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Performance Improvement of Low-Cost Iterative Learning-Based Fuzzy Control Systems for Tower Crane Systems

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Abstract

This paper is dedicated to the memory of Prof. Ioan Dziţac, one of the fathers of this journal and its founding Editor-in-Chief till 2021. The paper addresses the performance improvement of three Single Input-Single Output (SISO) fuzzy control systems that control separately the positions of interest of tower crane systems, namely the cart position, the arm angular position and the payload position. Three separate low-cost SISO fuzzy controllers are employed in terms of first order discrete-time intelligent Proportional-Integral (PI) controllers with Takagi-Sugeno-Kang Proportional-Derivative (PD) fuzzy terms. Iterative Learning Control (ILC) system structures with PD learning functions are involved in the current iteration SISO ILC structures. Optimization problems are defined in order to tune the parameters of the learning functions. The objective functions are defined as the sums of squared control errors, and they are solved in the iteration domain using the recent metaheuristic Slime Mould Algorithm (SMA). The experimental results prove the performance improvement of the SISO control systems after ten iterations of SMA.

Keywords: Iterative Learning Control; intelligent Proportional-Integral Controllers; fuzzy control; learning functions; Slime Mould Algorithm; tower crane systems.

1 Introduction

This paper treats a subject that belongs to the intersections of the fields of fuzzy logic control and the performance improvement of control systems based on experiments and few information available on the controlled process, also referred to as data-driven control or model-free control or data-driven model-free control. Comprehensive analyses of the theory and applications of fuzzy sets and fuzzy logic including fuzzy logic control are conducted in the papers [1] and [2] authored by Prof. Ioan

Dziţac and his co-authpors and friends, who acknowledge the exceptional contribution of Prof. Lotfi A. Zadeh, the creator of fuzzy sets.

As highlighted in the recent and popular surveys [3], [4], [5], [6] and [7], the systematic design and tuning of fuzzy control systems is supported by analyses that include stability, controllability, observability, sensitivity and robustness. The optimal tuning of fuzzy controllers is combined with these analyses. However, performance improvement is preferred instead of speaking about optimal fuzzy controllers because the proof of reaching the optimal solutions if fuzzy models are involved in the optimization problems is a relatively complicated task.

As shown in [8], Iterative Learning Control (ILC) carries out the improvement of various performance indices (including the empirical ones overshoot, settling time, etc., specified in [9] and [10]) of control systems executing repetitively the same tasks in terms of several experiments also referred to as cycles or trials or iterations. The information gathered from previous experiments is used in this regard. Several learning functions or learning rules are included in ILC structures designed around the control systems whose performance are improved [11], [12]. ILC is considered in [13] as an optimization paradigm, and its analysis is performed in [14].

The Proportional-Derivative (PD) learning functions or rules are embedded in ILC resulting in the PD-type ILC, which is based on derivative and proportional errors, it calculates the error and applies a correction. The PD-type ILC is applied to control several nonlinear systems as, for example, time-delay systems in [15] and along with convergence proofs in [16]. Although PD-type ILC is generally applied to processes modeled by linear or nonlinear ordinary differential equations, a recent application to hyperbolic equations is reported in [17].

Three classes of optimal ILC are discussed in [18]. The first class is the norm-optimal ILC, which makes use of the lifted system representation of ILC and supported by the representative papers [19], [20], [21] and [22]. The second class is stochastic ILC, and it mitigates the effects of random disturbances that depend on the iterations [23], [24]. The third class, referred to as data-driven ILC or model-free ILC, directly deals with nonlinear systems subject to unknown nonlinearities; popular papers in this class are [25], [26], [27], [28] in the general context of data-driven control, which ensures the performance improvement of control systems in terms of few information on the controlled process and using experiments conducted on the real-world operating control systems to compensate for that. Recent examples of data-driven model-free controllers are reported in the area of Model-Free Control [29], [30], Virtual Reference Feedback Tuning [31], data-driven dual-rate control [32], repetitive algorithms [33], Model-Free Adaptive Control [34], [35], data-driven model predictive control [36] and Active Disturbance Rejection Control [37], [38]. Moreover, as stated in [39] and highlighted afterwards in [30], Model-Free Control is a new and efficient tool for machine learning.

More than fifteen years ago the authors suggested in [40] the combination of fuzzy control and ILC in order to benefit from the advantageous of these two control strategies and to alleviate their shortcomings. Several low-cost controllers specific to this first approach were proposed in the subsequent papers [9], [41], [42], [43], [44] and [45] focusing on the Proportional-Integral (PI) fuzzy controllers, which replace the linear PI controllers and the performance of fuzzy control systems is improved in terms of ILC. In addition, fuzzy logic was also involved in the learning functions or learning rules specific to ILC algorithms to add more flexibility. A different approach to combine fuzzy control with ILC is the approximation of uncertain dynamics by fuzzy models in order to solve the problem of unknown nonlinear functions in the systems, and next include this in adaptive ILC structures. Recent results in this regard are reported for biotechnological processes [46], multi-agent systems [47] and transportation systems [48]. Neural networks can be used instead of fuzzy models in this second approach as suggestively illustrated in [49] and [50].

The first new contribution of this paper is the performance improvement of control systems for a representative family of Multi Input-Multi Output (MIMO) systems represented by tower crane systems, using the first approach mentioned above, namely and ILC control structure with PD learning functions. The MIMO control system structure makes use of low-cost fuzzy controllers included in the three SISO control loops (for cart position control, arm angular position control and payload position control) subjected to ILC, and the fuzzy controllers are represented by first order discrete-time intelligent PI controllers with Takagi-Sugeno-Kang PD fuzzy terms presented in [51] and [52].

