Model-based fuzzy control results for networked control systems

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ABSTRACT

This paper discusses aspects concerning the design of model-based fuzzy controllers for Networked Control Systems (NCSs). The stability analysis is related to the characteristic equation of these control systems, where the variable time delays create numerical problems. These numerical problems are first briefly investigated, along with signal processing aspects concerning NCSs. The popular Hilbert-Huang transform is applied to smooth the signals and also the variable time delay, also called latency, due to the communication in the network. The design of Takagi-Sugeno-Kang Proportional-Integral-fuzzy controllers dedicated to temperature control applications is next carried out; the stability of fuzzy NCSs is guaranteed by computing the controller tuning parameters as solutions to linear matrix inequalities. Experimental results for a laboratory equipment that models a first-order plus time delay process are included to validate the theoretical findings.

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1. Introduction

Networked Control Systems (NCSs) proved several benefits in the framework of the technologies pointed out in Tipsuwan et al (2003), Gupta and Chow (2010) and Zhang et al (2017), namely the benefits are gained in relation with those technologies that connect various data points as computers, enable remote data transfers and data exchanges among users, reduce the complexity in wiring connections and the costs of medias, and ensure a relatively easy maintenance process. Due to these attractive features, NCSs gained widespread interest in networked control and applications including remote industrial control, factory automation (Tipsuwan et al., 2003; Gupta and Chow, 2010) and telesurgery (Haidegger et al., 2011; Takács et al., 2015).

One typical NCS structure referred to as direct structure is presented in Figure 1 (where plant can also be replaced with process) to highlight the effects of variable time delays in NCSs. For example, a time delay appears in the information transmission in applications that involve telemanipulation applications performed over long distances between the operator site and the remote site; they include outer space (Haidegger et al., 2011; Takács et al., 2015) or underwater (in manned or un-manned versions). The time delay can destabilize generally a control system but especially, for example, bilateral teleoperator systems because of the magnitude of the time delay. The instability caused by time delays is pointed out in (Sheridan and Ferrell, 1963) and several classical approaches to avoid this are reported in (Tipsuwan et al., 2003; Gupta and Chow, 2010; Kim et al., 1992; Lee and Lee, 1993; Luo et al., 2000; Kovács et al., 2004).

Fuzzy control has received great attention and proved to be successful in many areas (Precup and Hellendoorn, 2011; Ruano et al., 2014; Guerra et al., 2015; Precup et al., 2015; Dzitac et al., 2017) because it is considered in certain situations as a relatively easily understandable and transparent nonlinear control strategy. Stability analysis approaches are thoroughly discussed in (Lam, 2018) and the use of type-2 fuzzy systems in (Castillo and Melin, 2012, 2014). Recently, several fuzzy control strategies have been developed for NCSs, with a comprehensive overview on NCS-based model-based fuzzy control conducted in (Qiu et al., 2016). Some representative examples of fuzzy control applied to FCS are briefly discussed as follows. The probabilistic interval distribution of the communication delay is considered in (Peng and Yang, 2010) to develop a delay distribution-dependent approach for Takagi-Sugeno-Kang (TSK) fuzzy systems. A fuzzy predictive controller to counteract time delays in the feedback channel is designed in (Tong et al., 2014), where the fuzzy controller estimates the variations of the control signal based on the differences of two control errors. The membership functions and time delays in premise variables are inserted in (Chae and Nguang, 2014) in the controller design carried out by means of stability conditions expressed as Sum-Of-Squares (SOS)-based inequalities. The controller and scheduler design for NCS is suggested in (Mendez-Monroy et al., 2018) and referred to as fuzzy codesign. A predictive compensation strategy is proposed in (Wang et al., 2017). Other recent papers on fuzzy control of NCS include adaptive fuzzy control (with inverted pendulum control validation and TrueTime toolbox implementation) (Hamdy et al., 2017a, 2017b), and adaptive fuzzy predictive control (with Van der Pol oscillator control validation and TrueTime toolbox implementation) (Hamdy et al., 2018).

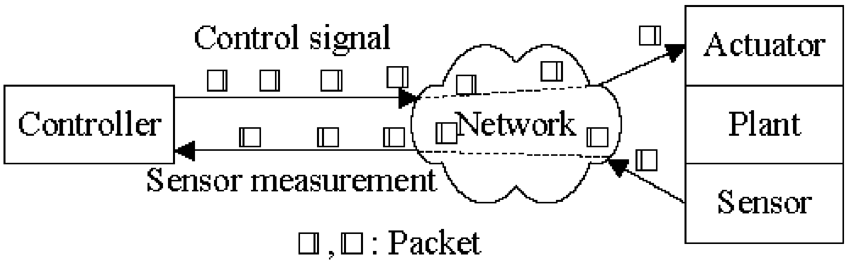

Figure 1. Direct structure of networked control system.

The communication illustrated in Figure 1 can be associated with the problem of lost packets, which is usually modeled by a Bernoulli process, and some representative fuzzy logic-based techniques are reported in Zhao et al (2010), Du (2012) and Li et al (2018). The recent results on event-triggered communication and control in NCS are analyzed in (Peng and Li, 2018), and fuzzy control techniques are presented in Li et al (2017) and Pan and Yang (2017).

