds for the first and second derivative of the speed. The FC calculates the throttle opening, passes it on to the actuator which applies it to the vehicle. If the throttle opening is too slow or too fast, i.e., the car accelerates too slow or to fast, the supervisor changes the membership functions of the fuzzy sets corresponding

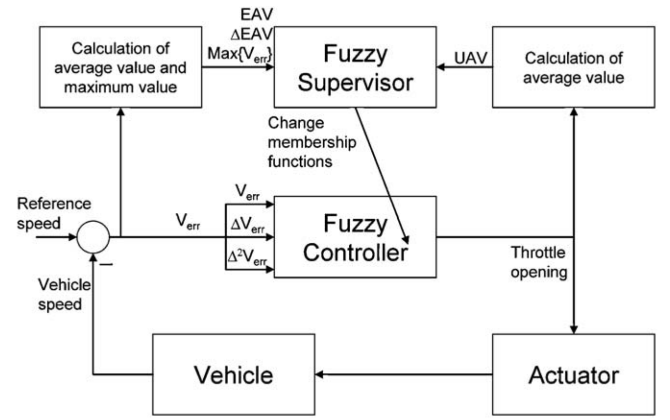

Fig. 5. Logical scheme of an adaptive fuzzy system for cruise control. EAV is the error average value, UAV is the average value of the throttle opening, V_{err} is the maximum value of the error [197].

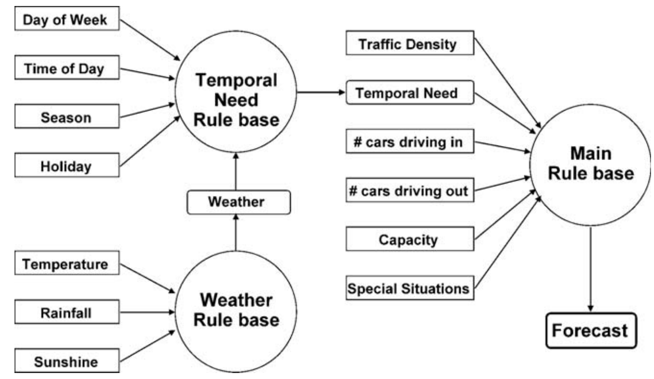

Fig. 7. Structure of fuzzy parking system.

Table 1
Parking garages and the prediction quality of the adapted fuzzy system.

Parking garage	Prediction quality July	Prediction quality August
PG1	0.9548	0.9239
PG2	0.9147	0.9086
PG3	0.9298	0.9272
PG4	0.9415	0.9051
PG5	0.9147	0.8849
PG6	0.9415	0.9374

to the linguistic terms of the fuzzy controller. The supervisor has four inputs: the error average value (EAV) and its first derivative (ΔEAV), the maximum value of the error (V_{err}) and the average value of the throttle opening (UAV). The error average value and its derivative give an indication how long it takes to bring the car back to its desired speed. If the car accelerates too slow this means, for example, that the car is fully loaded and the membership functions in the controller should be adapted to this situation.

4.2. Adaptation of the position of the membership functions

Another method to tune an FC or a fuzzy decision system is by repositioning the membership functions of the fuzzy sets corresponding to the linguistic terms of the fuzzy controller. Usually this is done in combination with a data clustering method. In a high dimensional system the data points are normally not evenly distributed over the whole data space, but occur in groups. If one uses a clustering algorithm to identify the data clusters then one can position the membership functions of the fuzzy sets in such a way that they correspond exactly to the data clusters. This enables one to work with a minimal number of fuzzy sets whose membership functions are well positioned to deal with the data. Fig. 6 illustrates this information processing, where v_1 and v_2 are the inputs, μ_{k1} and μ_{k2} are the membership functions of the input linguistic terms, $k = \overline{1,5}$. Overviews on data-driven clustering methods for adaptive fuzzy control are given in [198,199].