The second new contribution is the definition of optimization problems in the iteration domain in order to ensure the performance improvement of the fuzzy control systems in terms of expressing the objective functions of sums of squared control errors and considering that the variables are the parameters of the PD learning functions. The optimization problems are solved by the metaheuristic Slime Mould Algorithm (SMA) suggested in [53] and recently applied in [54] and [55] to optimally tune the parameters of type-1 and type-2 fuzzy controllers. Only few iterations of SMA are conducted, and SMA generally aims the optimal tuning of the parameters of the learning functions.

The limitations of the state-of-the-art to introduce the control strategy proposed in this paper are: (i) accurate linear models or nonlinear models of the process are needed including fuzzy logic-based ones, (ii) differences between the process models and the real process are not tackled, and (iii) the controller structures are rather complicated. These three limitations will be discussed as follows in order to highlight the motivation of the above new contributions. The motivation of the new contributions, which also highlights their importance in the context of the state-of-the-art, is three-fold. First, the second approach to the combination of fuzzy logic and ILC requires accurate fuzzy models of the process, which requires a deep understanding of the process models and also may result in a large number of fuzzy rules; this also leads to a large number of fuzzy rules of the fuzzy controllers if the Parallel Distributed Compensation principle is involved in their design and tuning. Accurate linear models are also needed for norm-optimal ILC, where the frequency domain calculation of the H_∞ norm is needed, which is avoided in this paper. Second, there are differences between the process models and the real process, which are important in the context of optimization as they affect the optimality. The evaluation of the objective functions in this paper is carried out in the iteration or experiment or trial or cycle domain, and it is actually performed in terms of conducting experiments on the real-world control system. Of course, this is generally a shortcoming in applications of metaheuristic optimization algorithms, but SMA does not require many evaluations of the objective functions, plus the number of iterations is small because the performance improvement of already operating control systems is targeted and not reaching the optimal solution. Third, low-cost fuzzy controllers are proposed as far as both their structure (and implementation) and design (and tuning) is concerned, and they do not make use anymore of mapping the tuning results from the linear controllers onto their fuzzy counterparts.

Besides SMA, other popular metaheuristic algorithms with fresh results are Gravitational Search Algorithm (GSA), Charged System Search, Particle Swarm Optimization [56], Grey Wolf Optimizer [57], Chicken Search Optimization [58], competitive multi-metaheuristic algorithms [59], Harmony Search Optimization [60] for the optimal tuning of fuzzy controllers, extremal optimization algorithms for nonlinear controller optimal tuning [61], [62], inclusion of information feedback models in metaheuristic algorithms [63], [64], hybrid GSA-Genetic Algorithm (GA) [65] for constrained optimization problems, water cycle [66] and bat [67] algorithms for combinatorial optimization, GWO with hierarchical fuzzy operator [68], hierarchical GA for multi-objective optimization of neural networks [69], Cross-Entropy algorithm for manufacturing processes [70], Water Circle algorithm for traveling salesman problem [71], Conflict Monitoring algorithm [72] and Jaya optimization algorithm for biped robots [73].

The paper is structured as follows: the tower crane system model, which plays the role of controlled process, is described in the next section. The control system structure and the design approach are presented in Section 3. The experimental results are discussed in Section 4. The conclusions are drawn in Section 5.

2 Process Model

The block diagram of the tower crane system is described in Figure 1 focusing on the tower crane system laboratory equipment [74] installed in the Intelligent Control Systems Laboratory of the Politehnica University of Timisoara, Romania. The blocks included in Figure 1 (a) enable the digital control of this system viewed as a controlled process.

Using the coordinate systems associated to each element of the crane and the centers of mass introduced in Figure 1 (b), the nonlinear state-space model of the tower crane system is [52]

$$
\begin{aligned}
&\dot{x}_1 = x_5,\\
&\dot{x}_2 = x_6,\\
&\dot{x}_3 = x_7,\\
&\dot{x}_4 = x_8,\\
&\dot{x}_5 = f_5(\prod),\\
&\dot{x}_6 = f_6(\coprod),\\
&\dot{x}_7 = -(1/T_{\Sigma 1})x_7 + (k_{P1}/T_{\Sigma 1})m_1,\\
&\dot{x}_8 = -(1/T_{\Sigma 2})x_8 + (k_{P2}/T_{\Sigma 2})m_2,\\
&\dot{x}_9 = x_{10},\\
&\dot{x}_{10} = f_{10}(\aleph),\\
&y_1 = x_3,\\
&y_2 = x_4,\\
&y_3 = x_9,
\end{aligned}
\tag{1}
$$

with the following expressions of the functions f_5, f_6 and f_{10} [52]:

$$
\begin{aligned}
&f_5(\prod) = f_5(x_1, x_2, x_3, x_5, ..., x_{10}, m_1, m_2)\\
&= [-4x_5x_{10} + 4x_6x_8x_9\cos^2 x_1\cos x_2 - x_6^2x_9\sin 2x_1\\
&+x_8^2x_9\sin 2x_1\cos^2 x_2 - 2g\sin x_1\cos x_2 - 4x_7x_8\cos x_1\\
&+2x_3x_8^2\sin x_1\sin x_2 + 2(x_7/T_{\Sigma 1})\sin x_1\sin x_2\\
&-2(k_{P1}/T_{\Sigma 1})m_1\sin x_1\sin x_2 + 4x_8x_{10}\sin x_2\\
&+2(x_3x_8/T_{\Sigma 2})\cos x_1 - 2(k_{P2}/T_{\Sigma 2})x_3m_2\cos x_1\\
&-2(x_8x_9/T_{\Sigma 2})\sin x_2 + 2(k_{P2}/T_{\Sigma 2})x_9m_2\sin x_2]/(2x_9),\\
&f_6(\coprod) = f_6(x_1, x_2, x_3, x_5, ..., x_{10}, m_1, m_2)\\
&= [-2x_6x_{10}\cos x_1 - 2x_5x_8x_9\cos x_1\cos x_2\\
&+2x_5x_6x_9\sin x_1 - g\sin x_2 - 2x_8x_{10}\sin x_1\cos x_2\\
&-x_3x_8^2\cos x_2 + x_8^2x_9\cos x_1\cos x_2\sin x_2 - (x_7/T_{\Sigma 1})\cos x_2\\
&+(k_{P1}/T_{\Sigma 1})m_1\cos x_2 + (x_8x_9/T_{\Sigma 2})\sin x_1\cos x_2\\
&-(k_{P2}/T_{\Sigma 2})x_9m_2\sin x_1\cos x_2]/(x_9\cos x_1),\\
&f_{10}(\aleph) = f_{10}(x_1, x_2, x_3, x_5, ..., x_{10}, m_1, m_2, m_3)\\
&= [-(\mu_L/m_L)x_{10} + g + 2x_6x_{10}\sin x_2\cos x_1\\
&+2x_5x_{10}\sin x_1\cos x_2 - 2x_5x_6x_9\sin x_1\sin x_2\\
&+x_9f_6(\coprod)\sin x_2\cos x_1 + x_9f_5(\prod)\sin x_1\cos x_2\\
&+x_9(x_5^2 + x_6^2)\cos x_1\cos x_2 + (k_{P3}m_3/m_L)]/(1 + \cos x_1\cos x_2).
\end{aligned}
\tag{2}
$$

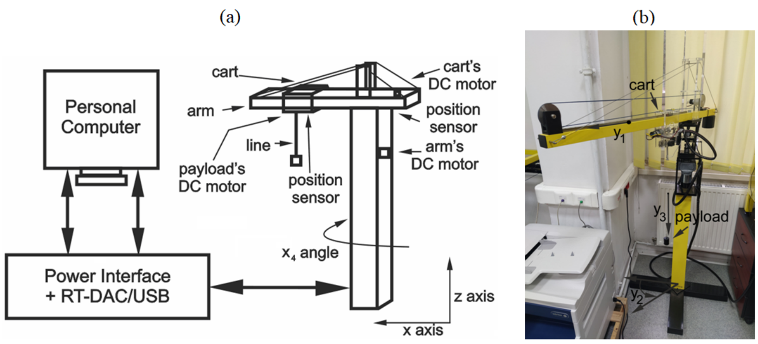

Figure 1: The block diagram of the tower crane system laboratory equipment (adapted from [75], [76] and [77]) (a) and coordinate systems associated to each element of the crane and the centers of mass (adapted from [52]) (b).

The Denavit-Hartenberg methodology can be used to obtain the dynamic model in (1) and (2) and simplify it to justify the control scheme. As pointed out in [52], x_1 (rad) and x_2 (rad) are the angles that describe the payload position in xz plane, x_3 (m) $\in [-0.25,\ 0.25]$ is the first (controlled) output of the tower crane system, i.e. the cart position, x_4 (rad) $\in [-1.57,\ 1.57]$ is the second (controlled) output of the tower crane system, i.e. the arm angular position, x_5 (rad/s) and x_6 (rad/s) are the angular velocities that describe the payload position in xz plane, x_7 (m/s) is the cart velocity, x_8 (rad/s) is the arm angular velocity, x_9 (m) $\in [-0.4,\ 0.4]$ is the lift line position and also the third (controlled) output of the tower crane system, x_{10} (m/s) is lift line velocity. The expressions of the saturation and dead zone (sdz) static nonlinearities specific to the three actuators, which are Direct Current (DC) motors, are [52]

$$m_i = \begin{cases} -1, & \text{if } u_i \leq -u_{bi}, \\ (u_i + u_{ci})/(u_{bi} - u_{ci}), & \text{if } -u_{bi} < u_i < -u_{ci}, \\ 0, & \text{if } -u_{ci} \leq |u_i| \leq u_{ai}, \\ (u_i - u_{ai})/(u_{bi} - u_{ai}), & \text{if } u_{ai} < u_i < u_{bi}, \\ 1, & \text{if } u_i \geq u_{bi}, \end{cases} \quad (3)$$

$m_1 \in [-1,\ 1]$ is the output of the sdz static nonlinearity specific to the first actuator, $u_1(\%) \in [-100,\ 100]$ and next $u_1 \in [-1,\ 1]$ is the first control signal, i.e. the Pulse Width Modulation (PWM) duty cycle of DC motor for cart position control, $m_2 \in [-1,\ 1]$ is the output of sdz static nonlinearity specific to the second actuator, $u_2(\%) \in [-100,\ 100]$ and next $u_2 \in [-1,\ 1]$ is the second control signal, i.e. the PWM duty cycle of DC motor for arm angular position control, $m_3 \in [-1,\ 1]$ is the output of sdz static nonlinearity specific to the third actuator, $u_3(\%) \in [-100,\ 100]$ and next $u_3 \in [-1,\ 1]$ is the third control signal, i.e. the PWM duty cycle of DC motor for payload position control, the parameters in (3) obtained experimentally are $u_{a1} = 0.1925$, $u_{b1} = 1$, $u_{c1} = 0.2$, $u_{a2} = 0.18$, $u_{b2} = 1$, $u_{c2} = 0.1538$, $u_{a3} = 0.1$, $u_{b3} = 1$ and $u_{c3} = 0.13$, m_L=0.33 kg is the payload mass, $\mu_L = 1600$ kg/s is the viscous coefficient associated with the payload motion, $k_{P1} = 0.188$ m/s $k_{P2} = 0.871$ rad/s and $k_{P3} = 200$ kg.m/s^2 are the process gains (of the three DC motors), $T_1 = 0.1$ s and $T_2 = 0.1$ s are the small time constants of the first two DC motors, and $g = 9.81$ m/s^2 is the gravitational acceleration.

