**FINAL SCIENTIFIC REPORT**

The research team who carried out research activities in the project "Data-driven fuzzy control with experimental validation", project number 192 / 19.02.2021, registration code PN-III-P4-ID-PCE-2020-0269, is the one nominated in the funding application form: Prof.Dr.Eng. Radu-Emil Precup (project leader), Assoc.Prof.Dr.Eng. Claudia-Adina Bojan-Dragoş, Assoc.Prof.Dr.Eng. Adriana Albu, Lect.Dr.Eng. Alexandra-Iulia Szedlak-Stînean, Lect.Dr. Ciprian Hedrea, Lect.Dr. Raul-Cristian Roman, M.Sc.Eng. Ion-Cornel Mituleţu, Phd student, Assist.Lect.Dr. Elena-Lorena Hedrea.

This report is posted at https://www.aut.upt.ro/~rprecup/RS_PCE_2023.pdf.

The link to the webpage of the project, which summarizes the results obtained during the three years of the project, is https://www.aut.upt.ro/~rprecup/grant2021.html.

## A. FORESEEN AND ACHIEVED OBJECTIVES

**The main objectives** of the project were fulfilled according to the funding application form. The objectives (1) (scheduled in 2021), (2) (scheduled in 2022) and (3) (scheduled in 2023) are described as follows along with the planned activities.

**(1)** The analysis of the theoretical research concerning the improvement of the existing control solutions and the design of new controllers aiming the performance improvement of control systems designed for nonlinear processes including processes with shape memory alloy (SMA) actuators. The activities carried out to achieve this objective are focused on:

- **1.1.** The analysis of the actual stage of theoretical research and experimental applications conducted on several laboratory equipments, which also include processes with shape memory alloy (SMA) actuators. The above mentioned analysis was carried out and the synthetic information related to this analysis along with the corresponding references is presented in the scientific report of the year 2021, which can be found on the webpage of the project. The analyzed processes and equipment are: servo systems [D1], population and epidemic [D2], SMA [D3], monetary policy [D4], electromagnetic actuated clutch systems [D5], tower crane systems [D6], mobile robots [D7] (details given in the published papers).
- **1.2.** The research of possibilities meant to improve the existing control solutions for nonlinear processes including processes with shape memory alloy (SMA) actuators and the design of new data–driven and fuzzy control solutions. New controllers such as fuzzy controllers [D5], [D6], [D7] and Iterative Feedback Tuning–based controllers [D6] were proposed and analyzed (details given in the published papers).

**(2)** The analysis, the design, the implementation and the validation of new Data-Driven Control (DDC) and Fuzzy Control (FC) algorithms through experiments made on several laboratory equipment also including Shape Memory Alloy (SMA) actuators and through cooperation with our external partners. The performed activities are:

- **2.1.** The analysis of the actual stage of the research concerning the possibility of designing new DDC and FC algorithms used for improving the performance of the control system structures. The analysis was conducted and the brief results along with the corresponding references are presented in the scientific report of the year 2022.
- **2.2.** Ensuring the desired control performance for the control system structures with controllers designed using DDC and FC algorithms and also ensuring the stability of these structures using stability criteria. The results of a stability analysis are presented in the scientific report of the year 2022, which can be found on the webpage of the project. New controllers were analyzed and designed such as: fuzzy controllers [D8], [D11], [D12], [D15]–[D17], [D25]–[D27], Iterative Feedback Tuning-based controllers [D14], [D28], Virtual Reference Feedback Tuning-based controllers [D28], Active Disturbance Rejection Control, Model-Free Adaptive Control and Model Free Control-based controllers [D18], tensor product model transformation-based controllers [D22], [D27], artificial neural networks combined with reinforcement learning and metaheuristic optimization algorithms [D10] (details given in the published papers).

**2.3.** The design, testing and validation of new control system structures with controllers designed using DDC and FC algorithms through real time experiments conducted on several laboratory equipment including SMA processes. The processes and the equipment on which the design, testing and validation of the new control system structures were conducted are: servo systems [D8], [D10], [D11], tower crane systems [D12], [D14]–[D16], [D19], big data systems [C6], SMA systems [D17], [D18], [D28], and magnetic levitation systems [D25], [D29]. Many preparations were made concerning the development of new control system structures through the analysis of processes and derivation of models for systems such as: strip winding systems [D9], [D20], mobile robots [D21], [D24], brain-computer interfaces [D23], prosthetic hands [D26], electromagnetic actuated clutch systems [D25], continuously variable transmission vehicles [D25] (details given in the published papers).

