On the Use of Iterative Learning Control in Fuzzy Control System Structures

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Abstract: The paper suggests new fuzzy control system structures incorporating Iterative Learning Control (ILC) algorithms. After the presentation of basics in ILC, elements of fuzzy control system structures and their design are highlighted. One of the fuzzy control system structures is validated in terms of a real-world application in the area of servo systems.

Keywords: Iterative Learning Control, fuzzy control systems, servo systems

1 Introduction

Fuzzy control, viewed as particular case of intelligent control, aims to ensure better control system (CS) performance (in dynamic and steady-state regimes and from the robustness point of view). The CS performance indices are more and more important the complexity of applications increases, well-known applications being those in servo systems as part of nonlinear plants characterized by benchmark type models used in mechatronic and embedded systems. Ensuring these very good CS performance indices in the conditions of low-cost can be performed only in the conditions of systematic development of fuzzy controllers.

On the other hand, Iterative Learning Control (ILC) represents a tuning technique based on the fact that CS performance executing repetitively the same tasks can be improved using previous experiments in CS operation. The scope of ILC, well presented in the position paper [1], is in the iterative solving of a parametric optimisation problem, called learning, which ensures the minimization of an objective function which specifies CS performance indices. In order to solve this optimisation problem there are implemented ILC algorithms that ensure CS performance enhancement from one experiment to another (one iteration to another) by including the information gained from previous experiments / iterations using adequate memorizing techniques.

From the point of view of the operating principle of ILC algorithms, they generate an open-loop signal, which does the approximate inversion of plant model for the sake of reference tracking and repetitive disturbance rejection. In order to cope with non-anticipative disturbances ILC algorithms are combined with controllers resulting in several actual design techniques for ILC algorithms including:

- learning functions of PD-type PD [2, 3, 4, 5], which allow controller tuning without requiring the detailed mathematical model of the controlled plant,
- learning functions based on the plant model inversion [6, 7], which guarantee a rapid convergence but are in turn sensitive to modelling errors,
- H_∞ techniques [8, 9], which permit the design of robust and convergent ILC algorithms but having shortcomings in CS dynamic performance,
- quadratic optimisation (Q-ILC) [10, 11, 12], based on minimizing integral indices expressed as quadratic objective functions.

There have been approached various updated applications of ILC in robot control [4, 13, 14, 15], machine-tools control [16], electrical and electromechanical drive control [17, 18], autonomous vehicle control [19], ABS control [20], thermal plant control [21, 22], chemical plant control [23], and those specific to servo systems in computing systems [24, 25].

The main advantages of ILC with respect to other control or feedforward approaches, which result from the analysis of all papers mentioned before, with focus on [1, 4, 24], are:

- ILC has anticipatory character and can ensure the compensation for repetitive external disturbances by learning (associated with memorization) based on previous iterations,
- ILC does not require knowing the variations of reference and disturbance inputs being necessary just repeating these signals from one iteration to another,
- in some well-stated conditions ILC ensure the CS robustness with respect to process modelling uncertainties.

However, the ILC technique has shortcomings structured, as follows [1, 15, 25], under the form of absence of:

- formalizing the connection between robustness and dynamic and steady-state CS performance and ensuring the best of these requirements simultaneously,
- treating the situations in which the reference and disturbance inputs do not have repetitive variations,
- convergence conditions related generally to any iterative technique.

The aim of combining the ILC technique with fuzzy control is to achieve CS performance enhancement in conditions of low-cost, few papers dealing with this until now (for example, [26, 27]). The CS performance enhancement results from merging in the same CS structure the benefits of both feedback (due to fuzzy control) and feedforward compensation (due to ILC). This paper presents new fuzzy control system structures incorporating ILC algorithms.

The paper is structured as follows. The following Section is dedicated to the problem setting in ILC. Then, Section 3 deals with presenting elements regarding the original fuzzy control system structures and their design. Section 4 is focused on preliminary real-time experimental results for a case study concerning DC-based servo system speed control in order to validate one of the new fuzzy control system structures, and the conclusions end the paper.