The controlled outputs are the cart position y_1 (m) = x_3 (m), the arm angular position y_2 (rad) = x_4 (rad) and the payload position y_3 (m) = x_9 (m).

3 Control System Structure and Design Approach

As specified in Section 1, a MIMO control system structure is employed in controlling the three outputs of the tower crane system. This MIMO control system structure consists of three separate SISO control systems (or control loops), separately designed for cart position control, arm angular position control and payload position control. For the sake of simplicity, a SISO generic control system structure will be presented as follows, and this structure has to be replicated considering separately the three controlled outputs.

The fuzzy control system structure with PD learning function or learning rule is presented in Figure 2, where: ILC – Iterative Learning Control algorithm, r – reference input or set-point, assumed to be repetitive, d – disturbance input, which can be additive on the process input or output, and it is also assumed to be repetitive, e – control error, u – control signal elaborated by the ILC algorithm, y – controlled output, M – memory block, C – fuzzy controller, P – controlled process (i.e. the tower crane system), q^{-1} – backward shift operator in the iteration domain, k_p – the proportional gain of the learning function, k_d – the derivative gain of the learning function, and j – subscript that indicates the current iteration or cycle or trial, but attention should be paid at the first three iterations in order to avoid the notation problem concerning one of the three controlled outputs.

The expression of the PD learning function is [40]

$$u_{j+1}(k) = u_j(k) + k_p e_j(k) + k_d[e_j(k+1) - e_j(k)], \quad (4)$$

where k is the index of the current sampling interval.

As pointed out in Section 1, the controller C in Figure 2 is represented by the first order discrete-time intelligent Proportional-Integral (iPI) controller with Takagi-Sugeno-Kang PD fuzzy term, with the following expression of the control law, adapted from [52]:

$$u(k) = u(k-1) + \alpha^{-1}(r(k+1) - r(k) - y(k) + y(k-1) - \varphi(k)), \quad (5)$$

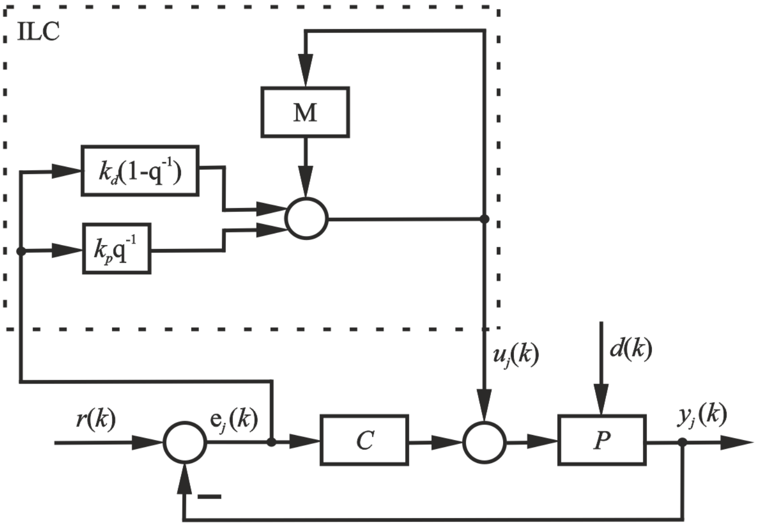

Figure 2: Fuzzy control system structure with PD learning function, where C denotes the controller, P the controlled process, and M the memory block.

where $\alpha \in \Re$ is a parameter specific to MFC and chosen by the designer such that $\Delta y(k+1) = y(k+1) - y(k)$ and $\alpha\, u(k)$ have the same order of magnitude, and $\varphi(k)$ is the output of the Takagi-Sugeno-Kang PD fuzzy term.

The discrete-time Takagi-Sugeno-Kang PD fuzzy term is built around the Two Inputs-Single Output Fuzzy Controller (TISO-FC) and the structure given in Figure 3 (a). Figure 3 (b) highlights the input (and also scheduling) membership functions and their parameters, $B_{e1} > 0$ and $B_{\Delta e} > 0$.

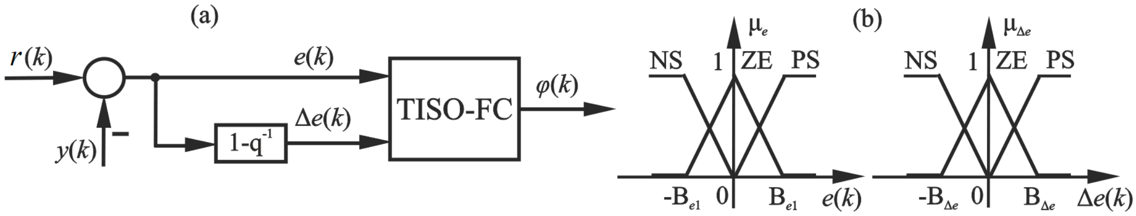

Figure 3: Discrete-time Takagi-Sugeno-Kang PD fuzzy term (a) and input membership functions (b) (adapted from [52]).

The weighted average method is implemented in the defuzzification module of this controller, actually TISO-FC. The SUM and PROD operators are employed in the inference engine. The rule base is given in Table 1 expressed for cart control, arm angular position control and payload position control of tower crane systems, with the following notations in the rule consequents [52]:

$$\varphi_i(k) = \chi_i\, \psi_{PD}(k), \;\; i = 1...3, \tag{6}$$

where $\chi_i > 0$, $i = 1...3$, are the parameters inserted in order to alleviate the overshoot of the control system, $\psi_{PD}(k)$ is the output of the linear PD term specific to MFC.