**2.4.** The validation of the new control system structures designed using DDC and FC algorithms with the support of the external partners (Continental Automotive Timisoara, Airbus Helicopters – through direct timely consolidated links, Ontario Centre of Excellence – through Prof. Emil M. Petriu, our Canadian partner, Centre of Autonomous and Cyber-Physical Systems of Cranfield University, UK – a fresh cooperation with Dr. Argyrios Zolotas, and ECU Security Research Institute, Australia – through the Project Leader and his colleagues from Edith Cowan University). Due to the pandemics, the experiments at the external partners could not be conducted. However, many experiments were conducted in the laboratories of the research team and the published papers contain the simulation and real-time experimental results obtained with the support of the external partners. These results concern the algorithms and models from the papers whose co-author is Prof. Emil M. Petriu, our partner from Canada: [D8]–[D11], [D14]–[D17], [D19]–[D21], [D28], and the book [D6] published in 2021 in CRC Press, Taylor & Francis with our external partner Dr. Ali Safaei from Canada. Three of the controllers are in the validation stage, to be finalized in 2023, at Continental Automotive Timişoara (the partnership was created in 2008-2011 through the project PCCA "Real-time informatics technologies for embedded-system-control of power-train in automotive design and applications (SICONA)", project leader, Prof.Dr.Eng. Corneliu Lazăr, "Gheorghe Asachi" Technical University of Iaşi; the partnership was materialized, among others, with a testing stand) and at the company from Canada where Dr. Ali Safaei works. Due to privacy and non-competition reasons, the results cannot be published. However, in the research report there will be presented minimal information on the processes on which the controllers designed by the research team were tested and the results obtained at the external partners. For protecting the algorithms proposed in this project, the design methodologies and the corresponding source programs of three Data-Driven Control, Fuzzy Control and Data-Driven Fuzzy Control algorithms will be registered in the National Register of Works handled by the Romanian Office for Copyright (ORDA) in 2023. In 2022 the contract of the project leader as Adjunct Professor at Edith Cowan University (Australia, 2016-2022) has ended; therefore, the connections with Australia weakened.

**(3)** The validation and testing of new control structures with controllers designed using Data-Driven Fuzzy Control (DDFC) algorithms through experiments on various laboratory equipment and through cooperation with our partners in the private sector. The performed activities are:

**3.1.** Ensuring the required control system performance with controllers designed using DDFC algorithms and their stability using various stability criteria. The results of a stability analysis are presented in the scientific report of the year 2022. All DDFC algorithms guarantee the control system performance indices as the controllers are optimally tuned as solutions to optimization problems, where the minimization of the objective functions guarantees the performance specifications.

**3.2.** The validation of new control structures with controllers designed using DDFC algorithms, through experiments carried out on various laboratory equipment. The processes and the equipment on which the design, testing and validation of the new control system structures were conducted are: three-tank systems [D30], servo systems [D31], tower crane systems [D32], [D35], [D37], [D39], [D40], [D45], biomonitoring [D33], pandemic [D34], robots [D36], SMA actuators [D38], [D41], strip winding systems [D42], [D43], [D46], and pendulum-cart systems [D44] (details given in the published papers). Since several details on controllers and processes are presented in the scientific reports of 2021 and 2022, additional details on a new family of DDFC algorithms proposed by the research team of this project are offered as follows.

The Single Input-Single Output (SISO) fuzzy control system structure with direct Proportional-Derivative (PD) learning rule with current control error is given in Fig. 1, where the ILC algorithm with PD learning rule is placed at the higher hierarchical level, and the notations: $r$ – the reference input or the set-point, assumed to be repetitive, $u$ – the control signal, $d$ – the disturbance input also assumed to be repetitive, $e$ – the control error, $y$ – the controlled output, $F$ – the set-point filter, $C$ – the fuzzy controller at the lower hierarchical level, $P$ – the controlled process (namely, a SISO sub-system of the tower crane (TC) system), M – the memory block, $k_p$ and $k_d$ –the proportional gain and the derivative gain of the PD learning rule, $k$ – the index of the current sampling interval or the discrete time index, $q^{-1}$ – the backward shift operator in the iteration domain, and $j$ – the subscript that indicates the current iteration (or cycle or trial or experiment).

