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A LOW-COST APPROACH TO DATA-DRIVEN FUZZY CONTROL OF SERVO SYSTEMS

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Abstract. *Servo systems become more and more important in control systems applications in various fields as both separate control systems and actuators. Ensuring very good control system performance using few information on the servo system model (viewed as a controlled process) is a challenging task. Starting with authors' results on data-driven model-free control, fuzzy control and the indirect model-free tuning of fuzzy controllers, this paper suggests a low-cost approach to the data-driven fuzzy control of servo systems. The data-driven fuzzy control approach consists of six steps: (i) open-loop data-driven system identification to produce the process model from input-output data expressed as the system step response, (ii) Proportional-Integral (PI) controller tuning using the Extended Symmetrical Optimum (ESO) method, (iii) PI controller parameters mapping onto parameters of Takagi-Sugeno PI-fuzzy controller in terms of the modal equivalence principle, (iv) closed-loop data-driven system identification, (v) PI controller tuning using the ESO method, (vi) PI controller parameters mapping onto parameters of Takagi-Sugeno PI-fuzzy controller. The steps (iv), (v) and (vi) are optional. The approach is applied to the position control of a nonlinear servo system. The experimental results obtained on laboratory equipment validate the approach*.

Key words: *Closed-loop data-driven system identification, Data-driven fuzzy control, Extended Symmetrical Optimum method, Servo systems*

1. INTRODUCTION

As specified in the project [1], in contrast to model-based control, data-driven control avoids the system (process) identification by constructing controllers directly from data. That is the reason why data-driven control is also referred to as model-free control (i.e. no

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model in controller tuning), justifying the high interest in nonlinear controllers whose parameters are tuned using process input-output data after conducting few experiments, or, more generally, data-driven model-free control [2]. Instead, one or more experiments are conducted in order to use the information in controller tuning, and non-parametric system or process models) can be employed in this regard.

A concise discussion on the popular data-driven control techniques is given in Precup et al. [3] pointing out the following ones that ensure the iterative experiment-based update of controller parameters: Iterative Feedback Tuning (IFT) [4], [5], Model-free Adaptive Control (MFAC) [6], [7], Simultaneous Perturbation Stochastic Approximation [8], [9], Correlation-based Tuning [10], [11], Frequency Domain Tuning [12], [13], Iterative Regression Tuning [14], and adaptive online IFT [15]. A review on data-driven control [16] offers classifications and highlights the role of observers and estimation in control, also leading to non-iterative data-driven control techniques: Model-Free Control (MFC) [17], [18], Virtual Reference Feedback Tuning (VRFT) [19], [20], Active Disturbance Rejection Control (ADRC) [21], [22], data-driven predictive control [23], [24], unfalsified control [25], [26], Data-Driven Inversion Based Control [27], [28], and the investigation of equivalent conditions on the given data under which different analysis and control problems can be solved [29]. Other representative techniques are emphasized in book [2]. It is suggestively stated in [3] and [30] that MFC is an efficient tool for Machine Learning; moreover, as specified earlier in [25], unfalsified control is also an efficient tool for Machine Learning.

As pointed out in the studies conducted in [1] and [31], fuzzy control is an important subject in the area of nonlinear control as the fuzzy controllers are relatively easily understandable and also offer very good control system performance indices. However, the heuristic approach to design and tune fuzzy controllers is compensated by the systematic design of fuzzy controllers that can employ the stable design of fuzzy control systems, the optimal and robust controller design and tuning. Classical and recent applications of fuzzy control deal with Popov-type stability analysis [32], embedded fuzzy control system for machining processes [33], tire slip control [34], predictive functional control based on fuzzy models [35], stability and sensitivity analysis of fuzzy control systems [36], stability analysis dedicated to the fuzzy control of nonlinear processes [37], robust evolving cloud-based control [38], power control of series hybrid electric vehicles [39], vehicle navigation by fuzzy cognitive maps [40], fuzzy control for the iron ore sintering process [41], type-2 fuzzy control for line following [42], and Singularity-free fixed-time fuzzy control for robotic systems [43].