The analysis and synthesis of NCSs as far as time delays and packet losses are concerned is a challenging problem. This paper will treat time delays.

The presence of time delay in both the control signal and the sensor measurement transmission in Figure 1 due to the network creates challenging control problems. One such problem is the transcendental characteristic equation of the closed-loop system that is not simple at all even if linear controlled processes and controllers are accepted. Numerical problems arise in this regard, and they are treated in Jarlebring (2008). The transmission lines illustrated in Figure 1 bring other problems. First, the variable time delay is not simple, especially when rapid processes need to be controlled. Second, several disturbances and noises affect the signals (control signals and controlled outputs), and they have to be filtered. The additional signal processing of the controlled outputs (measured from the process and transmitted through the network) by the Hilbert-Huang transform (Huang et al., 1998; Huang and Shen, 1999; Huang et al., 2003) was treated in Precup et al (2008) along with the brief presentation of several numerical methods to compute the closed-loop poles of NCSs.

This paper is built upon on our results on NCSs reported in Precup et al (2008) and fuzzy control for robotic telesurgery systems (Precup et al., 2014), and proposed the design of TSK Proportional-Integral (PI)-fuzzy controllers for NCSs. The design is focused on a case study that deals with the temperature control of the Amira LTR 701 air stream and temperature control plant (Amira, 2002) implemented in one of the laboratories of the

Process Control Group of the Politehnica University of Timisoara, Romania. The slow process specific to this laboratory equipment approximates well a time delay system. Due to the technical constraints regarding the controller implementation, the TSK PI-fuzzy controllers are implemented as PI sliding mode. The controller parameters are tuned by means of a metaheuristic optimization algorithm that solves an optimization problem focused on minimizing an objective function expressed as the integral of squared differences of the two nonlinear controller output signals (control signals).

Summing up, the paper discusses aspects concerning the design of model-based fuzzy controllers for NCSs. Experimental results for laboratory equipment that models a first-order plus time delay process are included to validate the theoretical findings.

The paper is structured as follows: Section 2 discusses some signal processing aspects of NCSs. Section 3 is dedicated to the TSK PI-fuzzy controller design and offers a simple two-step design approach. Useful Linear Matrix Inequalities (LMIs) are given to guarantee stable fuzzy control systems. The validation of the control system structure is presented in Section 4 and experimental results are included. The conclusions are outlined in Section 5.

2. Signal processing

The block diagram of the control system considered in its simple control loop version is presented in Figure 2, where: r – the reference input, d – the disturbance input, e – the control error

$$e(t) = r(t) - y(t) \tag{1}$$

u – the control signal, C – the controller, P – the controlled process (or plant as pointed out in Figure 2), and y – the controlled output. The transfer function $P(s)$ of the process is not a rational form in case of plants with time delays

$$P(s) = \frac{B_P(s)}{A_P(s)} e^{-sT_d} \tag{2}$$

where $A_P(s)$ and $B_P(s)$ are the polynomials specific to process model, and T_d is the time delay.

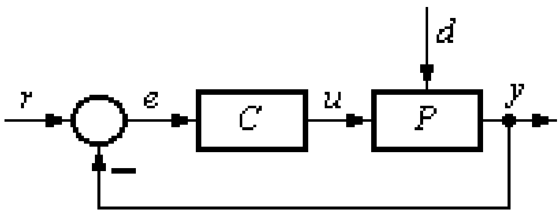

Figure 2. Control system structure.

Assuming a linear controller C, the controller transfer function $C(s)$ is supposed to be a proper rational form

$$C(s) = \frac{B_C(s)}{A_C(s)} \tag{3}$$

where $A_C(s)$ and $B_C(s)$ are the polynomials specific to controller model. The transfer function $H_0(s)$ of the open-loop system is

$$H_0(s) = C(s)P(s) = \frac{B_C(s)B_P(s)}{A_C(s)A_P(s)} e^{-sT_d} \tag{4}$$

and the transfer function $H_r(s)$ of the closed-loop system with respect to r is

$$H_r(s)=\left.\frac{y(s)}{r(s)}\right|_{d=0}=\frac{H_0(s)}{1+H_0(s)}=\frac{B_C(s)B_P(s)}{A_C(s)A_P(s)+B_C(s)B_P(s)e^{-sT_d}}e^{-sT_d} \quad (5)$$

where both transfer functions in (4) and (5) are obtained accepting initial conditions. Using the denominator in (6), the characteristic equation of the closed-loop system is (Precup et al., 2008)

$$A_C(s)A_P(s)+B_C(s)B_P(s)e^{-sT_d}=0. \quad (6)$$

Equation (6) has an infinite number of complex solutions, namely the closed-loop system poles. These solutions cannot be expressed explicitly as elementary functions, thus creating serious problems because the poles affect the behavior of the control system in the time and operational domains. However, an explicit formula valid in some special cases to give the solutions to (6) can be expressed in terms of the Lambert W function analyzed in Jarlebring and Damm (2007) and applied in Gerov and Jovanović (2019a, 2019b). Another approach to the numerical solving of (6), given in Breda et al (2006), is based on the discretization of its partial differential equation representation and obtaining the poles as the eigenvalues of a certain matrix. The solution operator (the linear operator transforming the initial function segment to the solution segment at some time point) is applied in Bueler (2007) after its discretization. On the other hand, as shown in Precup et al (2008), the problem of finding the solutions to (6) can be regarded as part of the general class of nonlinear eigenvalue problems treated in Jarlebring and Damm (2007).