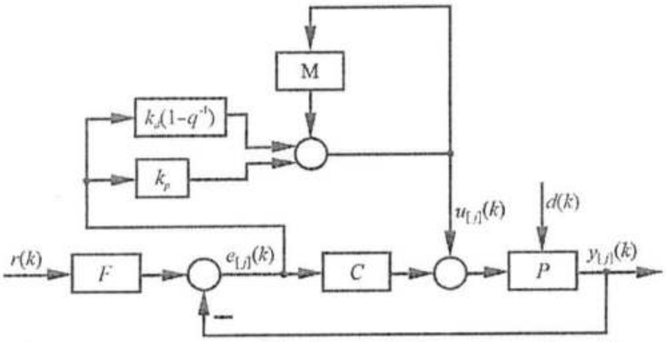


Fig. 1. Fuzzy control system structure with direct PD learning rule with current control error (adapted from [D15]).

The expression of the PD learning rule employed in Fig. 1 is expressed as follows after adapting the PD learning rules given in [12] and [D15]:

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

where the control error is

$$e_{[j]}(k) = r(k) - y_{[j]}(k), \tag{2}$$

and $r(k)$ is the set-point of the control system, i.e. the imposed value of the controlled output.

The SISO fuzzy control system structure with direct PD learning rule with previous control error is given in Fig. 2. The expression of the PD learning rule employed in Fig. 2 is obtained in terms of adapting the PD learning rules given in [1] and [D12]:

$$u_{[j]}(k) = u_{[j-1]}(k) + k_p e_{[j-1]}(k) + k_d [e_{[j]}(k) - e_{[j-1]}(k)]. \tag{3}$$

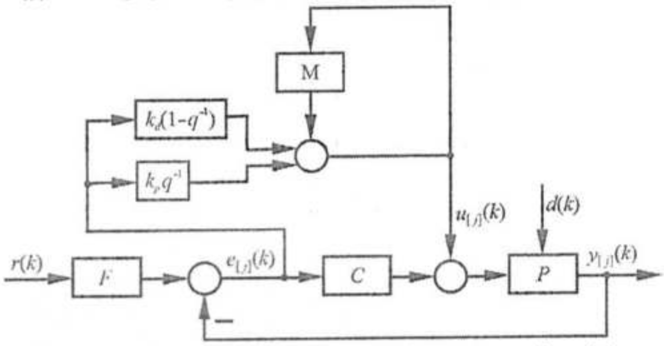


Fig. 2. Fuzzy control system structure with direct PD learning rule with previous control error (adapted from [D12]).

The SISO fuzzy control system structure with indirect PD learning rule is given in Fig. 3. The following expression of the PD learning rule employed in Fig. 3 is obtained in terms of adapting the PD learning rule given in [D37]:

$$r_{[j]}(k) = r_{[j-1]}(k) + k_p e_{[j]}(k) + k_d[e_{[j]}(k) - e_{[j-1]}(k)], \tag{4}$$

and it outlines a second notation for the set-point, namely $r_{[j]}(k)$ indicating the set-point produced by the ILC algorithm and applied to the control loop at the lower hierarchical level.

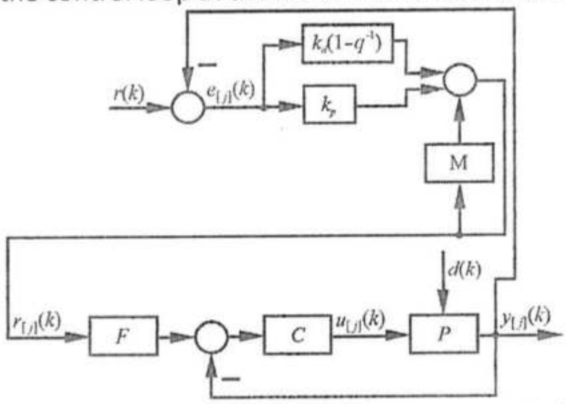


Fig. 3. Fuzzy control system structure with indirect PD learning rule (adapted from [D37]).