2 Overview on Iterative Learning Control

In order to simplify the presentation of ILC the controlled plant is considered characterized by the following discrete-time linear time-invariant SISO system:

$$y_j(k) = P(q)u_j(k) + d(k), \tag{1}$$

where: y – controlled output, u – control signal, d – exogenous input signal (for example, load-type disturbance input) that repeats each iteration, k –index of current sampling interval, j – index of current iteration / trial, q – forward time-shift operator, $P(q)$ – proper rational function of the plant, with a delay of mT_s (having the relative degree of $m \in N^*$), T_s – sampling period. $P(q)$ is supposed to be asymptotically stable. If not, it can be stabilized firstly in a conventional control system, the ILC being applied afterwards to the closed-loop system.

Considering the following sequences of N samples of plant inputs and output and the reference input sequence is $r(k)$:

$$\begin{aligned} &u_j(k), k \in \{0,1,...,N-1\}, y_j(k), k \in \{m, m+1,..., N+m-1\}, \\ &d(k), k \in \{m, m+1,..., N+m-1\}, r(k), k \in \{m, m+1,..., N+m-1\}, \end{aligned}, \tag{2}$$

the control error signal is defined in terms of (3):

$$e_j(k) = r(k) - y_j(k) \,. \tag{3}$$

A widely used ILC algorithm [1, 3, 8, 14] is expressed as:

$$u_{j+1}(k) = Q(q)[u_j(k) + L(q)e_j(k+1)] \,, \tag{4}$$

where $Q(q)$ is referred to as the Q-filter and $L(q)$ as the learning function. The presence of Q in (3) makes to be refereed as Q-ILC algorithm.

In order to perform the analysis of the control system with ILC having the structure in terms of (1) and (4) in the time-domain the controlled plant in (1) is expanded firstly as an infinite power series doing the polynomial division:

$$P(q) = p_m q^{-m} + p_{m+1} q^{-m-1} + p_{m+2} q^{-m-2} + \dots \,, \tag{5}$$

with the Markov coefficients p_m, m = 1, 2, … Then, the plant dynamics can be expressed in the following matrix form referred to as lifted form [1]:

$$\begin{aligned} \mathbf{y}_j &= \mathbf{P}\,\mathbf{u}_j + \mathbf{d}, \\ \mathbf{e}_j &= \mathbf{r} - \mathbf{y}_j, \end{aligned} \tag{6}$$

with the matrix and vectors defined according to (7):

$$\begin{aligned} \mathbf{y}_j &= [y_j(m) \quad y_j(m+1) \quad \dots \quad y_j(m+N-1)]^T, \\ \mathbf{P} &= \begin{bmatrix} p_m & 0 & \dots & 0 \\ p_{m+1} & p_m & \dots & 0 \\ \dots & \dots & \dots & \dots \\ p_{m+N-1} & p_{m+N-2} & \dots & p_m \end{bmatrix}, \\ \mathbf{u}_j &= [u_j(0) \quad u_j(1) \quad \dots \quad u_j(N-1)]^T, \\ \mathbf{d} &= [d(m) \quad d(m+1) \quad \dots \quad d(m+N-1)]^T, \\ \mathbf{e}_j &= [e_j(m) \quad e_j(m+1) \quad \dots \quad e_j(m+N-1)]^T, \\ \mathbf{r} &= [r(m) \quad r(m+1) \quad \dots \quad r(m+N-1)]^T, \; j = 1,2,\dots. \end{aligned} \tag{7}$$

The lifted form of the ILC algorithm (4) can be expressed in a similar way using the fact that $Q(q)$ and $L(q)$ can be non-causal functions having the impulse responses (8):

$$\begin{aligned} Q(q) &= \dots + q_{-2}q^2 + q_{-1}q + q_0 + q_1 q^{-1} + q_2 q^{-2} + \dots, \\ L(q) &= \dots + l_{-2}q^2 + l_{-1}q + l_0 + l_1 q^{-1} + l_2 q^{-2} + \dots. \end{aligned} \tag{8}$$

Therefore, the lifted form of (4) is:

$$\mathbf{u}_{j+1} = \mathbf{Q}(\mathbf{u}_j + \mathbf{L}\,\mathbf{e}_j) \,, \tag{9}$$

where the two matrices introduced are:

$$\mathbf{Q} = \begin{bmatrix} q_0 & q_{-1} & \cdots & q_{-N+1} \\ q_1 & q_0 & \cdots & q_{-N+2} \\ \cdots & \cdots & \cdots & \cdots \\ q_{N-1} & q_{N-2} & \cdots & q_0 \end{bmatrix}, \quad (10)$$

$$\mathbf{L} = \begin{bmatrix} l_0 & l_{-1} & \cdots & l_{-N+1} \\ l_1 & l_0 & \cdots & l_{-N+2} \\ \cdots & \cdots & \cdots & \cdots \\ l_{N-1} & l_{N-2} & \cdots & l_0 \end{bmatrix}.$$