The model-free tuning of fuzzy controllers is an alternative approach to the model-based design resulting in data-driven fuzzy control [1] to benefit from the advantages of data-driven control and fuzzy control and to mitigate their drawbacks. The combinations of data-driven model-free and fuzzy control include H_∞ fuzzy control [44], fault tolerant fuzzy control [45], parameterized data-driven fuzzy control [46], data-driven interpretable fuzzy control [47], MFC merged with Proportional-Derivative (PD) Takagi-Sugeno fuzzy control [48], [49], MFAC merged with PD Takagi-Sugeno fuzzy control [50], [51], ADRC mixed with PD Takagi-Sugeno fuzzy control [52] and tuned by VRFT [22] as well, fuzzy logic-based adaptive ADRC [53], data-driven arithmetic fuzzy control using the distending function [54], and data-driven MFC developed around continuous-time intelligent Proportional-Integral (PI) control [31]. The indirect model-free tuning of fuzzy controllers has initially been proposed in authors' papers [55] and [56], and continued in

[48] and [50] by controller structures that combine data-driven control and fuzzy control in order to incorporate model-free features in fuzzy control system structures.

According to the studies carried out in [57]–[59], several auto-tuning approaches, using a single relay, a sequential array of relays or decentralized relays, are available in the literature. Relay identification can achieve fine tuning of controllers including fuzzy controllers. Since experiments are conducted with the control system, it is justified to consider auto-tuning as an approach to data-driven fuzzy control. Some recent approaches to the auto-tuning of fuzzy controllers include the auto-tuning of PI-fuzzy controllers for variable speed wind turbines [60], the PI-fuzzy logic-based tuning of controllers for hybrid wind & photovoltaic power systems [61], the auto-tuning of Proportional-Integral-Derivative (PID)-fuzzy controllers for pitch angle control of wind turbines [62], telescope tracking systems [63], and indoor control for renewable air-conditioning [64].

Building upon authors' results on the indirect model-free tuning on fuzzy controllers [55], [56] and the auto-tuning of PI controllers [65], [66], this paper suggests a low-cost approach to data-driven fuzzy control of servo systems focusing on servo systems that can be modeled by second-order systems with an integral (I) component and a small time constant. These servo systems are controlled by Takagi-Sugeno PI-fuzzy controllers. The data-driven fuzzy control approach consists of six steps which include open-loop and closed-loop data-driven system identification to produce the process model from input-output data expressed as system step responses (i.e. non-parametric models), tuning the linear PI controller using the Extended Symmetrical Optimum (ESO) method [67], [68], and mapping the parameters of the PI controller onto the parameters of the Takagi-Sugeno PI-fuzzy controller in terms of the modal equivalence principle [69]. The approach is important with respect to the state-of-the-art because it is relatively simple as far as both the theoretical support and the implementation are concerned. Nevertheless, only few of the steps must be proceeded, depending on the interests of the control systems designers, who do not need to possess strong knowledge on the control systems and the controlled processes.

Concluding, this work presents a low-cost approach to data-driven fuzzy control. This approach is novel and feasible in practical applications.

The rest of the paper treats the following topics: the tuning approach is presented in the next section. Section 3 is dedicated to the validation in the illustrative example of position control of a nonlinear servo system using a Takagi-Sugeno PI-fuzzy controller. Experimental results obtained on laboratory equipment [70] are included. The conclusions are pointed out in Section 4.

2. THE TUNING APPROACH

It is assumed that the servo system as a controlled process can be modeled by the transfer function $P(s)$:

$$P(s) = \frac{k_P}{s(1+T_\Sigma s)}, \tag{1}$$

where k_p is the process gain and $T_\Sigma > 0$ is the process small time constant or parasitic time constant. The transfer function in (1) includes the actuator dynamics and the measurement instrumentation dynamics.

The presence of the I component in the transfer function (1) increases the difficulty of system identification, namely the computation of the two parameters such that (1) to approximate with an acceptable accuracy the behavior of the real-world servo system. Two data-driven identification approaches, (i) and (ii) discussed as follows, are considered to be adequate for the process with the transfer function given in (1).