The numerical problems related to finding the roots to (6) become simpler if the system is treated in the frequency domain by means of open-loop Bode plots. This is treated in Preitl et al (2007).

Connecting the structures in Figure 1 and Figure 2, the Hilbert-Huang transform is applied to filter y in order to avoid the disturbances and variable time delay related to the transmission channels specific to NCS. The analytic signal $a(t)$ (with t – the independent time variable) is actually obtained as result of the Huang transform / filter from the measured signal $y(t)$ (Precup et al., 2008)

$$a(t)=y(t)+j\,z(t)=m(t)e^{j\ \arg(t)} \quad (7)$$

where: $z(t)$ – the imaginary part, $m(t)$ – the instantaneous modulus (amplitude) and $\arg(t)$ – the instantaneous argument (phase). The instantaneous frequency, $\omega(t)$, is obtained as the time derivative of the argument

$$\omega(t)=\frac{\mathrm{d}\arg(t)}{\mathrm{d}\,t} \quad (8)$$

Therefore, the instantaneous phase should be a single-valued function of time in order to offer the physical meaning of the process of extracting the instantaneous frequency. Since $\arg(t)$ is constructed on the basis of the measured signal (controlled output) $y(t)$ and its Hilbert transform, it is necessary that $y(t)$ must be a single-valued function as well. However, the signals measured in practical NCS applications contain multiple frequency components at each time moment. Therefore, the Empirical Mode Decomposition (EMD) method (Huang et al., 1998) is applied to decompose the measured signal into a series of so-called Intrinsic Mode Functions (IMFs), each IMF being a mono-component function before extracting the instantaneous frequency information in terms of the Hilbert transform. The Hilbert transform is applied and, as shown in Precup et al (2008), it is actually a filter. The process of extracting the IMFs from the decomposition of the $y(t)$ in the framework of EMD, known as the sifting process, will be described briefly as follows.

The sifting process starts with the extraction of the local maxima and minima of $y(t)$ viewed as a time series, perfectly valid in case of discrete-time control systems. Although the presentation before has been done in continuous-time, the quasi-continuous digital control (in the presence of the zero-order hold) is accepted. Cubic splines are next applied to link the local maxima and minima in order to construct the upper and lower envelopes, followed by the calculation of the mean envelope. The difference between the raw series and the mean envelope, expressed as a difference series, is next calculated. That difference series is the first IMF if it satisfies the constraints (i) and (ii) (Precup et al., 2008; Yan and Gao, 2007): (i) within the data set, the number of optimal solutions (maxima and minima) and the number of zero crossings must be either equal to each other or differ by at most one, (ii) at any point, the mean value between the envelopes defined by local maxima and minima is zero.

If not, the process described before is repeated using the difference series as the "old" time series associated to $y(t)$. The first IMF is subtracted from the time series, and a new iteration process is done in order to extract the subsequent IMFs until the time series becomes a monotonic function. The result of this processing is the decomposition of the measured signal $y(t)$ in terms of

$$y(t)=\sum_{i=1}^{n} c_i(t)+r_n(t) \quad (9)$$

where $c_i(t)$ is i^{th} IMF, i=1...n, and $r_n(t)$ is the residue of the signal decomposition.

Once the EMD has been applied, a time-frequency distribution of the measured signal can be represented by extracting instantaneous frequency components from each of the IMFs using (6) and (8). The combination of EMD and Hilbert transform represents, as highlighted in Precup et al (2008), the Hilbert-Huang transform.

3. Fuzzy controller design

The TSK PI-fuzzy controller is inserted in Figure 1 as the nonlinear controller C. The two input and also scheduling variables of this fuzzy controller are the control error $e(t)$ and the integral of control error $e_I(t)$

$$e_I(t)=\int_0^t e(\tau)d\tau \quad (10)$$

and the input membership functions are presented in Figure 3.

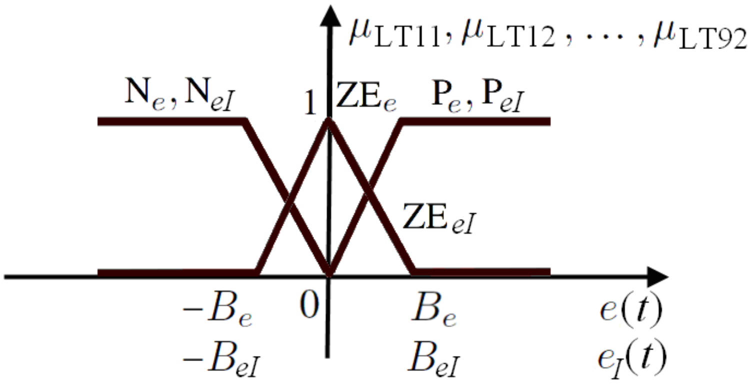

Figure 3. Input membership functions of Takagi-Sugeno-Kang Proportional-Integral fuzzy controller.