The block $C$ represents a low-cost Takagi-Sugeno Proportional-Integral (PI)-fuzzy controller, and its design and tuning start with the tuning of the linear PI controller. A simplified model of the controlled process ($P$) with the following transfer function with respect to the control signal is used:

$$P(s) = k_P /[s(1 + T_\Sigma s)], \tag{5}$$

with the parameters $k_P$ (the process gain) and $T_\Sigma$ (the small or parasitic time constant) partly known in the process model, and partly obtained, as in [D37], by least-squares identification making use of input-output data obtained after real-time experiments conducted on the real process.

PI controllers are recommended in [2] and [3] to control the processes with transfer functions of type (5). The transfer function of the (linear) PI controller is

$$C(s) = k_C[1 + 1/(T_i s)], \tag{6}$$

where $k_C$ is the controller gain and $T_i$ is the controller integral time constant.

As specified in [2] and [3], the ESO method is successful in tuning the PI controller parameters as it ensures a convenient tradeoff to a set of empirical control system performance indices. The tradeoff is reached in terms of a single design parameter, $\beta$, within the domain $1 < \beta \le 20$, in terms of Fig. 4, which illustrates the empirical performance indices $\sigma_1$ – overshoot, $\hat{t}_r = t_r / T_\Sigma$ – normalized rise time, $\hat{t}_s = t_s / T_\Sigma$ – normalized settling time, both times defined in the unit step modification of $r$, and $\varphi_m$ – phase margin.

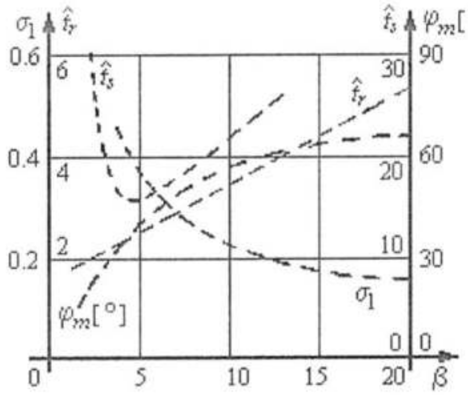


Fig. 4. Empirical performance indices versus design parameter $\beta$ [2], [3].

The PI tuning conditions specific to the ESO method are [2], [3]

$$k_C = 1/(\sqrt{\beta}\, k_P\, T_\Sigma), T_i = \beta T_\Sigma, \tag{7}$$

and the transfer function of one simple version of set-point filter $F$, which improves the performance by the cancellation of a zero in the closed-loop transfer function with respect to $r$, is [2], [3]

$$F(s) = 1/(1 + \beta T_\Sigma s). \tag{8}$$

The control system performance is next improved by replacing the linear PI controller with the Takagi-Sugeno PI-fuzzy controller illustrated in Fig. 5 (structure and input membership functions), with th notations $z^{-1}$ – the backward shift operator in the discrete time domain, TISO-FC – the strictly speaking (i.e. without dynamics) Two Inputs-Single Output fuzzy controller sub-system, $e(k)$ – the control error, $u(k)$ – the control signal, $\Delta e(k)$ – the increment of the control error, and $\Delta u(k)$ – the increment of the control signal. The subscript [$j$] is dropped out in Fig. 5 for the sake of simplicity.

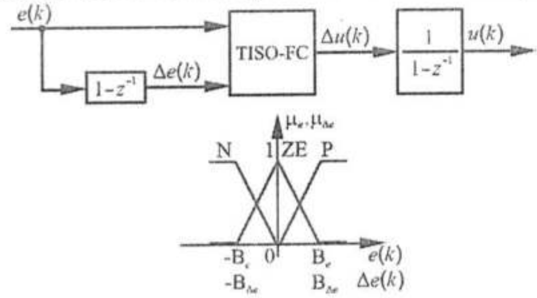


Fig. 5. Low-cost Takagi-Sugeno PI-fuzzy controller structure and input membership functions (adapted from [D37]).

The recurrent expression of the incremental discrete-time PI controller is obtained using Tustin's discretization method

$$\Delta u(k) = K_P[\Delta e(k) + \mu\, e(k)], \tag{9}$$

with the parameters [4], [5]

$$K_P = k_C(1 - 0.5T_s / T_i),\ \mu = 2T_s / (2T_i - T_s), \tag{10}$$

where $T_s > 0$ is the sampling period, which is set to meet the requirements of quasi-continuous digital control.