(i) *The open-loop approach*. A step signal input is applied to the servo system around the operating point of interest on a time horizon of approximately $10T_\Sigma$.

If the step signal $u(t)$ of magnitude u_∞:

$$u(t) = u_\infty \sigma(t) \tag{2}$$

is applied to the input of the servo system, as shown in Fig. 1, then a system response expressed in Fig. 1 is illustrated, where $y(t)$ is the servo system (or process) output and also the controlled system output, $\sigma(t)$ is the unit step signal, and the subscript ∞ indicates the steady-state value of a certain variable. The step signal $u(t)$ is also the control signal if the servo system is included in a control system structure, and u_∞, which is used in the controller is assumed to be known, and matches one of the operating regimes that are important for the servo control system.

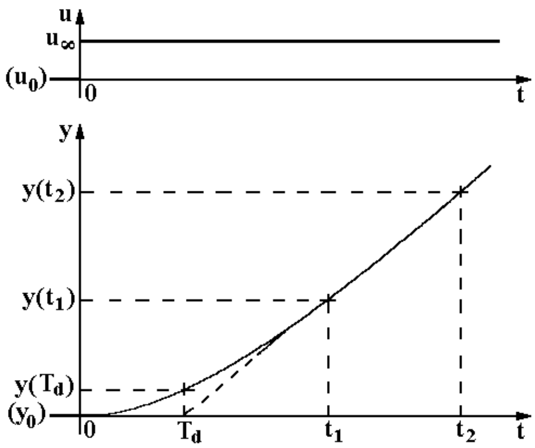

Fig. 1 Input step signal applied as control signal and servo system response. This figure is adapted from Preitl et al. [66]

Fig. 1 highlights that it is not necessarily impose to the servo system to evolve starting with zero initial conditions. The initial conditions are stated by means of the pair of input-output data values (u_0, y_0), which define the initial operating point. Therefore, nonzero initial conditions can be accepted, which is the usual situation in servo control systems operation.

The expression of the system response is:

$$y(t) = y_0 + k_P[t - T_\Sigma(1 - T_\Sigma e^{-t/T_\Sigma})]u_\infty \sigma(t). \tag{3}$$

For large values of time, i.e. $t >> T_\Sigma$, the exponential component is vanishing because $\lim_{t\to\infty} e^{-t/T_\Sigma} = 0$, so the steady-state response can be approximated by:

$$y(t) \approx y_0 + k_P(t - T_\Sigma)u_\infty. \tag{4}$$

As shown in [65] and [66], the time constant $T_d = T_\Sigma$, where the asymptote to the system response cuts the t axis in Fig. 1, plays the role of a pure time delay for which:

$$y(T_d) = y_0 + 0.368 k_P T_\Sigma u_\infty. \tag{5}$$

The data-driven identification approach (i) is carried out in terms of the steps (i1), (i2) and (i2) described as follows:

Step (i1). A unit step signal defined in (2) is applied as a control signal to the servo system viewed as a controlled output and the system response is recorded.

Step (i2). Considering two time moments t_1 and t_2, the corresponding output values $y(t_1)$ and $y(t_2)$ are measured on the basis of Fig. 1. The expression of the process small time constant is [65], [66]:

$$T_\Sigma = T_d = \frac{t_1 y(t_2) - t_2 y(t_1)}{y(t_2) - y(t_1)}. \tag{6}$$

Step (i3). The expression of the process gain results after the manipulation of (5):

$$k_P = \frac{y(T_d) - y_0}{0.368 T_\Sigma u_\infty}. \tag{7}$$

Using (4), another (approximate) way to compute k_P is:

$$k_P \approx \frac{y(t_1) - y_0}{(t_1 - T_\Sigma)u_\infty}. \tag{8}$$

(ii) *The closed-loop approach*. A Proportional (P) controller with the transfer function $C(s)$:

$$C(s) = k_C \tag{9}$$

is included in a control loop that represents the control system for the servo system (Fig. 2), where k_c is the controller gain.