The rule base of TSK PI-fuzzy controller is expressed as follows by inserting nine separate linear PI controllers, with the parameters k_C^k (gains) and T_i^k (integral time constants), in the rule consequents, where k=1...9 is the index of the current rule in a complete rule base obtained as the modification of the rule base given in Precup et al (2014):

$$\begin{aligned}
&\text{Rule } 1: \text{IF } e(t) \text{ IS } \mathrm{LT}_{11}=\mathrm{N}_e \text{ AND } e_I(t) \text{ IS}\\
&\mathrm{LT}_{12}=\mathrm{P}_{eI} \text{ THEN } u^1(t)=k_C^1 e(t)+(k_C^1/T_i^1)e_I(t),\\
&\text{Rule } 2: \text{IF } e(t) \text{ IS } \mathrm{LT}_{21}=\mathrm{ZE}_e \text{ AND } e_I(t) \text{ IS}\\
&\mathrm{LT}_{22}=\mathrm{P}_{eI} \text{ THEN } u^2(t)=k_C^2 e(t)+(k_C^2/T_i^2)e_I(t),\\
&\text{Rule } 3: \text{IF } e(t) \text{ IS } \mathrm{LT}_{31}=\mathrm{P}_e \text{ AND } e_I(t) \text{ IS}\\
&\mathrm{LT}_{32}=\mathrm{P}_{eI} \text{ THEN } u^3(t)=k_C^3 e(t)+(k_C^3/T_i^3)e_I(t),\\
&\text{Rule } 4: \text{IF } e(t) \text{ IS } \mathrm{LT}_{41}=\mathrm{N}_e \text{ AND } e_I(t) \text{ IS}\\
&\mathrm{LT}_{42}=\mathrm{ZE}_{eI} \text{ THEN } u^4(t)=k_C^4 e(t)+(k_C^4/T_i^4)e_I(t),\\
&\text{Rule } 5: \text{IF } e(t) \text{ IS } \mathrm{LT}_{51}=\mathrm{ZE}_e \text{ AND } e_I(t) \text{ IS}\\
&\mathrm{LT}_{52}=\mathrm{ZE}_{eI} \text{ THEN } u^5(t)=k_C^5 e(t)+(k_C^5/T_i^5)e_I(t),\\
&\text{Rule } 6: \text{IF } e(t) \text{ IS } \mathrm{LT}_{61}=\mathrm{P}_e \text{ AND } e_I(t) \text{ IS}\\
&\mathrm{LT}_{62}=\mathrm{ZE}_{eI} \text{ THEN } u^6(t)=k_C^6 e(t)+(k_C^6/T_i^6)e_I(t),\\
&\text{Rule } 7: \text{IF } e(t) \text{ IS } \mathrm{LT}_{71}=\mathrm{N}_e \text{ AND } e_I(t) \text{ IS}\\
&\mathrm{LT}_{72}=\mathrm{N}_{eI} \text{ THEN } u^7(t)=k_C^7 e(t)+(k_C^7/T_i^7)e_I(t),\\
&\text{Rule } 8: \text{IF } e(t) \text{ IS } \mathrm{LT}_{81}=\mathrm{ZE}_e \text{ AND } e_I(t) \text{ IS}\\
&\mathrm{LT}_{82}=\mathrm{N}_{eI} \text{ THEN } u^8(t)=k_C^8 e(t)+(k_C^8/T_i^8)e_I(t),\\
&\text{Rule } 9: \text{IF } e(t) \text{ IS } \mathrm{LT}_{91}=\mathrm{P}_e \text{ AND } e_I(t) \text{ IS}\\
&\mathrm{LT}_{92}=\mathrm{N}_{eI} \text{ THEN } u^9(t)=k_C^9 e(t)+(k_C^9/T_i^9)e_I(t),
\end{aligned} \tag{11}$$

where $u^k(t)$ is the control signal produced by k^{th} rule, k=1...9. Using the PROD operator to model the AND function in the rule antecedent, each fuzzy rule generates a firing degree α_k, $0 \le \alpha_k \le 1$

$$\alpha_k(t) = \mu_{\mathrm{LT}k1}(e(t))\mu_{\mathrm{LT}k2}(e_I(t)),\ k = 1...9, \tag{12}$$

where $\mu_{\mathrm{LT}kl}$ are the membership functions of the input linguistic terms LT_{kl}, k=1...9, $l \in \{1,2\}$, pointed out in Figure 3 and in (11).

Using the notation $h_k(t)$ for the normalized firing degree of k^{th} rule, k=1...9

$$h_k(t) = \frac{\alpha_k(t)}{\sum_{k=1}^{9} \alpha_k(t)} \tag{13}$$

the weighted average defuzzification method produces the output of the TSK PI-fuzzy controller, i.e., the control signal $u(t)$

$$\begin{aligned}
u(t) &= \frac{\sum_{k=1}^{9} \alpha_k(t) u^k(t)}{\sum_{k=1}^{9} \alpha_k(t)} = \sum_{k=1}^{9} h_k(t) u^k(t)\\
&= \sum_{k=1}^{9} h_k(t)[k_C^k e(t) + (k_C^k / T_i^k) e_I(t)]
\end{aligned} \tag{14}$$

Equation (14) is important in the real-world implementation of the TSK PI-fuzzy controller as it gives the control law expressed in continuous time.