The expression of the PD term is [52]

$$\psi_{PD}(k) = \mathrm{M}_1 \Delta e(k) + \mathrm{M}_2 e(k) = -K_2 \Delta e(k) + (K_1 + K_2) e(k), \tag{7}$$

where $K_1 \in \Re$ and $K_2 \in \Re$ are the gains of the iPI controller, and $\Delta e(k) = e(k) - e(k-1)$ is the increment of control error. Using $\psi_{PD}(k)$ instead of $\varphi(k)$ in (5) leads to the linear iPI controller, an important type of MFC, which is replaced by the fuzzy controller for control system performance improvement.

Table 1: Rule base of Takagi-Sugeno-Kang PD fuzzy term (adapted from [52])

$e(k)$ / $\Delta e(k)$	**NS**	**ZE**	**PS**
PS	$\varphi_2(k)$	$\varphi_3(k)$	$\varphi_1(k)$
ZE	$\varphi_2(k)$	$\varphi_3(k)$	$\varphi_3(k)$
NS	$\varphi_2(k)$	$\varphi_2(k)$	$\varphi_2(k)$

The parameters of one of the three first order discrete-time iPI controllers with Takagi-Sugeno-Kang PD fuzzy terms are α, K_1, K_2, B_{e1}, $B_{\Delta e}$ and $\chi_i > 0$, $i = 1...3$. The values of these parameters are set according to the recommendations given in [52] including their computation as solutions to adequately defined optimization problems. The modal equivalence principle is applied to obtain the value of the parameter $B_{\Delta e}$ [52]:

$$B_{\Delta e} = -(\mathrm{M}_2/\mathrm{M}_1)B_{e1} = (1 + K_1/K_2)B_{e1}. \tag{8}$$

As specified in Section 1, the parameters k_p and k_d of the PD learning function can be obtained as the two elements of the vector solutions $\boldsymbol{\rho}^*_{(\psi)}$ to the optimization problems

$$\boldsymbol{\rho}^*_{(\psi)} = \arg \min_{\boldsymbol{\rho}_{(\psi)} \in D_{\boldsymbol{\rho}_{(\psi)}}} J_{(\psi)}(\boldsymbol{\rho}_{(\psi)}), \;\; J_{(\psi)}(\boldsymbol{\rho}_{(\psi)}) = \textstyle\sum_{k=1}^{N_s} [e_{(\psi)}(k, \boldsymbol{\rho}_{(\psi)})]^2, \tag{9}$$

where $J_{(\psi)}(\boldsymbol{\rho}_{(\psi)})$ is the objective function that measures and assesses the performance of each SISO control system structure with first order discrete-time iPI controllers with Takagi-Sugeno-Kang PD fuzzy terms, $\boldsymbol{\rho}_{(\psi)}$ is the general notation for the parameter vector of each controller, $\boldsymbol{\rho}^*_{(\psi)}$ is the optimal parameter vector of each controller

$$\boldsymbol{\rho}_{(\psi)} = [\; k_{p(\psi)} \quad k_{d(\psi)} \;]^T, \;\; \boldsymbol{\rho}^*_{(\psi)} = [\; k^*_{p(\psi)} \quad k^*_{d(\psi)} \;]^T, \tag{10}$$

where the superscript T indicates matrix transposition, and $D_{\boldsymbol{\rho}_{(\psi)}} \subset \Re^2$ in (9) is the feasible domain of $\boldsymbol{\rho}_{(\psi)}$. The subscript $\psi \in \{c, a, p\}$ in (9) and (10) specifies, in accordance with [52], both the controlled output and its corresponding controller, namely c – the cart position (i.e. $y_{(c)} = y_1$), a – the arm angular position (i.e. $y_{(a)} = y_2$) and p – the payload position (i.e. $y_{(p)} = y_3$), and $e_{(\psi)} = r_{(\psi)} - y_{(\psi)}$ is the control error involved in the three control loops. The sampling period is $T_s = 0.01$ s and the time horizon is set to 70 s, resulting a number of $N_s = 70/0.01 = 7000$ data samples.

SMA is involved in solving the optimization problems defined in (9). SMA operates with a total number of N agents, and each agent, which is an element of the slime mould, is assigned to a position vector $\boldsymbol{X}_i(j)$ [54], [55]

$$\boldsymbol{X}_i(j) = [x_i^1(j) \;...\; x_i^f(j) \;...\; x_i^q(j)]^T \in D_{\boldsymbol{\rho}_{(\psi)}} \subset \Re^q, \; i = 1...N, \tag{11}$$

where $x_i^f(j)$ is the position of i^{th} agent in f^{th} dimension, $f = 1...q$, $q = 2$ in order to map the SMA onto the optimization problem in (9), j is the index of the current iteration, which is also the current iteration in the ILC structure in Figure 2 and maps the SMA onto this ILC structure, $j = 1...j_{\max}$, and $j_{\max}$ is the maximum number of iterations. The expression of the search domain $D_{\boldsymbol{\rho}_{(\psi)}} \subset \Re^q = \Re^2$ in (9) and (11) is [54], [55]

$$D_{\boldsymbol{\rho}_{(\psi)}} = [l^1, u^1] \times ... \times [l^f, u^f] \times ... \times [l^q, u^q] \subset \Re^q, \tag{12}$$

l^f are the lower bounds, u^f are the upper bounds, $f = 1...q$, $q = 2$, and [54], [55]

$$x_i^f(j) \in [l^f, u^f], \; i = 1...N, \; f = 1...q. \tag{13}$$

As pointed out in an easily understandable way in [54] and [55], SMA consists of seven steps. They start with the initialization of the random population such that to fulfill (11), (12) and (13), continue with the evaluation of the performance of each member of the population (which can be carried out making use of experiments or simulation), the calculation of the best fitness obtained in all iteration, the calculation of the vector of weights, the update of each agent's position, and ends with incrementing the iteration index until the maximum number of iterations is reached. Additional details on the relationships involved in this regard are given in [53], [54] and [55].