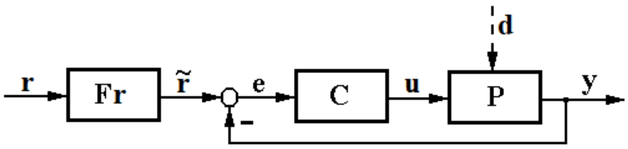

Fig. 2 Servo system control system structure as a control loop

The variables and blocks in Fig. 2 are: r – reference input or set-point, $\tilde{r}$ – filtered reference input, FR – reference input filter, d – disturbance input, which can be applied to the process input, the process output or, as shown in Fig. 2, in a certain (informational) place in the process structure, C – controller (a P controller in the framework of the approach (ii)), P – controlled process, i.e. the servo system, which can be modeled using (1), $e = \tilde{r} - y$ – control error.

Using the control system structure illustrated in Fig. 2, the transfer functions of the blocks in (1) and (9), assuming the absence of the block Fr, the closed-loop control system transfer function with respect to the reference input (assuming a zero disturbance input) is expressed as:

$$H_r(s) = \frac{\omega_0^2}{s^2 + 2\zeta\omega_0 s + \omega_0^2}, \tag{10}$$

with the parameters ω_0 – natural frequency [65], [66]:

$$\omega_0 = \sqrt{\frac{k_C k_P}{T_\Sigma}}, \tag{11}$$

and ζ – damping factor [65], [66]:

$$\zeta = \frac{0.5}{\sqrt{k_C k_P T_\Sigma}}. \tag{12}$$

For an adequately chosen value of k_C the control system can be brought in the situation to have two complex conjugated poles and the system response with respect to a step reference input of magnitude r_∞, which is also supposed to be known as u_∞ in relation with (2):

$$r(t) = r_\infty \sigma(t), \tag{13}$$

to exhibit the oscillatory behavior illustrated in Fig. 3.

The expression of the control system response is:

$$y(t) = y_0 + [1 - \frac{e^{-\zeta\omega_0 t}}{\sqrt{1-\zeta^2}} \sin(\omega_0 \sqrt{1-\zeta^2}\, t + \arccos\zeta)] r_\infty \sigma(t). \tag{14}$$

The following notations are introduced:

$$\omega_n = \omega_0 \sqrt{1-\zeta^2},\ T_n = \frac{1}{\omega_n} = \frac{1}{\omega_0 \sqrt{1-\zeta^2}} \tag{15}$$

for the damped natural frequency ω_n and the period of oscillations T_n of the response.

Fig. 3 highlights, similar to the approach (i), that it is not necessarily imposed to the control system to evolve starting with zero initial conditions. In this context, the initial conditions are stated by means of the pair of input-output data values (r_0, y_0), which define the initial operating point, and nonzero initial conditions can be accepted as well. The considered situation is normal because this approach is applied only if the control systems designer considers that it is of interest to apply it for possible re-tuning the controller.

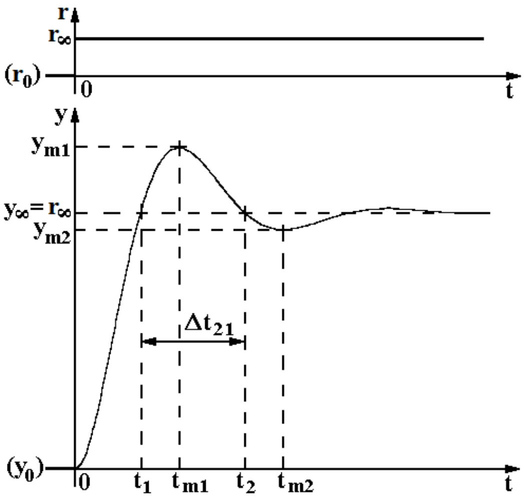

Fig. 3 Reference input step signal (without Fr) and control system response. This figure is adapted from Preitl et al. [66] and it assumes that all sub-systems of the control systems are implemented accurately