The expression of the Single Input-Single Output (SISO) state-space model of the controlled process used in NCS, which includes time delay, is

$$\begin{aligned}
\dot{\mathbf{x}}(t) &= \mathbf{A}\ \mathbf{x}(t) + \mathbf{B}\ u(t - T_d),\\
y(t) &= \mathbf{C}\ \mathbf{x}(t)
\end{aligned} \tag{15}$$

where $\mathbf{x}(t)$ is the state vector, $\mathbf{x}(t) \in \Re^{n}$, and the matrices are $\mathbf{A} \in \Re^{n \times n}$, $\mathbf{B} \in \Re^{n \times 1}$ and $\mathbf{C} \in \Re^{1 \times n}$.

The calculation of the derivatives of both terms in (10) using (1) and (15) leads to the dynamics of $e_I(t)$

$$\dot{e}_I(t) = r(t) - \mathbf{C}\,\mathbf{x}(t) \quad (16)$$

Using (11), the unified expression of k^{th} rule in the rule base of the TSK PI-fuzzy controller

$$\begin{aligned}&\text{Rule } k: \text{IF } e(t) \text{ IS } \mathrm{LT}_{k1} \text{ AND } e_I(t) \text{ IS } \mathrm{LT}_{k2}\\ &\text{THEN } u^k(t) = k_C^k e(t) + (k_C^k / T_i^k) e_I(t),\ k = 1...9\end{aligned} \quad (17)$$

Using next (1) and the second equation in (15) substituted in (14), the expression of the control signal $u(t)$ is transformed into

$$\begin{aligned}u(t) &= \sum_{k=1}^{9} h_k(t)[k_C^k e(t) + (k_C^k / T_i^k) e_I(t)]\\ &= -\sum_{k=1}^{9} h_k(t) k_C^k \mathbf{C}\,\mathbf{x}(t) + \sum_{k=1}^{9} h_k(t)(k_C^k / T_i^k) e_I(t)\\ &+ \sum_{k=1}^{9} h_k(t) k_C^k r(t).\end{aligned} \quad (18)$$

Since

$$\sum_{k=1}^{9} h_k(t) = 1 \quad (19)$$

the substitution of $u(t)$ from (18) in (15) according to (16) leads to the state-space model of the fuzzy control system (Precup et al., 2014)

$$\begin{aligned}\dot{\mathbf{x}}(t) &= \sum_{k=1}^{9} h_k(t)[\mathbf{A}\,\mathbf{x}(t) - k_C^k\ \mathbf{B}\ \mathbf{C}\ \mathbf{x}(t - T_d)\\ &\quad + (k_C^k / T_i^k)\ \mathbf{B}\ e_I(t - T_d) + k_C^k\ \mathbf{B}\ r(t)],\\ \dot{e}_I(t) &= \sum_{k=1}^{9} h_k(t)[-\mathbf{C}\ \mathbf{x}(t) + r(t)],\\ y(t) &= \mathbf{C}\ \mathbf{x}(t).\end{aligned} \quad (20)$$

The extended state vector $\mathbf{v}(t)$ of the fuzzy control system is next defined by inserting and merging $e_I(t)$ to $\mathbf{x}(t)$ (Precup et al., 2014)

$$\mathbf{v}(t) = [\mathbf{x}^T(t) \quad e_I(t)]^T \quad (21)$$

where the superscript T indicates matrix transposition.

Using in (20) the notation defined in (21), the expression of the state-space model of the fuzzy control system employed in the LMI-based stability analysis of fuzzy control system is transformed in the compact form (Precup et al., 2014)

$$\begin{aligned}\dot{\mathbf{v}}(t) &= \sum_{k=1}^{9} h_k(t)[\mathbf{A}_0 \mathbf{v}(t) + \mathbf{A}_{kd} \mathbf{v}(t - T_d) + \mathbf{B}_{kr} r(t)],\\ y(t) &= \sum_{k=1}^{9} h_k(t)\ \mathbf{C}_0 \mathbf{v}(t)\end{aligned} \quad (22)$$

with the matrix expressions [39]

$$\mathbf{A}_0 = \begin{bmatrix} \mathbf{A} & \mathbf{0} \\ -\mathbf{C} & 0 \end{bmatrix},\ \mathbf{A}_{kd} = \begin{bmatrix} -k_C^k \mathbf{B}\ \mathbf{C} & (k_C^k / T_i^k)\mathbf{B} \\ 0 & 0 \end{bmatrix}, \mathbf{B}_{kr} = \begin{bmatrix} k_C^k \mathbf{B} \\ 1 \end{bmatrix},\ \mathbf{C}_0 = [\mathbf{C} \quad 0],\ k = 1...9 \quad (23)$$