SMA is mapped onto the optimization problem defined in (9) in terms of the following relations:

$$\begin{aligned}&q=2,\\&\boldsymbol{X}_i(j)=\boldsymbol{\rho}_{(\psi)},\ i=1...N,\\&S_i(j)=J_{(\psi)}(\boldsymbol{\rho}_{(\psi)}),\ i=1...N,\\&\boldsymbol{X}_b(j_{\max})=\boldsymbol{\rho}^*_{(\psi)},\end{aligned} \tag{14}$$

where $S_i(j)$ is the fitness (i.e. the value of the objective function) of i^{th} agent with the position vector $\boldsymbol{X}_i(j)$, and $\boldsymbol{X}_b(j)$ is the best agent, leading to the best solution obtained so far (i.e. until the current iteration j).

The design approach that ensures the tuning of a SISO fuzzy controller with PD learning function is carried out in terms of the following steps:

Step 1. The performance specifications imposed to the fuzzy control system are expressed in an aggregate form in terms of the optimization problem defined in (9), which ensures the desired/imposed dynamics of the fuzzy control system. The sampling period T_s is set.

Step 2. The maximum number of iterations or cycles or trials $j_{\max}$ is set.

Step 3. The parameters α, K_1, K_2, B_{e1}, $B_{\Delta e}$ and $\chi_i > 0$, $i = 1...3$, of the discrete-time iPI controller with Takagi-Sugeno-Kang PD fuzzy term are tuned using the approach specific to MFC combined with fuzzy logic specified in [52]. Experiments with the real-world fuzzy control system (which conducts the process) are conducted in order to evaluate the values of the objective function.

Step 4. The SMA is applied to obtain the parameters $k^*_{p(\psi)}$ and $k^*_{d(\psi)}$ of the PD learning function or the PD learning rule.

This design approach is applied three times, separately, for the cart position controller, the arm angular position controller and the payload position controller.

4 Experimental Results

The design approach and the low-cost ILC-based fuzzy control systems are validated in this section by real-time experiments conducted on the tower crane system laboratory equipment installed in the Intelligent Control Systems Laboratory of the Politehnica University of Timisoara, Romania. A photo of the experimental setup is given in Figure 1 (b).

As specified in the previous sections, three SISO control loops are involved in the MIMO control system. The main details on the four design steps will be outlined in the next paragraphs.

The dynamic regimes imposed to the experimental setup for all three SISO control loops are: zero initial conditions in relation with the model (1), no additional disturbances are applied and only random ones can appear, the sampling period set to T_s=0.01 s in step 1, and the reference trajectories will be displayed as follows along with the system responses. This description of the dynamic regimes is also actually related to step 4, where the evaluation of the objective functions is done.

The parameters of the PD learning functions are obtained separately for the three SISO control loops. Each of them is calculated using SMA after $j_{\max} = 10$ iterations, set in step 2.

The parameters of the three discrete-time iPI controllers with Takagi-Sugeno-Kang PD fuzzy terms are set in step 3 using the information given in [52] leading to the parameters of the fuzzy controller for crane position control, where the subscripts are dropped out to simplify the notations

$$\begin{aligned}&\alpha=0.0015,\ \ K_1=-0.85,\ \ K_2=0.53,\ \ B_{e1}=0.7,\\&B_{\Delta e}=0.2635,\ \ \chi_1=0.4,\ \ \chi_2=1.2,\ \ \chi_3=1.7,\end{aligned} \tag{15}$$

and the parameters of the fuzzy controller for payload position control

$$\begin{aligned}&\alpha=0.0015,\ \ K_1=-0.72,\ \ K_2=0.4,\ \ B_{e1}=0.7,\\&B_{\Delta e}=0.3111,\ \ \chi_1=1,\ \ \chi_2=0.6,\ \ \chi_3=1.4.\end{aligned} \tag{16}$$

The parameters of SMA were set in step 4 of the design approach using the recommendations given in [53], i.e. $z = 0.03$ and $\epsilon = 0.001$. The number of agents was set, as in [54] and [55], to $N = 20$. The search domains were set to

$$\begin{aligned} D_{\boldsymbol{\rho}_{(c)}} &= \{k_{p(c)}|0.5 \le k_{p(c)} \le 2\} \times \{k_{d(c)}|2 \le k_{d(c)} \le 4\}, \\ D_{\boldsymbol{\rho}_{(a)}} &= \{k_{p(a)}|0.5 \le k_{p(a)} \le 2\} \times \{k_{d(a)}|0.5 \le k_{d(a)} \le 2\}, \\ D_{\boldsymbol{\rho}_{(p)}} &= \{k_{p(p)}|0.1 \le k_{p(p)} \le 2\} \times \{k_{d(c)}|0.5 \le k_{d(p)} \le 2\}. \end{aligned} \tag{17}$$

The initial values of the parameters of the three PD learning rules are (listed in averaged values after ten separate runs of SMA)

$$\begin{aligned} &k_{p(c)}(0) = 1, \quad k_{d(c)}(0) = 3, \quad k_{p(a)}(0) = 1, \quad k_{d(a)}(0) = 0.6, \\ &k_{p(p)}(0) = 0.1, \quad k_{d(p)}(0) = 1.2. \end{aligned} \tag{18}$$

The parameters of the three PD learning rules obtained after the application of the design approach are (also given in averaged values after ten separate runs of SMA)

$$\begin{aligned} &k^*_{p(c)} = k_{p(c)}(10) = 1, \quad k^*_{d(c)} = k_{d(c)}(10) = 2.45, \quad k^*_{p(a)} = k_{p(a)}(10) = 1.1, \\ &k^*_{d(a)} = k_{d(a)}(10) = 0.9, \quad k^*_{p(p)} = k_{p(p)}(10) = 1, \quad k^*_{d(p)} = k_{d(p)}(10) = 1.5. \end{aligned} \tag{19}$$

The evolutions of the reference inputs, controlled outputs and control signals versus time with the initial and the final ILC algorithms are presented in Figure 4 for cart position control, Figure 5 for arm angular position control and Figure 6 for payload position control. The subscripts 1, 2 and 3 are inserted to represent the cart position control, arm angular position control and payload position control, respectively. The initial responses are represented with blue color and the final ones with red color. For a better view, two enlarged intervals of the plots are included.