An example of this method is a fuzzy system for forecasting the number of empty places in a number of parking garages downtown [200]. The system has a large number of inputs like weather data, time information and traffic information as shown in Fig. 7. The weather is supposed to influence the number of people that go downtown for shopping or to visit the theatre, hence the three weather inputs (temperature, rainfall and sunshine) influence the number of cars downtown. Time information concerns the time of the day, the day of the week, the season and special days like holidays or large events. Together with the weather information they will give a forecast of the number of cars that will go downtown in the next hours. Traffic information concerns the traffic density, and therefore the time people need to arrive at the parking garage, and the time people need to enter the parking garage, as many of them have narrow passages and long waiting times when other people are manoeuvring through the garage. When one considers data points over a longer period of time for each parking garage separately, different patterns of data will lead to a different positioning of the membership functions and therefore to different fuzzy rule bases. In six different parking garages in Düsseldorf, Germany, the initial prediction quality of the described system was around 80%. After repositioning and resizing the membership functions of the fuzzy sets with a neural network, the prediction quality changed as described in Table 1.

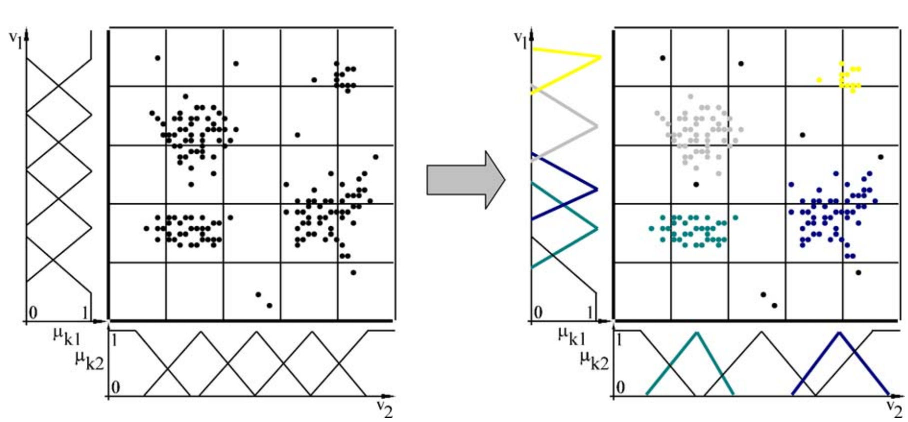

Fig. 6. Repositioning fuzzy sets such that they fit to clusters of input data.

4.3. Adaptation of the rule base

A third adaptation method option is to change the rule weights depending on the contribution of each rule to the performance of the fuzzy control system. Each rule has a rule weight r_i, usually these r_i's are initially 1. If a control action was successful the rule weights of the involved rules in this action are increased. If an action was unsuccessful the weights of the involved rules are decreased. Rules that after some time have rule weight 0 are not involved anymore and will be removed.

This is an easy and straightforward method. Of course the quality of this method highly depends on the performance measure and the selection of the training data. One should always check which rules were removed, in some cases these rules concern exception cases and should be reintroduced by hand. This method is used in identifying and controlling a large paper mill [201], and in traffic modelling and control [202].

4.4. Adaptation of the link values

A fourth adaptation method is to change the link values. This is derived from neural networks and is actually not natural for fuzzy systems. It means the following. Consider a rule base with two inputs X_1 and X_2 and one output Y, and three fuzzy sets P, Z, and N, on each input domain. One can translate the fuzzy system to a neural network as described in Fig. 8. If one takes, for example, the fifth node in the Inference column, this corresponds to the rule "if X_1 is N and X_2 is P then Y is Z". According to [203,204], the logarithms and exponentials are needed in this scheme to cope with several neural network properties.

Now one can feed the neural network with input and output data pairs and train the network. Consider, for example, the rule "if X_1 is Z and X_2 is P then Y is P", corresponding to the lowest node in the Inference column of Fig. 8. After training the network this may have become "if (0.5 X_1 is Z) and (0.3 X_2 is P) then (0.8 Y is P)", because the neural network has adapted the link values. This rule is hard to interpret but will probably describe the situation exactly.