The stable design of the TSK PI-fuzzy controller is carried out on the basis of the globally asymptotically stability of the equilibrium point of the fuzzy control system. Using $\mathbf{B}_{kr} = \mathbf{0},\ k = 1...9,$ in the model (22), with these matrices considered as gains of an additional disturbance input, the stability is guaranteed if there exists the common (i.e., for all rules) matrices $\mathbf{P} > 0$ and $\mathbf{R} > 0$, $\det \mathbf{R} \neq 0$, such that the following sufficient LMIs are fulfilled (Precup et al., 2014)

$$\mathbf{P}\ \mathbf{A}_0 + (\mathbf{A}_0)^T \mathbf{P} + \mathbf{P}\ \mathbf{A}_{kd} \mathbf{R}^{-1} (\mathbf{A}_{kd})^T \mathbf{P} + \mathbf{R} < 0, k = 1...9 \quad (24)$$

The nine LMIs given in (24) are derived using the results given in Gu et al (2001), and their solving is assisted by numerical algorithms. The basis for selecting the parameters of the controller and also details of different operating conditions considered in the design of the controller are presented as follows in terms of a design approach.

The design approach dedicated to TSK PI-fuzzy controllers consists of the following two steps, which guarantee stable fuzzy control systems:

Step 1. The linear PI controllers placed in the rule consequents in (11) are designed and tuned. The nine rules in (11) specify several regions in the input (or scheduling) space, with important operating points in all regions. Each local linear PI controller is designed and tuned at a certain operating point in the controller input space specific to that rule, and a specific process model can be assigned to that operating point. The frequency domain tuning is recommended in this design and tuning because it is convenient to cope with time delays. This step leads to the values of the parameters k_C^k (gains) and T_i^k (integral time constants), in the rule consequents, where k=1...9.

Step 2. Once the linear PI controllers in the rule consequents in (11) are tuned, (24) is employed to set the parameters of input membership functions defined in Figure 3.

The stability analysis approach centered on (24) can be replaced with other stability analysis approaches. Such representative ones are those dedicated to NCSs and time delay systems [19], but other specific ones for fuzzy and nonlinear systems as those given in Baranyi (2004), Sadeghi-Tehran et al (2012), Guechi et al (2014) and Precup et al (2014a) can be adapted such that to work in the NCS framework; the formulations are given for SISO systems and Multi Input-Multi Output (MIMO) ones.

The problem of different operating conditions and operating points leads to the idea of data-driven control, with recent successful combinations reported and validated experimentally in Roman and Precup (2018), Roman et al (2019, 2019a) but not in the context of NCS. However, a discussion on the knowledge on process models (model-free versus model-based) is needed in this regard as the models are essential in stability analysis and model-based controller tuning.

4. Experimental results

The experimental setup to validate the TSK PI-fuzzy controller is built around the Amira LTR 701 laboratory equipment which is installed in the Intelligent Control System Laboratory of the Politehnica University of Timisoara, Romania (Figure 4). This is a MIMO process with two control signals (that correspond to two actuators) represented by the ventilator motor speed and the control input of the heating element, and five possible controlled outputs, which can be measured, namely the air stream, the air temperature in two points, the air pressure and the position of the air admission throttle.

Figure 4. Air stream and temperature control experimental setup in the Intelligent Control System Laboratory of the Politehnica University of Timisoara, Romania.

This paper considers a SISO sub-system of this process, where the control signal *u* is the control input of the heating element and the controlled output *y* is the air temperature in the point placed at the largest distance to the actuator in order to get a relatively slow dynamics. The process transfer function that describes first-order plus time delay systems is

$$P(s)=\frac{k_P}{1+sT}e^{-sT_d} \tag{25}$$

where k_P is the process gain and T is the process time constant, which are obtained by least-squares identification. However, all parameters in (25) are variable, with values depending (slowly) on the operating points. Least-squares identification also leads to another approximate process transfer function that is convenient for controller design and tuning (Precup et al., 2008)

$$P(s)=\frac{k_P}{(1+sT_1)(1+sT_2)} \tag{26}$$

where T_1 and T_2 are time constants.

The three parameters in (26) are within with the following intervals that correspond to the regions in the input space delimitated by the nine rules in (11):

$$0.9\le k_P\le 0.96,\ 2\text{ s}\le T_1\le 2.8\text{ s},\ 0.89\text{ s}\le T_2\le 0.97\text{ s} \tag{27}$$

The form (26) was used in Precup et al (2008) to design and tune two sliding mode controllers for temperature control, with the process parameter values $k_P = 0.93$, $T = 2.4$ s and $T_d = 0.93$ s.

The frequency domain design was applied in step 1 of the design approach dedicated to TSK PI-fuzzy controllers presented in the previous section. Imposing a phase margin of 60^o and the process parameter values according to (27), the values of parameters of linear PI controllers in the rule consequents belong to the intervals

$$1.9\le k_C^k\le 2,\ 2\text{ s}\le T_i^k\le 2.7\text{ s},\ k=1...9 \tag{28}$$

Step 2 was next applied to set the values of input membership functions parameters in Figure 3 and solve the LMIs in (24).