The lifted form of the mathematical model of the control system with ILC having the structure in terms of (1) and (4) becomes

$$\mathbf{u}_{j+1} = \mathbf{Q}(\mathbf{I} - \mathbf{L}\,\mathbf{P})\mathbf{u}_j + \mathbf{Q}\,\mathbf{L}(\mathbf{r} - \mathbf{d})\,. \quad (11)$$

In the z-domain the mathematical model of the control system with ILC having the structure in terms of (1) and (4) is (12):

$$u_{j+1}(z) = Q(z)[1 - zL(z)P(z)]u_j(z) + zQ(z)L(z)[r(z) - d(z)]\,. \quad (12)$$

It can be observed from (11) and (12) that the system properties including the transient behaviour depend mainly on the matrix $\mathbf{Q}(\mathbf{I} - \mathbf{L}\,\mathbf{P})$ and the function $Q(z)[1 - zL(z)P(z)]$. Therefore, the necessary and sufficient condition for the asymptotic stability of the control system with ILC having the structure in terms of (1) and (4) can be expressed as follows [28]:

$$\rho(\mathbf{Q}(\mathbf{I} - \mathbf{L}\,\mathbf{P})) < 1\,, \quad (13)$$

with ρ – spectral radius. The sufficient asymptotic stability condition for the control system with ILC having the structure in terms of (1) and (4), in the condition $N = \infty$, is [28]:

$$\| Q(z)[1 - zL(z)P(z)] \|_\infty < 1\,. \quad (14)$$

In addition, the control steady-state control error is zero for an asymptotically stable system if and only if:

$$Q(1) = 1\,. \quad (15)$$

If the control system with ILC having the structure in terms of (1) and (4) is asymptotically stable, then the asymptotic error can be expressed for the lifted form and the z-domain in terms of (16) and (17), respectively:

$$\mathbf{e}_\infty = \{\mathbf{I} - \mathbf{P}[\mathbf{I} - \mathbf{Q}(\mathbf{I} - \mathbf{L}\,\mathbf{P})]^{-1}\mathbf{Q}\,\mathbf{L}\}(\mathbf{r} - \mathbf{d})\,, \quad (16)$$

$$e_\infty(z) = [1 - Q(z)]/\{1 - Q(z)[1 - zL(z)P(z)]\}[r(z) - d(z)]\,. \quad (17)$$

The ILC algorithm (4) can be combined with conventional control systems with feedback controllers in two ways at least generating corresponding control system structures:

- a serial form, where the ILC control signal $u_j(k)$ is added to the reference input before the feedback loop,
- a parallel form, where the ILC control signal $u_j(k)$ is added to the feedback controller control signal.

Other versions of ILC algorithms are:

- the current-iteration ILC algorithm, given by [1]:

$$u_{j+1}(k) = Q(q)[u_j(k) + L(q)e_j(k+1)] + C(q)e_j(k+1)\,, \tag{18}$$

where $C(q)$ stands for the proper rational function of the feedback controller,

- the PD-type learning function in two forms, (17) and (18):

$$u_{j+1}(k) = u_j(k) + k_p e_j(k+1) + k_d[e_j(k+1) - e_j(k)]\,, \tag{19}$$

$$u_{j+1}(k) = u_j(k) + k_p e_j(k) + k_d[e_j(k+1) - e_j(k)]\,, \tag{20}$$

where k_p is the proportional gain and k_i is the derivative gain.

3 Fuzzy Control Systems Incorporating ILC

The new fuzzy control structures are suggested in order to fulfil the mentioned aim, represented by CS performance enhancement in the conditions of low-cost. Therefore, the fuzzy controller structures incorporating ILC are presented in Fig. 1 … Fig. 4. The following nomenclature is used in these fuzzy control system structures: ILCA – Iterative Learning Control algorithm, FILCA – Fuzzy Iterative Learning Control algorithm, F – feedforward filter, r_1 – filtered reference input, d_1, d_2, d_3 – load-type disturbance input types, assumed to be repetitive, M – memory block, FC – fuzzy controller, B-FC – basic two input-single output (TISO) fuzzy controller, and the other variables keep the nomenclature presented in the previous Sections.