The expressions of the time moments specific to the response and illustrated in Fig. 3 are as follows [65], [66]:

$$\Delta t_{21} = \frac{\pi}{2\omega_0\sqrt{1-\zeta^2}} = \frac{\pi T_n}{2},\ t_{m\xi} = \frac{\pi\xi}{\omega_0\sqrt{1-\zeta^2}},\ \xi \in \{1,2\}, \tag{16}$$

and the relationship between the system response (output) values in Fig. 3, which also gives the overshoot σ_1, is [65], [66]:

$$\frac{y_{m1} - y_\infty}{y_\infty} = e^{-\pi\zeta/\sqrt{1-\zeta^2}} = \sigma_1. \tag{17}$$

Aiming an as accurate as possible data-driven identification, the control system must be brought in the situation $0.25 < \zeta < 0.707$ (it is recommended in [65] and [66] to set $\zeta = 0.5$) by the appropriate modification of k_C. This "ideal" value $\zeta = 0.5$ is convenient in order to measure relatively easily the specific numerical values on both axes in Fig. 3.

The relationships (16) and (17) are equivalent to the following reversed relationships [65], [66]:

$$\zeta = \frac{1}{\sqrt{1+(\frac{\pi}{\ln \sigma_1})^2}},\ T_n = \frac{2\Delta t_{21}}{\pi},\ \omega_0 = \frac{1}{T_n\sqrt{1-\zeta^2}} = \frac{\pi}{2\Delta t_{21}\sqrt{1-\zeta^2}}. \tag{18}$$

In the conditions of known k_C, measured σ_1 and T_n, and computed ζ and ω_0, the expressions of the two parameters in (1) are [65], [66]:

$$T_{\Sigma} = \frac{\sqrt{1-\zeta^2}}{\zeta} \frac{T_n}{4\pi}, \; k_P = \frac{T_{\Sigma}}{k_C} \omega_0^2. \tag{19}$$

The data-driven identification approach (ii) is carried out in terms of the steps (ii1), (ii2) and (ii2) described as follows:

Step (*ii*1). A unit step signal defined in (13) is applied as a reference input to the control system and the system response is recorded.

Step (*ii*2). The controller gain k_C is set such that to obtain a system response with $0.25 < \zeta < 0.707$. If the system response fulfils this condition, the approach continues with the step (ii3). Otherwise, the step (ii1) is repeated.

Step (*ii*3). The values of y_{m1}, y_{∞} and Δt_{21} are measured. Relationships in (18) are next applied to obtain the values of ζ and ω_0. Finally, relationships in (19) are applied to compute the values of T_{Σ} and next k_p.

PI controllers can cope with the process modeled in (1). The transfer function of a PI controller is $C(S)$:

$$C(s) = \frac{k_c(1+sT_i)}{s} = k_C(1+\frac{1}{T_i s}), \; k_C = k_c T_i, \tag{20}$$

where $k_C > 0$ or $k_c > 0$ are two expressions of the controller gain, with their relation specified in (20), and $T_i > 0$ is the integral time constant. The ESO method [67], [68] is successfully applied to tune the PI controller parameters in (20) as it guarantees a trade-off to the empirical control system performance specifications (expressed as maximum values of percent overshoot, settling time and rise time) of the linear control system making use of a single design parameter β within the largest recommended domain $1 < \beta \le 20$. The PI tuning conditions specific to the ESO method are as follows [67], [68]:

$$k_c = \frac{1}{\beta\sqrt{\beta}\, k_P\, T_{\Sigma}^2}, k_C = \frac{1}{\sqrt{\beta}\, k_P\, T_{\Sigma}}, T_i = \beta\, T_{\Sigma}. \tag{21}$$

The transfer function of the simplest reference input filter out of the two ones recommended in the papers [67] and [68] is:

$$Fr(s) = \frac{1}{1+\beta\, T_{\Sigma} s}. \tag{22}$$

The Takagi-Sugeno fuzzy controller is designed and tuned in terms of transferring in a fuzzy logic-like interpretation the knowledge from the PI controller structure. The structure and the input membership functions of a the low-cost Takagi-Sugeno fuzzy controller are presented in Fig. 4, where q^{-1} indicates the backward shift operator, t_d indicates the discrete time index, TISO-FC is the Two Inputs-Single Output fuzzy controller, $\Delta e(t_d)$ is the increment of control error, and $\Delta u(t_d)$ is the increment of control signal.