The controller implementation is done using the MCON software (Amira, 2002), which allows for controller schemes using linear and nonlinear blocks. Since the implementation of fuzzy controllers is complicated, their approximation by other nonlinear controllers is used and sliding mode controllers are involved in this regard. The quasi-relay variable structure-PI controller was used in this paper as a representative but also simple sliding mode controller, with the expression of the control law (Hedrea et al., 2019)

$$u(t) = \Psi(t)e(t) + \frac{1}{T_i}\int_0^t (\Psi(\tau)e(\tau))d\tau \quad (29)$$

where T_i, $T_i > 0$, is the integral time constant, the nonlinear quasi-relay term Ψ is

$$\Psi(t) = \alpha\,\mathrm{sgn}(g(t)e(t)),\ \alpha > 0 \quad (30)$$

and the switching variable g is defined in terms of

$$g(t) = c\ e(t) + \dot{e}(t),\ c > 0 \quad (31)$$

Equations (29), (30) and (31) point out the three tuning parameters of this sliding mode controller, which are grouped in the parameter vector $\boldsymbol{\rho}$ of the quasi-relay variable structure-PI controller

$$\boldsymbol{\rho} = [T_i \quad \alpha \quad c]^T \in \Re^3 \quad (32)$$

The optimization problem that ensures the reduction (by minimization) of the differences of the two nonlinear controller output signals (control signals) is

$$\boldsymbol{\rho}^* = \arg\min_{\boldsymbol{\rho} \in D_{\boldsymbol{\rho}}} J(\boldsymbol{\rho}),\ J(\boldsymbol{\rho}) = \int_0^\infty (u^{FC}(\tau) - u^{SM}(\tau))^2 d\tau \quad (33)$$

where u^{FC} is the control signal produced by the PI-fuzzy controller, u^{SM} is the control signal produced by the sliding mode controller, $\boldsymbol{\rho}^*$ is the optimal parameter vector, i.e., the optimal value of $\boldsymbol{\rho}$, and D_ρ is the feasible domain of $\boldsymbol{\rho}$. The stability analysis of the sliding mode control system should be accounted for in setting the domain D_ρ; however, as pointed out in (29) – (31), all parameter values (and also variables of the objective function J) should be strictly positive. The time horizon is infinite in (33), but a finite value is practically used in order to capture all transients in the possible regimes of interest concerning the operation of the two nonlinear controllers in the control systems.

A metaheuristic Grey Wolf Optimizer (GWO) algorithm was used to solve the optimization problem defined in (33). The GWO algorithm was implemented according to Precup et al (2016) using a population of 200 agents (i.e., grey wolves) and the maximum number of iterations was set to 100. GWO was also applied in Roman et al (2019, 2019a) in combination with data-driven control. The optimal parameter vector obtained after running the GWO algorithm is

$$\boldsymbol{\rho}^* = [T_i^* \quad \alpha^* \quad c^*]^T = [2.83 \quad 1.32 \quad 6.25]^T \quad (34)$$

The MCON implementation of the control system with quasi-relay variable structure-PI controller is given in Figure 5. Figure 5 also illustrates, in its lower part, the open-loop blocks that transfer the process to the desired operating point; the controller and the control system start their operation only after that moment. The “A-In” (analog input) and “A-Out” (analog output) blocks in Figure 5 outline that real-time experiments were carried out. The block diagram given in Figure 5 illustrates the flow of the proposed control approach.

The variation of the control signal and the fuzzy control system response (with PI-fuzzy controller implemented as quasi-relay variable structure-PI controller) with respect to the step modification of the reference input followed by a step modification of the disturbance input (represented by the ventilator motor speed) are illustrated in Figure 6. All signals in Figure 6 are expressed in b (bits) as they are measured variables in the control system.

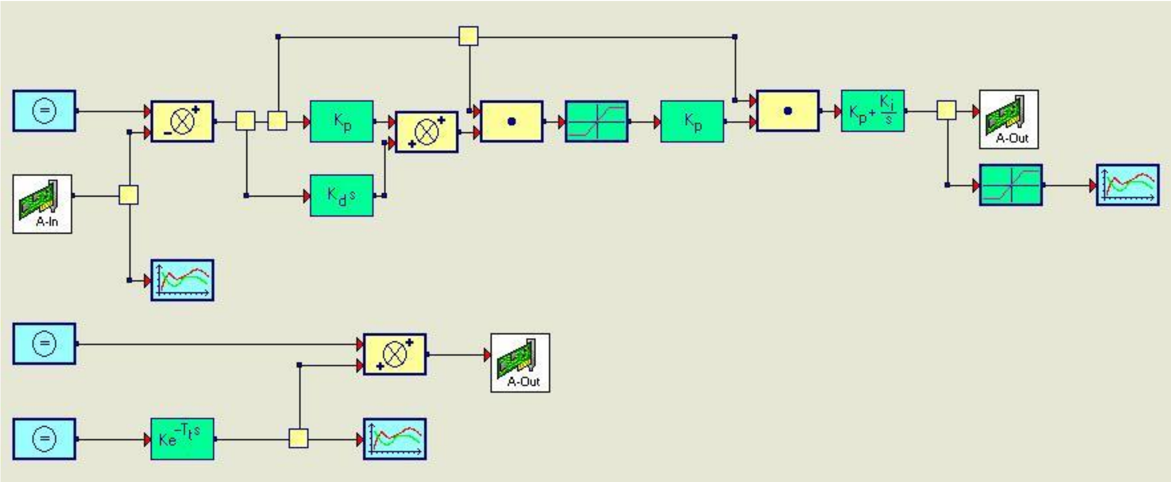

Figure 5. MCON implementation of control system with quasi-relay variable structure-PI controller