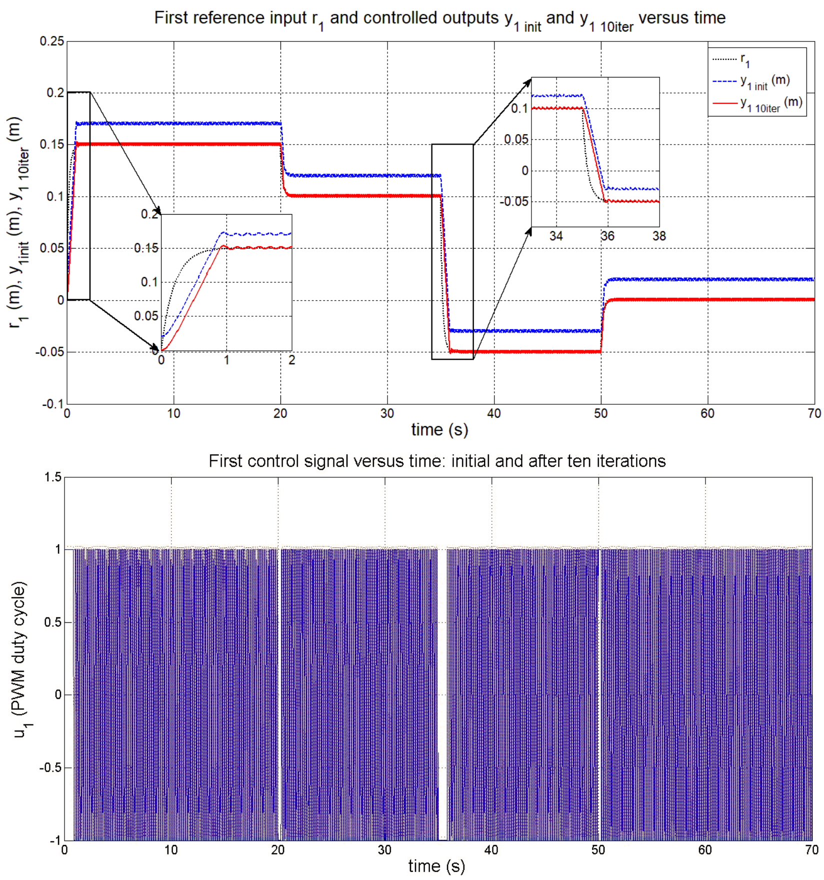

Figure 4: Reference input, controlled output and control signal, initial and after ten iterations of ILC algorithm, for cart position control.

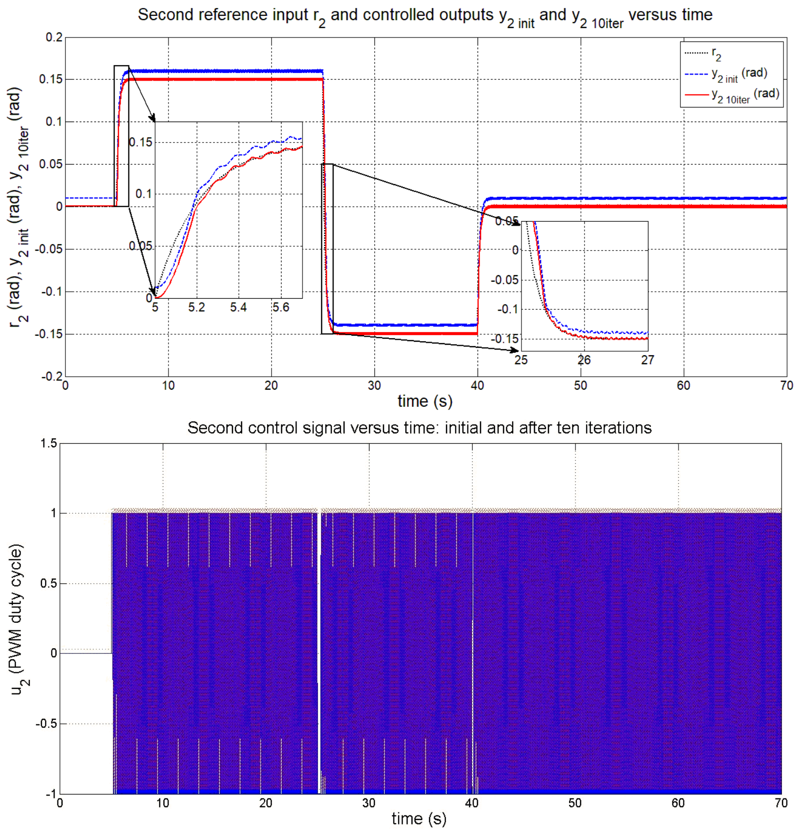

Figure 5: Reference input, controlled output and control signal, initial and after ten iterations of ILC algorithm, for cart position control.