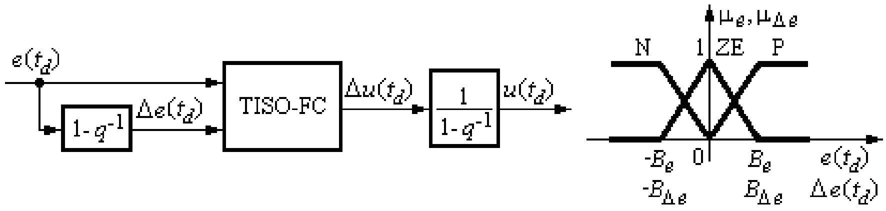

Fig. 4 Structure (A) and input membership functions (B) of low-cost Takagi-Sugeno fuzzy controller. This figure is adapted from Precup et al. [71]

Discretizing the continuous-time PI controller by Tustin's method, the recurrent equation of the incremental discrete-time PI controller is as follows [71]:

$$\Delta u(t_d) = K_P[\Delta e(t_d) + \mu\, e(t_d)], \tag{23}$$

where [71]:

$$K_P = k_c(T_i - \frac{T_s}{2}),\ \mu = \frac{2\,T_s}{2\,T_i - T_s}, \tag{24}$$

and $T_s > 0$ is the sampling period.

The TISO-FC block employs the weighted average method for defuzzification, and the SUM and PROD operators in the inference engine. The complete rule base of the TISO-FC block is expressed as [71]:

$$\begin{aligned}
&\text{IF } (e(t_d) \text{ IS N AND } \Delta e(t_d) \text{ IS N) OR } (e(t_d) \text{ IS P} \\
&\quad \text{AND } \Delta e(t_d) \text{ IS P) THEN } \Delta u(t_d) = \eta\, K_P[\Delta e(t_d) + \mu\, e(t_d)], \\
&\text{F } (e(t_d) \text{ IS ZE) OR } (e(t_d) \text{ IS N AND } \Delta e(t_d) \text{ IS ZE) OR} \\
&\quad (e(t_d) \text{ IS N AND } \Delta e(t_d) \text{ IS P) OR } (e(t_d) \text{ IS P} \\
&\quad \text{AND } \Delta e(t_d) \text{ IS ZE) OR } (e(t_d) \text{ IS P AND } \Delta e(t_d) \text{ IS P)} \\
&\quad \text{THEN } \Delta u(t_d) = K_P[\Delta e(t_d) + \mu\, e(t_d)].
\end{aligned} \tag{25}$$

The role of the additional parameter η, with the largest domain $0 < \eta < 1$, is to reduce the overshoot of the control system. Therefore, (25) and the fuzzy controller structure make this low-cost fuzzy controller behaves as a bumpless interpolator between two linear PI controllers.

The modal equivalence principle [69] applied to this Takagi-Sugeno PI-fuzzy controller leads to the tuning equation:

$$B_{\Delta e} = \mu\, B_e, \tag{26}$$

where the parameter B_e should be chosen according to the experience of the control systems designer. The parameter η is chosen in a similar way. The optimal tuning can be performed with very good results [71] to get the values of these parameters.

Summarizing all aspects presented in this section, the low-cost data-driven fuzzy control approach consists of the six steps (dd1) to (dd6):

Step (*dd*1). The open-loop data-driven system identification approach (i) is applied to produce the process model in (1) using the input-output data of the controlled process (the servo system) expressed as the servo system step response shown in Fig. 1.

Step (*dd*2). The linear PI controller is tuned using the ESO method such that to meet the performance specifications imposed to the control system.

Step (*dd*3). The parameters of the PI controller are mapped onto the parameters of the Takagi-Sugeno PI-fuzzy controller using (26).

Step (*dd*4). This step is optional and conducted only if the control systems designer considers that it is relevant. For example, such situations occur if the control system performance indices are deteriorated in time. The closed-loop data-driven system identification approach (ii) is applied to produce the process model in (1) using the input-output data of the control system expressed as the (closed-loop) control system step response shown in Fig. 3.