This method is, for example, used in a system with many sensors in a car that had to diagnose the kind of road and traffic conditions the car was driving in [204]. There was an initial rule base describing the logical relation between the sensors and the driving situation. Test data were generated by driving the car with a video camera several days in all kinds of situations. The test data were categorized to several driving situations. After translating the rule base to a neural network all rule weights, the positions of the membership functions and the link weights were adapted which resulted in a much improved fuzzy rule base. The customer demanded a rule base that could be checked by hand afterwards instead of a black box neural network. The combination of a neural network learning system and a readable fuzzy rule base is perfect for automotive industry.

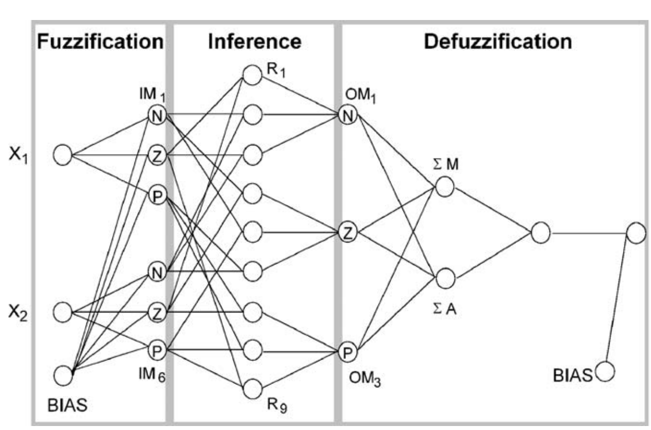

Fig. 8. A neural network translation from a fuzzy rule base.

The neuro-fuzzy control systems can identify fuzzy control rules and tune membership functions of the fuzzy controller making use of the learning algorithms specific to neural networks due to the well accepted functional equivalence between certain classes of fuzzy systems and certain architectures of neural networks [161]. Neuro-fuzzy control is in fact fuzzy control that ensures enhanced control system performance due to the learning capabilities and parallel processing brought by the neural networks. ANFIS [205] is the most popular approach with this regard. Industrial applications of adaptive fuzzy control can be found in batch processes [206–210], robotics [58,137,211–213], aircrafts [214–217] or servo systems and electrical drives [218–221]. An attractive application concerning the development of an intelligent distributed and supervised control system for high-volume production systems is suggested in [222]. A neural-fuzzy-based force model for controlling band sawing process in the framework of an intelligent adaptive control and monitoring system is given in [223]. An adaptive control solution for a ventilating and air-conditioning (HVAC) system is proposed in [224].

Topics of interest in adaptive fuzzy control include robust adaptive control, the combination with sliding mode control and the inclusion of derivative-free optimization techniques to minimize the objective function that specifies the performance measure of the FCS. The derivative-free optimization techniques are needed in industrial applications due to the complicated expression of the objective function with several possible local minima and to the specific constraints associated to the optimization problem. Several fuzzy rule interpolation techniques can be used in real-time applications which have sparse or incomplete rule bases [225–227].

4.5. Fuzzy model-based predictive control

One illustrative industrial application of fuzzy model-based predictive control is presented in [228]. A predictive controller is suggested to modify the parameters of a T-S FC using the prediction of the future process output. Use is made of the fact that if you have a fuzzy model, you can test assumed future situations by putting data into the model. It is possible to compare the outcomes of different control inputs and take the best to proceed with. The results presented in [228] involve a fuzzy model of a chemical plant under the form of the following six fuzzy rules:

$$\begin{aligned} R_j &: \text{IF } C_A(k) \text{ IS } A_j \text{ THEN } C_A(k+1) \\ &= -a_{1j}C_A(k) - a_{2j}C_A(k-1) + b_{1j}q_c(k-T_{D_m}) + r_j,\ j = \overline{1,6}, \end{aligned} \tag{17}$$