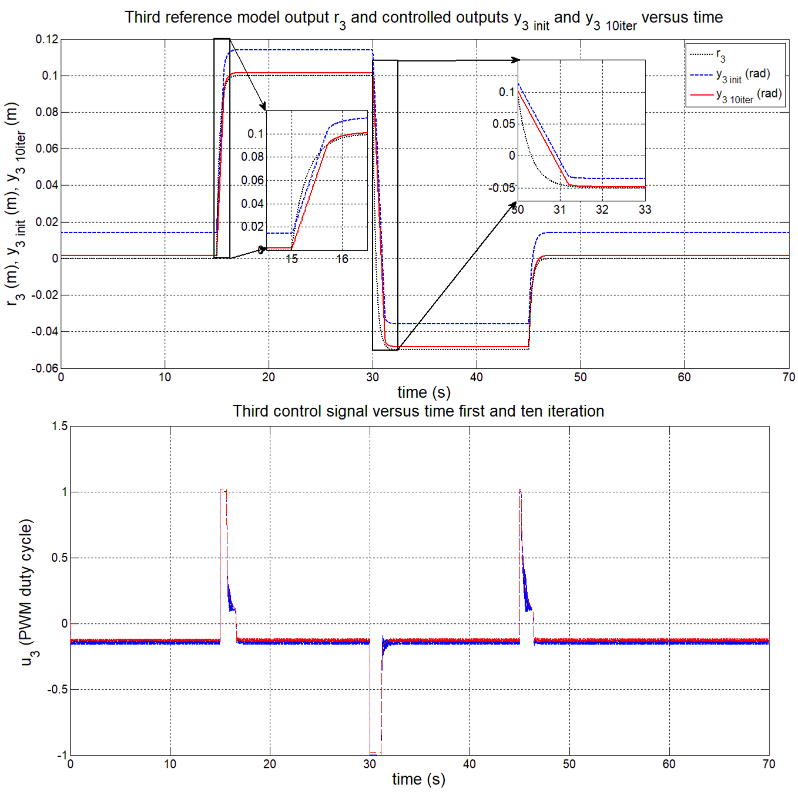

Figure 6: Reference input, controlled output and control signal, initial and after ten iterations of ILC algorithm, for cart position control.

The effects of interactions in the MIMO process control are reflected in the results presented in Figures 5 to 7. The reference input modifications are carried out at different time moments for the three control loops. Equations (1) and (2) also indicate that the first two SISO control loops are decoupled, and only effects on the third control loop are of interest.

The results presented in Figures 5 to 7 clearly show the benefits and performance improvement of ILC and the PD learning function specific to this ILC structure. The large oscillations of the first two control signals are caused by the specific structure of the controlled processes of these two SISO control systems; these sub-systems are series connection of integrators and first order systems with small time constants, which are difficult to stabilize and/or control.

This performance improvement would be certainly different for control systems dedicated to other challenging processes. Such processes include medical applications [78], [79], [80], transportation systems [81], [82], [83], robotics [84], [85], [86], [87], and fault detection [5], [88]. However, the only constraint imposed to these control systems is that they should carry out repetitive tasks. This constraint is normal because learning and optimization are involved in the ILC structures considered in this paper.

Other challenging control solutions worth to be applied are those based on evolving fuzzy systems [89], [90], [91], and Tensor Product–based (TP–based) model transformation to position control of tower crane system. The main purpose of TP–based model transformation is to map a given Linear Parameter Varying (LPV) or quasi–Linear Parameter Varying (qLPV) state–space model onto a TP model made of Linear Time Invariant (LTI) systems using the Higher Order Singular Value Decomposition. The TP–based model transformation technique was successfully applied recently to tower crane system modeling [92], pendulum cart system modeling [93], [94], black box system modeling [95], induction machine modeling [96], and white noise process modeling [97]. This transformation technique was also used in the TP–based controller design; TP controllers were designed for a big number of processes including more recent ones such as Lotka–Volterra fractional order model [98] and aeroelastic systems [99], but they could be applied to other systems as, for instance, networked control systems [100].

5 Conclusion

This paper suggested an approach to the performance improvement of low-cost fuzzy controllers for crane systems in the framework of ILC by the optimal tuning of the PD learning rule using the metaheuristic SMA. Three SISO control structures, each with one first order discrete-time iPI controller with Takagi-Sugeno-Kang PD fuzzy term, were considered separately to control this representative MIMO nonlinear process.

The formulation of the optimization problem in the iteration domain and the experimental evaluation of the values of the objective functions expressed as sums of squared control errors justify to assign the data-driven model-free control feature to this approach. This is important as there is no need for much information on the controlled process and the initial controller design and tuning. The initial controller design and tuning can be done for simple linear controllers, which are next mapped onto the fuzzy controllers in terms of the modal equivalence principle.

As specified in Section 1, MFC is considered, according to [39] and next also highlighted in [30], as a new and efficient tool for machine learning. In the context of the optimal tuning of the PD learning functions or learning rules carried out in this paper, one conclusion of this paper is that ILC is also a new and efficient tool for machine learning. This can be emphasized because of the controller part that in this paper is a fuzzy controller or the process part as well, where evolving fuzzy models can be employed [80], [89], [90], [91], and the controllers designed and tuned accordingly. Neural networks [46], [50], [61], [69], [79], [83] can be employed at the process and/or controller level as well, giving more weight to the learning feature, but in a close connection to optimization. In addition, fuzzy logic can be included in ILC algorithms as suggested in authors' past papers [9], [40], [41], [42], [43], [44] and [45].

Future research will be focused on the inclusion of fuzzy models and neural networks in the process and controller subsystems of the control system structures along with considering different learning functions or rules. Other optimization algorithms will be applied aiming a reduced number of evaluations of the objective functions.

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Author contributions

The authors contributed equally to this work.

Conflict of interest

The authors declare no conflict of interest.

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