Regarding the fuzzy control system structure presented in Fig. 4, it corresponds to fuzzifying the PD block appearing in (19), and (20), the block with the transfer function q^{-1} being necessary only in the fuzzified version corresponding to (20). This is necessary because in conventional ILC algorithms it is difficult to ensure the compromise to both converged error performance and robustness. Ensuring these requirements simultaneously can be achieved by means of the correct tuning of B-FC placed on the hierarchical level taking into account that B-FC is in fact a variable structure controller ensuring bumpless interpolation between linear ones.

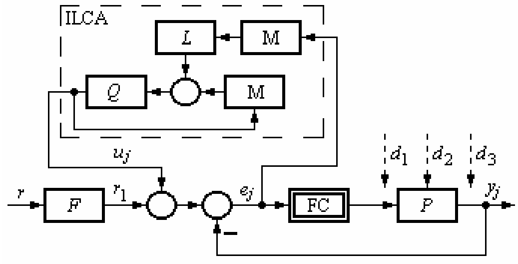


Figure 1
Fuzzy control system structure with serial ILC

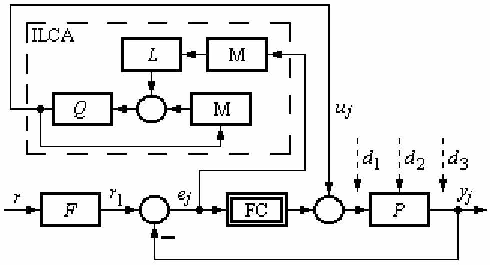


Figure 2
Fuzzy control system structure with parallel ILC

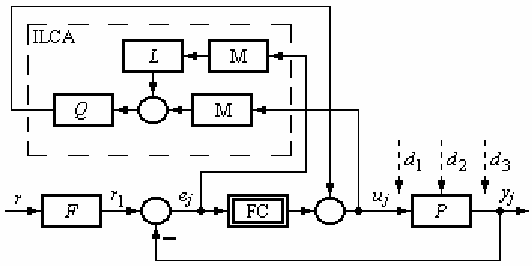


Figure 3
Fuzzy control system structure with current-iteration ILC

There are possible also other fuzzy control system structures by the proper combination of the first four ones. The general design method for the fuzzy controller structures in Figs. 1-3, will be presented in a unified manner, concentrated on the Mamdani PI-fuzzy controllers with the structure presented in Fig. 5 and membership function shapes in terms of Fig. 6. The key element in Fig. 5 is the basic fuzzy controller, B-FC, that represents a TISO nonlinear system, employs Mamdani's MAX-MIN compositional rule of inference that can be assisted by several rule bases and the centre of gravity method for defuzzification. The method consists of the following design steps:

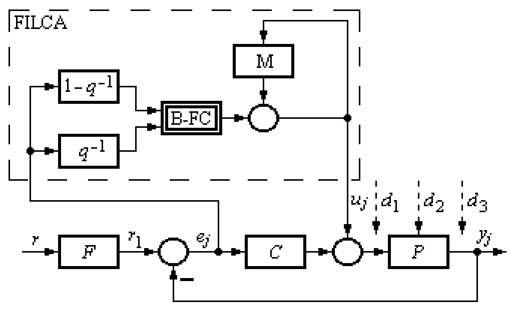


Figure 4

Fuzzy control system structure with PD-type learning function

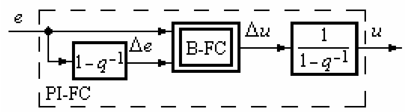


Figure 5

PI-fuzzy control system structure without scaling factors

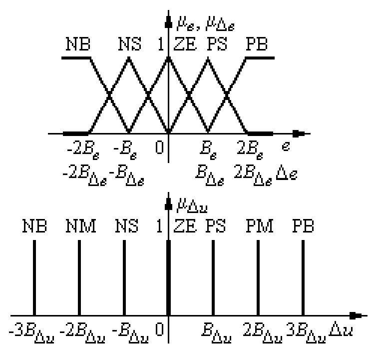


Figure 6

Membership function shapes

I Steps of the ILCA tuning that will differ from one structure to another.