Step (*dd*5). This step is also optional in the context of the step (dd4). The linear PI controller is tuned using the ESO method such that to meet again the performance specifications imposed to the control system.

Step (*dd*6). This step is also optional in the context of the step (dd4) and it is identical to the step (dd3). The parameters of the PI controller are mapped onto the parameters of the Takagi-Sugeno PI-fuzzy controller using (26).

Since the step (dd4) is applied in terms of the real-world operation of the control system, a special attention should be paid to the transfer from the Takagi-Sugeno PI-fuzzy controller to the P controller and vice-versa. Bumpless transfers should be ensured in this regard, meaning that the history of the “old” digital control algorithm requires to be modified in order to avoid big modifications of the control system, which might affect negatively the actuators and finally the control system behavior. A simple solution in the linear case is presented in the references [65] and [66].

3. EXPERIMENTAL RESULTS

The tuning approach presented in the previous section is validated as follows by applying it to the design and tuning of a Takagi-Sugeno PI-fuzzy controller to the angular position of a nonlinear servo system laboratory equipment [70]. Some details on the steps are given as follows. The state-space model of the servo system is expressed as [71]:

$$m(t) = \begin{cases} -1, & \text{if } u(t) \le -u_b, \\ \dfrac{u(t)+u_c}{u_b-u_c}, & \text{if } -u_b < u(t) < -u_c, \\ 0, & \text{if } -u_c \le |u(t)| \le u_a, \\ \dfrac{u(t)-u_a}{u_b-u_a}, & \text{if } u_a < u(t) < u_b, \\ 1, & \text{if } u(t) \ge u_b, \end{cases} \tag{27}$$

$$\begin{bmatrix} \dot{x}_1(t) \\ \dot{x}_2(t) \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ 0 & -\dfrac{1}{T_\Sigma} \end{bmatrix} \begin{bmatrix} x_1(t) \\ x_2(t) \end{bmatrix} + \begin{bmatrix} 0 \\ \dfrac{k_P}{T_\Sigma} \end{bmatrix} m(t),$$

$$y(t) = [1 \quad 0][x_1(t) \quad x_2(t)]^T,$$

where the control signal $u(t)$ applied to the Direct Current (DC) motor is a pulse width modulated duty cycle, $x_1(t) = \alpha(t)$ (rad) is the angular position, $x_2(t) = \omega(t)$ (rad/s) is the angular speed, and the superscript T indicates matrix transposition. The variable $m(t)$ is the output of the saturation and dead zone static nonlinearity, modeled in the first part in (27), with the parameters $u_a = 0.15$, $u_b = 0.1$ and $u_c = 0.15$. The application of the step (dd1) leads to the values of the servo system (i.e. process) parameters $k_P = 140$ and $T_\Sigma = 0.92$ s.

The first steps (dd1) and (dd2) of the approach presented in the previous section are applied. These two steps are applied simultaneously in terms of the optimal tuning [71] of the Takagi-Sugeno PI-fuzzy controller parameters such that to ensure a reduced parametric sensitivity with respect to one of the two parameters in (1). One set of linear PI controller and Takagi-Sugeno PI-fuzzy controller parameter values, which ensures the strongest mitigation of the parametric sensitivity with respect to T_Σ is recommended in [71]: $\beta = 16.9763$, $k_c = 0.001884$, $T_i = 15.618$ s, $B_e = 20$, $B_{\Delta e} = 0.01281$, and $\eta = 0.287$. Three optimization algorithms were applied in [71], however other ones could be of interest because of the nonlinearity of the process and the controller as, for example, parameterized genetic algorithms [72], [73], various algorithms adapted from their general formulation for community detection in networks [74], metaheuristic algorithms with information feedback models [75], MOEA/D [76], slime mould algorithms [77], grey wolf optimizers [78], and algorithms specific to neuro-fuzzy model training [79]. The optimization problems in this context should be defined with great care accounting for various constraints, which may be caused by man-computer symbiosis [80], stochastic demands [81], fault detection and isolation and recovery [82], trade-off to approximation accuracy and complexity [83], and specific structures of fuzzy systems [84], [85], requiring appropriate handling and the modification of the optimization algorithms.