The TISO-FC block uses the weighted average defuzzification method, and the inference engine employs the SUM and PRODS operators. The rule base of the TISO-FC block consists of only two rules, R1 and R2, defined as follows in order to enable the low-cost design and implementation of the PI-fuzzy controller [D27], [5]:

$$\begin{aligned}
&\mathrm{R1: IF}\ \{e(k)\ \mathrm{IS\ P\ AND}\ \Delta e(k)\ \mathrm{IS\ N}\}\ \mathrm{OR}\ \{e(k)\ \mathrm{IS\ P\ AND}\\
&\Delta e(k)\ \mathrm{IS\ ZE}\}\ \mathrm{OR}\ \{e(k)\ \mathrm{IS\ ZE\ AND}\ \Delta e(k)\ \mathrm{IS\ N}\}\ \mathrm{OR}\\
&\{e(k)\ \mathrm{IS\ ZE\ AND}\ \Delta e(k)\ \mathrm{IS\ ZZEOR}\ \{e(k)\ \mathrm{IS\ N\ AND}\\
&\Delta e(k)\ \mathrm{IS\ ZZ\ OR}\ \{e(k)\ \mathrm{IS\ N\ AND}\ \Delta e(k)\ \mathrm{IS\ P}\}\\
&\quad \mathrm{THEN}\ \Delta u(k) = K_{P[\psi]}[\Delta e(k) + \mu_{[\psi]}\, e(k)],\\
&\mathrm{R2: IF}\ \{e(k)\ \mathrm{IS\ N\ AND}\ \Delta e(k)\ \mathrm{IS\ N}\}\ \mathrm{OR}\\
&\{e(k)\ \mathrm{IS\ P\ AND}\ \Delta e(k)\ \mathrm{IS\ P}\}\\
&\quad \mathrm{THEN}\ \Delta u(k) = \eta K_P[\Delta e(k) + \mu\, e(k)],
\end{aligned} \tag{11}$$

where the parameter $\eta$, $0.25 \le \eta \le 0.75$, is inserted to further diminish the overshoot.

The modal equivalence principle [6] is next applied leading to the following tuning condition [5]:

$$B_{\Delta e} = \mu\, B_e. \tag{12}$$

Summing up, the parameters of the low-cost PI-fuzzy controller are $\beta$, which is set to ensure the trade-off to the empirical performance indices of the linear control system, $\eta$, which is set in relation to the overshoot alleviation, and $B_e$, which is set in relation to Fig. 5 to ensure the firing of both rules, possibly accounting for stability constraints [7], [8], or subjected to optimal tuning [5], [32].

As pointed out in Section I, the gains $k_p$ and $k_d$ of the PD learning rules in the three ILC-based fuzzy control system structures are obtained as the solutions to the following optimization problem, which is processed using [D12] and [D37]:

$$\boldsymbol{\rho}^* = \arg \min_{\boldsymbol{\rho} \in D_\rho} J(\boldsymbol{\rho}),\ J(\boldsymbol{\rho}) = \frac{1}{N} \sum_{k=1}^{N_s} k e_{[j]}^2(k, \boldsymbol{\rho}), \tag{13}$$

where $D_\rho \subset \Re^2$ is the feasible domain of the parameter vector $\rho$, $\rho^*$ is the optimal parameter vector, i.e. the vector solution to the optimization problem, with the expressions

$$\boldsymbol{\rho} = [k_p \quad k_d]^T,\ \boldsymbol{\rho}^* = [k_p^* \quad k_d^*]^T, \tag{14}$$

$T$ indicates matrix transposition, $J(\rho)$ is the objective function, and $N_s$ is the number of data samples, which sets the width of the time horizon, $N_sT_s$.