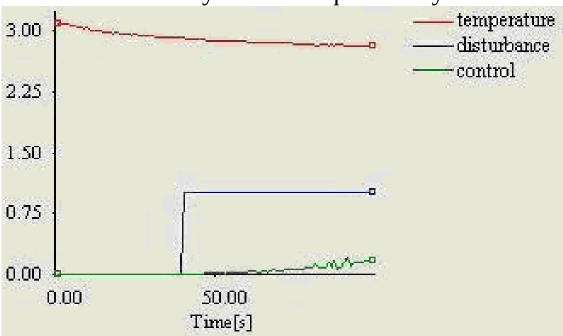

Figure 6. Controlled temperature (red), disturbance input (blue) and control signal (green) versus time.

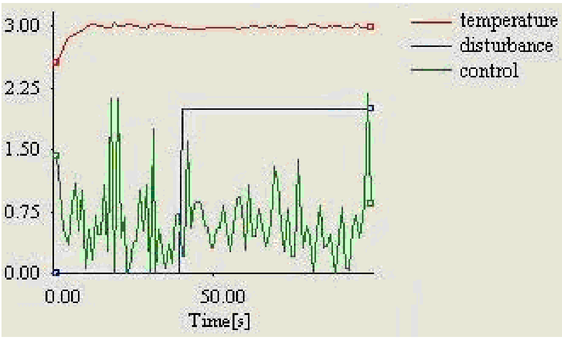

Figure 7. Controlled temperature (red), disturbance input (blue) and control signal (green) versus time for control system with de-tuned controller parameters.

The results given in Figure 6 show a good control system behavior. The robustness of the control system with respect to controller parameter variations was also discussed by de-tuning the parameters in (34) in terms of reducing their values with 25%. The responses are illustrated in Figure 7, and show that the control system keeps its good dynamic behavior with respect to both reference and disturbance inputs.

The idea to combine sliding mode with tensor product-based model transformation presented in Hedrea et al., 2019 leads to the discussion and further extension of the approaches in order to work with other nonlinear models that are more or less similar to fuzzy models and could be of interest in NCS after a deep analysis. Examples of such models are those derived from Bayesian filtering (Pozna et al., 2010), combinations of models in cascade control system structures (Hedrea et al., 2017, 2018; Bojan-Dragos et al., 2019), and evolving fuzzy models.

Since only a sample of experimental results is included in this section, the presentation quality for experimental results should be further improved. Moreover, the physical meaning for the discussion for results, which is very important, is given; the controlled output and the control signal are expressed in bits as the system responses illustrated in Figure 6 and Figure 7 are those measured by the digital control system (digital input and digital output).

The results might be too few to understand the performance of the system. However, the reasoning given in this section helps its explanation.

No comparisons are made with the results published in other pertinent references as the majority of these references is based on LMIs. In other words, the control system behavior is the same but the design conditions could be different depending on the stability conditions derived. In other words, the system's observation when compared with the state-of-the-art is the same. The system currently is not better than the existing solutions, but can be better if the optimal controller tuning is carried out. There are certain performance implications based on the model used for building the given system.

The CPU time for the proposed algorithm is not important because a simple implementation given in Figure 5 is used. The real-time fuzzy controller implementation is associated with a higher CPU time, and a discussion on the complexity of the control algorithms can be conducted.

5. Conclusions

This paper proposed a relatively simple fuzzy logic-based solution for networked control system. The two-step design approach for TSK PI-fuzzy controllers guarantees the fuzzy control system stability.

The validation of the theoretical results was carried out by means of a real-world temperature control application and shows very good results and also the potential to further apply fuzzy control to networked control systems. Since the time delay is not variable in the temperature control application, the TSK PI-fuzzy controllers require further testing in more realistic scenarios. One of the directions of further research is the discrete-time treatment of the controllers, which needs to be associated with different stability analysis approaches and robustness analyses.

The overall presentation and problem formulation are formulated in a relatively short and simple manner in order to help to understand the flow of the paper. The convergence analysis of the fuzzy design is not given and details of proofs are missing for the sake of simplicity of presentation.

Another direction of future research will be focused on solving other problems specific to networked control systems including cloud and secure computing (Mahmoud and Xia, 2019). This will be linked to modifying the controller structures by inserting nonlinear (Purcaru et al., 2013; Rotariu et al., 2014; Vaščák et al., 2016; Albu et al., 2019; Alvarez Gil et al., 2018) and fuzzy (Petrović et al., 2019) features. However, the control systems will be designed starting with the simple control structure given in this paper and further developing various control structures and algorithms (Korondi et al., 2003; Precup and Preitl, 2003; Andoga et al., 2018; Pozna and Precup, 2018) in order to guarantee systematically the control system performance. Modern optimization algorithms will be applied to optimally tune the parameters of fuzzy controllers, and representative examples are given in Precup and David (2019) and Fe-Perdomo et al (2019).

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