Using the above parameter values and implementing the low-cost Takagi-Sugeno fuzzy controller according to the details given in the previous section, Fig. 5 offers a sample of experimental results for the fuzzy control system. Fig. 5 illustrates that the

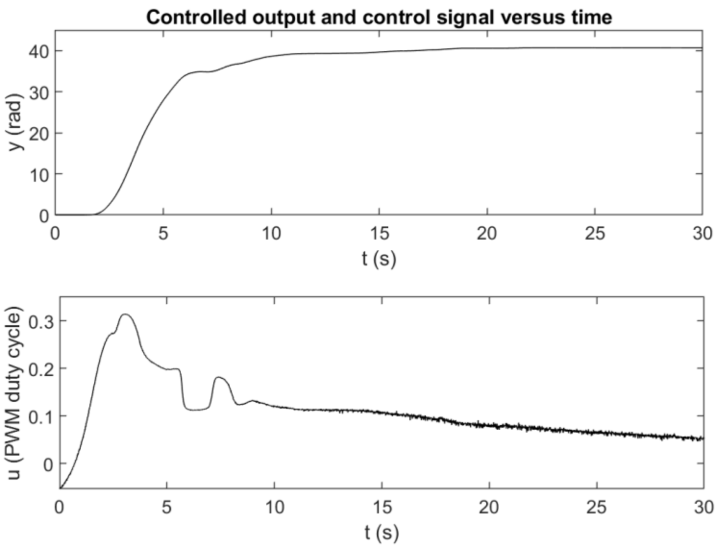

Fig. 5 Real-time experimental results expressed as fuzzy control system responses y and u (PWM indicates Pulse Width Modulation)

fuzzy control system exhibits good control system dynamics performance with respect to the 40 rad step modifications of the reference input. Fig. 5 also outlines the effects of the nonlinearity in (27).

The results considered in this section help the reader to understand the effectiveness and the efficacy of the proposed approach. More effective metrics and performance indices could be exploited to assess the advantages of the developed controllers.

5. CONCLUSIONS

Starting with a control structure with auto-tuning Proportional-Integral controller, which was previously developed by the authors, and two open-loop data-driven system identification approaches, this paper gave a low-cost approach to data-driven fuzzy control of servo systems focusing on Takagi-Sugeno Proportional-Integral-fuzzy controllers.

Using well stated tuning relations, which can ensure good control system performance indices, which are selectable according to the needs / application, the Extended Symmetrical Optimum method is initially used to tune the linear Proportional-Integral controllers. The modal equivalence principle is next involved in mapping the parameters of the linear controller onto the parameters of the fuzzy one. The paper also presented two identification approaches (i) and (ii) of a certain category of servo systems together with the relations for the computation of the parameters based on dynamic regime measurements, which are relatively easily performed and implemented. The authors helped the reader to understand the novelty issues of the developed scheme.

The approach suggested in this paper is advantageous as it can be generalized to processes of integral type and several dynamics and delays. The approach can be implemented automatically by the computer-aided computation of the process parameters in the two identification approaches instead of actually representing the system responses.

The data-driven approach presented in the paper proves the potential of auto-tuning approaches in data-driven control. The applications had in view belong to the field of electrical driving systems with fast / slow variable parameters as function of the process operation.

Section 2 should have addressed more details regarding the considered models and tools; in particular, it does not consider the robustness and reliability issues, due for example to uncertainty and disturbance effects, as well as the model-reality mismatch. This point is fundamental when the reliability and robustness features of the proposed solutions have to be verified and validated with respect to real engineering and safety critical systems. Therefore, the effectiveness of the methodology proposed in Section 2 is a suggested open problem and future issue that could require further investigations.

Another direction of open research direction is the combination of this data-driven technique with other data-driven techniques in order to reduce the heuristics in the steps (dd2) and (dd3). The optimal tuning of fuzzy controllers will be carried out accounting for stability constraints but with great care to preserve the data-driven feature of the future novel approaches. All these open problems and future issues will contribute to make data-driven fuzzy control clear and non-questionable.

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