The optimization problem expressed in (13) is solved in this paper using seven metaheuristic optimization algorithms. An important issue in this regard is to map the optimization onto the optimization problem. These algorithms operate with a total number of $N$ agents, and each agent is assigned to a position vector $\mathbf{X}_{i[j]}$

$$\mathbf{X}_{i[j]} = [x^1_{i[j]} \dots x^f_{i[j]} \dots x^q_{i[j]}]^T \in D_\rho \subset \Re^q, i = 1 \dots N, \tag{15}$$

where: $x^f_{i[j]}$ – the position of $i^{\text{th}}$ agent in $f^{\text{th}}$ dimension, $f$=1...$q$, $q$=2 in this particular case, $j$ – the index of the current iteration in both ILC (Fig. 1, Fig. 2 and Fig. 3) and the optimization algorithms, $j$=1...$j_{\max}$, and $j_{\max}$ – the maximum number of iterations. PSO is mapped onto (13) in terms of

$$\mathbf{X}_{i[j]} = \boldsymbol{\rho}, S_{i[j]} = J(\boldsymbol{\rho}), i = 1 \dots N, \mathbf{P}_{g,Best} = \boldsymbol{\rho}^*, \tag{16}$$

where $S_{i[j]}$ is the fitness function specific to PSO, and $\mathbf{P}_{g,Best}$ is the best swarm position vector. The metaheuristic algorithms GSA, CSS, GWO, WOA and SMA are mapped onto (13) in terms of

$$\mathbf{X}_{i[j]} = \boldsymbol{\rho}, S_{i[j]} = J(\boldsymbol{\rho}), i = 1 \dots N, \arg \min_{i=1 \dots N} J(\mathbf{X}_{i[j_{\max}]}) = \boldsymbol{\rho}^*, \tag{17}$$

where $S_{i[j]}$ is the fitness function specific to the metaheuristic algorithms GSA, CSS, GWO, WOA and SMA. The metaheuristic algorithm AVOA is mapped onto (13) in terms of

$$\mathbf{X}_{i[j]} = \boldsymbol{\rho}, S_{i[j]} = J(\boldsymbol{\rho}), i = 1 \dots N, \mathbf{X}^{BV1}_{[j_{\max}]} = \boldsymbol{\rho}^*, \tag{18}$$

where $S_{i[j]}$ is the fitness function specific to AVOA, and $\mathbf{X}^{BV1}_{[j_{\max}]}$ is the first best vector solution obtained at the iteration $j_{\max}$. In all algorithms, the search domain is the feasible domain $D_\rho \subset \Re^2$ in (13).

The unified design approach applied to the ILC-based fuzzy control systems with PD learning rules consists of the following steps resulted after organizing the steps [D12], [D15], [D37]:

*Step 1*. The sampling period $T_s$ is set. The performance specifications imposed to the fuzzy control system are expressed in terms of the optimization problems expressed in (13). The associated dynamic regimes are defined in order to assess the objective function values through experiments conducted on the real-world process.

*Step 2*. The value of $j_{\max}$ is set.

*Step 3*. The values of the parameters $\beta$, $\eta$ and $B_e$ of the Takagi-Sugeno PI-fuzzy controller are set. The tuning condition (12) is applied to obtain the value of $B_{\Delta e}$.

*Step 4*. The parameters specific to the metaheuristic optimization algorithms are set, and the algorithms are applied to compute the values of the gains $k_p^*$ and $k_d^*$.

The laboratory equipment involved in conducting the experiments and assessing the efficiency of the fuzzy controllers and design approach presented here is built around the TC system with technical information given in [10]. A photo of the laboratory equipment is illustrated in Fig. 6.

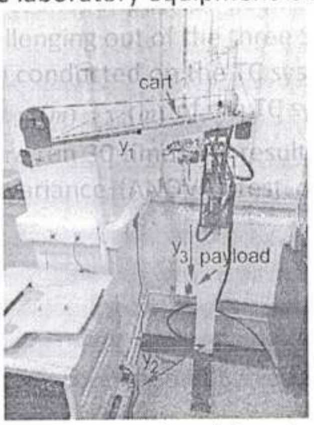


Fig. 6. Photo of tower crane system laboratory equipment [D6].

The TC system equipment is a Multi Input-Multi Output system focusing on controlling the cart position, the arm angular position and the payload position. A relatively simple control approach is to separately design three SISO control systems to control each position (output). In order to keep the paper to a reasonable length, only the results for payload position control are presented; moreover, the payload position control is the most challenging out of the three SISO ones.

The real-time experiments were conducted on the TC system experimental setup. The controlled output $y$ is actually the payload position $y_3(m) = x_9(m)$ of the TC system.