II Steps of the linear controller design, the initial controller replacing the block FC in the fuzzy control systems structures and representing in fact a two-degree-of-freedom (2-DOF) PI controller:

- tune the feedforward filter $F(s)$ (in continuous-time) and the continuous-time linear PI controller, $C(s)$:

$$C(s) = k_c(1+sT_i)/s = k_C[1+1/(sT_i)],\ k_C = T_i k_c, \tag{21}$$

  with k_C – controller gain and T_i – integral time constant, using a continuous-time design method depending on the controlled plant and on the desired / imposed CS performance indices,

- choose the sampling period, T_s, according to the requirements of quasi-continuous digital control,

- express the discrete-time equation of the digital PI controller $C(z)$ in its incremental version:

$$\Delta u(k) = K_P \Delta e(k) + K_I e(k) = K_P[(\Delta e(k) + \alpha \cdot e(k)], \tag{22}$$

  with Δx standing generally for the increment of a certain variable, x, and calculate the parameters $\{K_P, K_I, \alpha\}$. For example, the expressions of these parameters are presented in (23) in case of Tustin's method:

$$K_P = k_C[1 - T_s/(2T_i)],\ K_I = k_C T_s/T_i,\ \ \alpha = K_I/K_P = 2T_s/(2T_i - T_s). \tag{23}$$

III Steps of the PI-fuzzy controller design based on the transfer of results from the linear case to the fuzzy one in terms of the modal equivalence principle:

- set the value of the controller parameter B_e according to the experience of the control systems designer,

- apply the modal equivalence principle [31]:

$$B_{\Delta e} = \alpha B_e, B_{\Delta u} = K_I\, B_e. \tag{24}$$

4 Real-time Experimental Results

To validate the control system structure with ILC presented in Fig. 1 it is considered a case study focused on a PI-fuzzy controller design for the class of plants with the transfer function $P(s)$ characterizing simplified mathematical models used in servo systems as part of mechatronic and embedded systems:

$$P(s) = k_P/[s(1+T_\Sigma s)], \tag{25}$$

where k_P is the controlled plant gain and T_Σ is the small time constant or an equivalent time constant as sum of parasitic time constants. One solution to control this class of plants is represented by PI control [29]. A simple and efficient way to tune the parameters of the PI controller dedicated to this plant is represented by the Extended Symmetrical Optimum (ESO) method [30], characterized by only one design parameter, β. The choice of the parameter β within the domain 1 < β < 20, leads to the modification of the CS performance indices (σ_1 – overshoot, $\hat{t}_r = t_r / T_\Sigma$ – normalized rise time, $\hat{t}_s = t_s / T_\Sigma$ – normalized settling time defined in the unit step modification of *r*, φ_m – phase margin) according to designer's option and to a compromise to these performance indices using the diagrams presented in Fig. 7 in the situation without feedforward filter. The presence of the feedforward filter with the transfer function *F*(*s*) improves the CS performance indices.

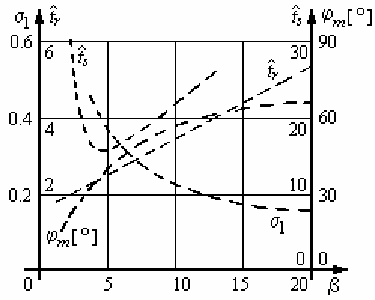


Figure 7
Control system performance indices versus β in the situation without feedforward filter

The PI tuning conditions, specific to the ESO method, are:

$$k_c = 1/(\beta\sqrt{\beta}T_\Sigma^2 k_P),\ T_i = \beta T_\Sigma\,, \tag{26}$$

and they highlight the presence of only design parameter, β. The experimental setup consists of speed control of a nonlinear laboratory DC drive (AMIRA DR300). The DC motor is loaded using a current controlled DC generator, mounted on the same shaft, and the drive has built-in analog current controllers for both DC machines having rated speed equal to 3000 rpm, rated power equal to 30 W, and rated current equal to 2 A. The speed control of the DC motor is digitally implemented using an A/D-D/A converter card. The speed sensors are a tacho generator and an additional incremental rotary encoder mounted at the free drive-shaft. A picture of the experimental setup, taken from the Intelligent Control Systems Laboratory of "Politehnica" University of Timisoara, is presented in Fig. 8.