where C_A is the measured product concentration and T_{D_m} is the temperature. It is possible to rewrite these under the classical form

$$\begin{aligned} \mathbf{x}_m(k+1) &= \bar{\mathbf{A}}_m\mathbf{x}_m(k) + \bar{\mathbf{B}}_m u(k-T_{D_m}) + \bar{\mathbf{R}}_m, \\ y_m(k) &= \bar{\mathbf{C}}_m\mathbf{x}_m(k). \end{aligned} \tag{18}$$

The system output is calculated as follows for H steps ahead:

$$\begin{aligned} y_m(k+H) = \bar{\mathbf{C}}_m[&\bar{\mathbf{A}}_m^H\mathbf{x}_m(k) + (\bar{\mathbf{A}}_m^H - I)(\bar{\mathbf{A}}_m - I)^{-1}(\bar{\mathbf{B}}_m u(k) \\ &+ \bar{\mathbf{R}}_m)], \end{aligned} \tag{19}$$

and it compares the output with the output of a reference model. It then calculates which parameters force the output to reach the reference trajectory in the best way and uses these parameters in the next control step. Other industrial applications of fuzzy model-based predictive control are reported in [229–236].

5. Conclusions

The paper addresses a brief survey on industrial applications of fuzzy control. The following classification of the control systems has been proposed with this regard:

- control systems with Mamdani fuzzy controllers,
- control systems with Takagi-Sugeno fuzzy controllers,
- adaptive and predictive control systems.

Although the literature makes a distinction between model-based and model-free fuzzy control, the model-based design of fuzzy control outlined in [237] is needed. The authors' opinion is that all fuzzy control applications should be tackled in the model-based design manner. This is the way that enables systematic analyses of the structural properties of the FCSs such as stability, controllability, parametric sensitivity and robustness. Furthermore, this is the only solution to guarantee the desired/imposed control system performance indices in several operating regimes, and it represents one of the perspectives of fuzzy control.

A lot of industrial applications of fuzzy control are known and reported today. This paper has highlighted just part of them. It contains both mathematics and concrete applications thus emphasizing the concrete connection between the industrial applications of fuzzy control and the necessity of understanding the basics of operating principle and mathematical characterizations of fuzzy controllers. The presentation of rather real-time experiments instead of digital simulation results is another perspective of fuzzy control. In this context the popularity of fuzzy control will increase only if future applications will exhibit significantly better performance compared to the non-fuzzy ones.

There are several challenges which deserve more study when fuzzy control is regarded from the point of view of its applicability:

- the design of rather general fuzzy controllers for well defined classes of systems instead of the particular controllers dedicated to certain narrow applications,
- the use of iterative tuning and learning techniques that start with initial fuzzy control systems and ensure next the performance enhancement making use of the variables measured from those closed-loop systems during their real-time operation [32,91],
- the identification of Takagi-Sugeno fuzzy models with trade-off to transparency, approximation accuracy and controller design possibility,
- the connection between the parameter settings and tuning of the fuzzy controller, and the imposed control system performance in terms of performance indices like overshoot and settling time,
- the alleviation of the conservatism and sufficient conditions-like character in the stable design of fuzzy control systems in case of Lyapunov's approach in connection with LMIs,
- the need for low-cost fuzzy controllers from the points of view of design in tuning transparency as well as implementation costs,
- the need for smooth control signals to be elaborated by all fuzzy controllers,
- the use of the additional parameterization offered by type-2 fuzzy logic in handling the uncertainties specific to industrial processes [238–244].

These challenges will attract the researchers and practitioners. The immediate results will be reflected in more industrial applications of fuzzy control illustrated in conference and journal publications. The 244 reference positions cited here present a sample of the results reported in the literature, and they can be viewed as a guarantee that future successful applications will be constructed.

Acknowledgements

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