The optimization algorithms were run 30 times. All results are presented in averaged values. The results obtained after conducting the variance (ANOVA) test of the minimum objective function $J_{\min}$

evaluated after running these seven optimization algorithms on the three ILC-based fuzzy control system structures are presented in Fig. 7, with the general notation M-Q, where M indicates the optimization algorithm, M ∈ {PSO, GSA, CSS, GWO, WOA, SMA, AVOA} and Q indicates the ILC-based control system structure with different PD learning rules, Q ∈ {C, P, I}, C – direct PD learning rule with current control error (Fig. 1), P – direct PD learning rule with previous control error (Fig. 2), and I – indirect PD learning rule (Fig. 3).

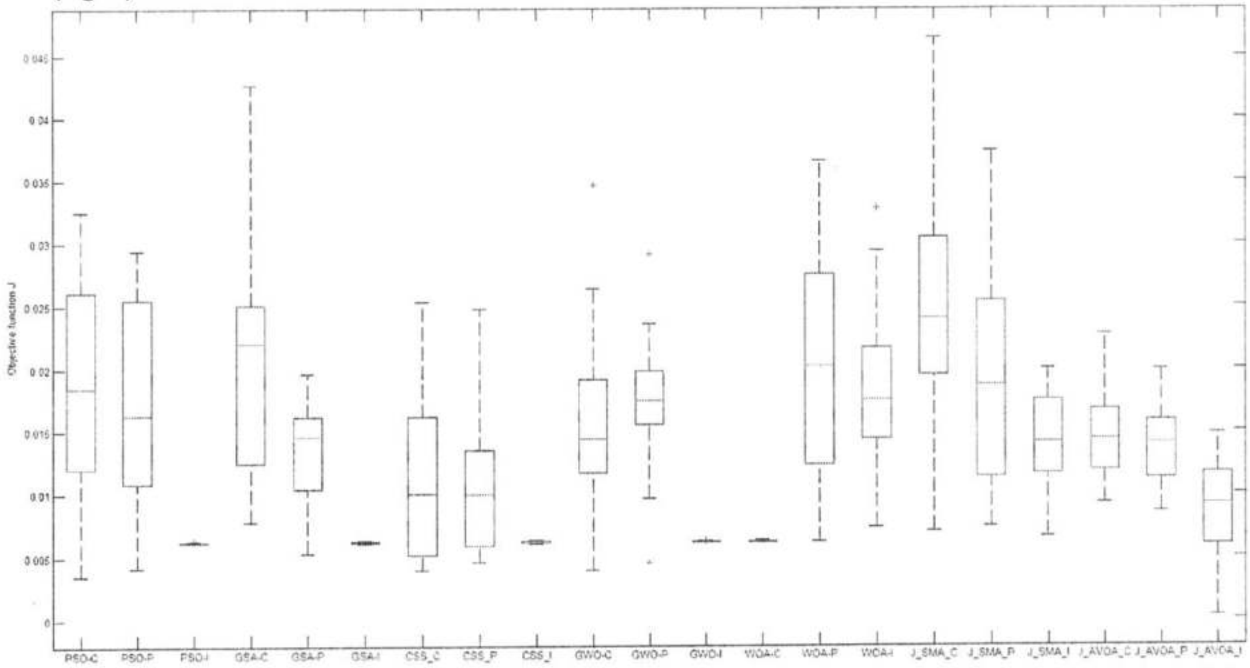

Fig. 7. ANOVA test of minimum objective function $J$ for all seven optimization algorithms and three ILC-based fuzzy control system structures.

Fig. 7 shows that the best $J_{min}$ is achieved by the GWO-I algorithm and ILC structure, followed by the WOA-C algorithm and ILC structure, the CSS-I algorithm and ILC structure, the PSO-I algorithm and ILC structure, and the GSA-I algorithm and ILC structure, with small differences. Therefore, the indirect PD learning rule proves to be the best one for this process and fuzzy controller.

A sample of real-time experimental results is given in Fig. 8 as typical fuzzy control system responses. Fig. 8 illustrates the reference input trajectories (with the black line, and the notation $r_3$), the initial controlled output (i.e., the payload position, with the notation $y_3$) and control signal versus time (with the red line for the initial controller, and the notation $u_3$) and the final controlled output and control signal (with the blue line for the final controller after ten iterations) for the CSS-I algorithm and ILC structure, namely the ILC-based fuzzy control system structure with indirect PD learning rule designed using the CSS algorithm. The initial responses (i.e., measured before the application of ILC) are highlighted with the blue line, and the last ones (i.e., measured after the application of ILC) are highlighted with a different color line (the red one).