The mathematical model of the plant can be well approximated by the transfer function *P*(*s*) in (20), with k_P = 4900 and T_Σ = 0.035 s. The design method proposed in the previous Section is applied, and for the sake of simplicity only the main parameter values are presented. The method starts with the choice of the design parameter β = 6. The following values of the PI-fuzzy controller tuning parameters have been obtained: B_e = 0.3, $B_{\Delta e}$ = 0.03, $B_{\Delta u}$ = 0.0021, and the ILCA employs a Q-filter of 20 Hz bandwidth and a PD-type learning function.

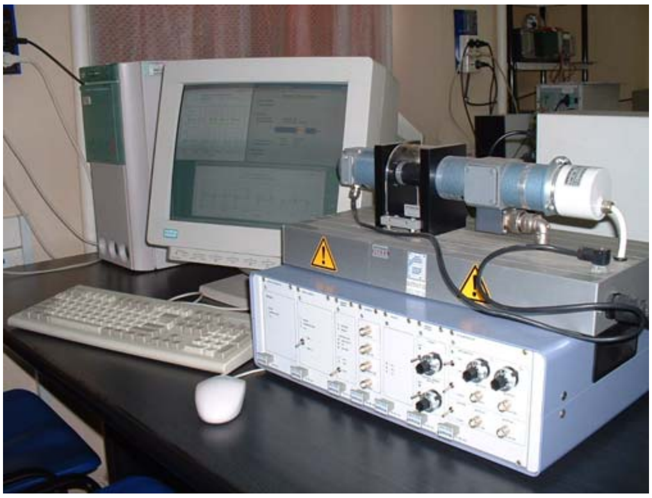
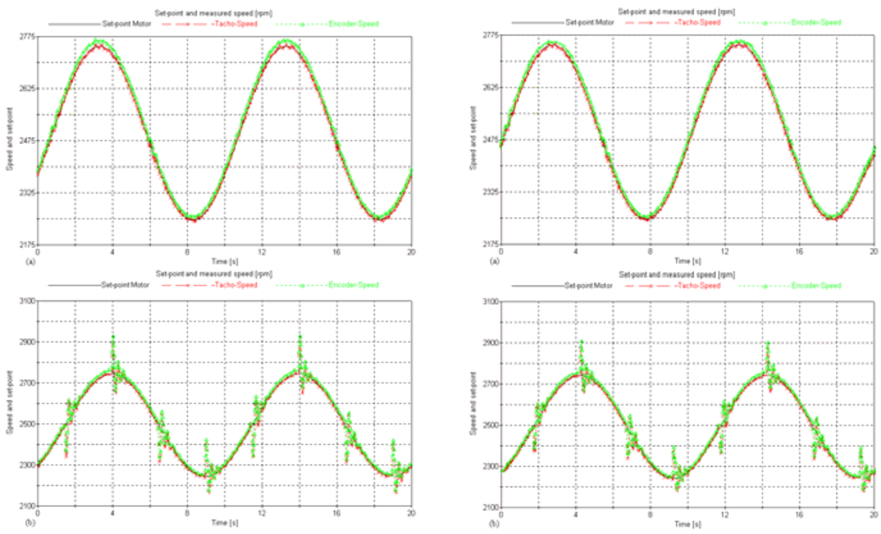


Figure 8
Picture of experimental setup

Part of the real-time experimental results – the variations of r and y versus time – are presented in Fig. 9 for the linear CS (with linear PI controller) in Fig. 9 (a) and for the fuzzy CS in Fig. 9 (b), without load in the upper pictures and with a 5 s period of 10% d_2-type rated load and $r = 2500$ rpm in the lower pictures.



(a) (b)

Figure 9
Control system behaviour with PI controller (a) and PI-fuzzy controller (b)

Conclusions

The paper deals with original ways to combine fuzzy control and Iterative Learning Control to achieve the aim of control system performance enhancement in the conditions of low-cost.

Preliminary real-time experimental results validate one of the fuzzy control system structures and the design method employing PI-fuzzy controllers, and representing versions of 2-DOF PI-fuzzy controllers, implemented as low-cost automation solutions.

Future research will be concentrated on deriving simple and transparent design methods for all fuzzy control system structures suggested in this paper accompanied by systematic analyses in all situations.

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