The ranks, the statistics, and the probability p-values corresponding to the Friedman, Friedman aligned and Quade tests for the minimum cost function $J_{min}$ obtained after running the seven algorithms for the three ILC-based fuzzy control system structures were carried out by the research team. The Wilcoxon signed ranks tests were applied to the best five combinations of metaheuristic optimization algorithms and ILC-based fuzzy control system structures.

The evolution of the average value of the objective function is illustrated in Fig. 9 for the CSS-I algorithm and ILC structure, namely the ILC-based fuzzy control system structure with indirect PD learning rule designed using the CSS algorithm. The evolutions of the average value of the objective function and the average values of the parameters of the PD learning rules are presented on $1 + j_{max} = 1 + 10 = 11$ iterations.

The evolutions of the average values of the two parameters of the PD learning rules are shown in Fig. 10 for the CSS-I algorithm and ILC structure. The graphics in Fig. 9 and Fig. 10 are obtained as the average values of the objective function and the parameters after 30 separate runs of the optimization algorithm.

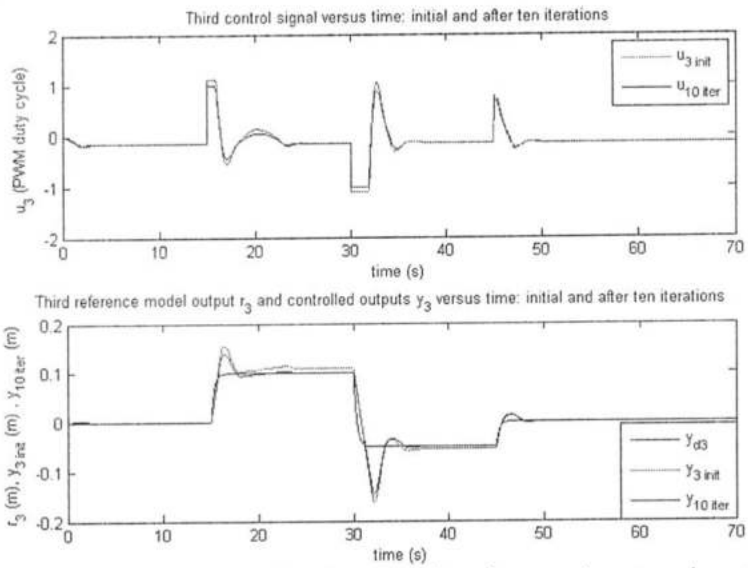


Fig. 8. Controlled output (i.e., payload position), reference input and control signal, initial and after ten iterations of ILC for fuzzy control signal with direct PD learning rule with current control error designed using WOA.

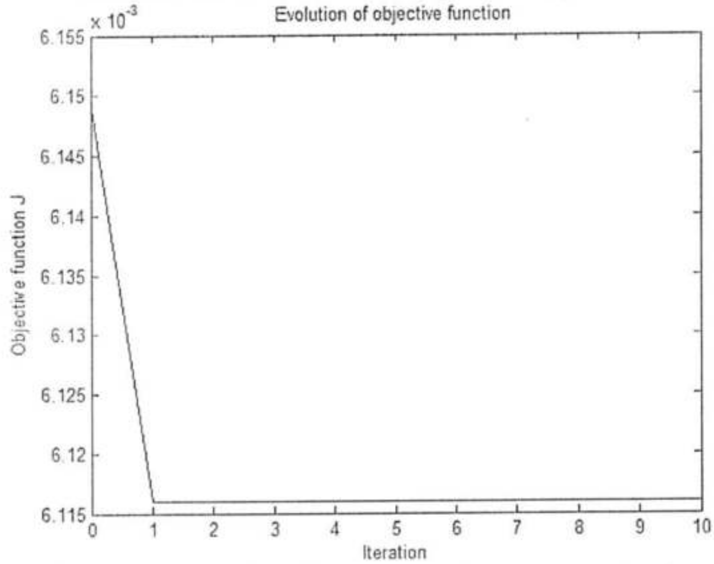


Fig. 9. Average objective function versus iteration number along 1 + 10 = 11 iterations of CSS algorithm applied to indirect PD learning rule.

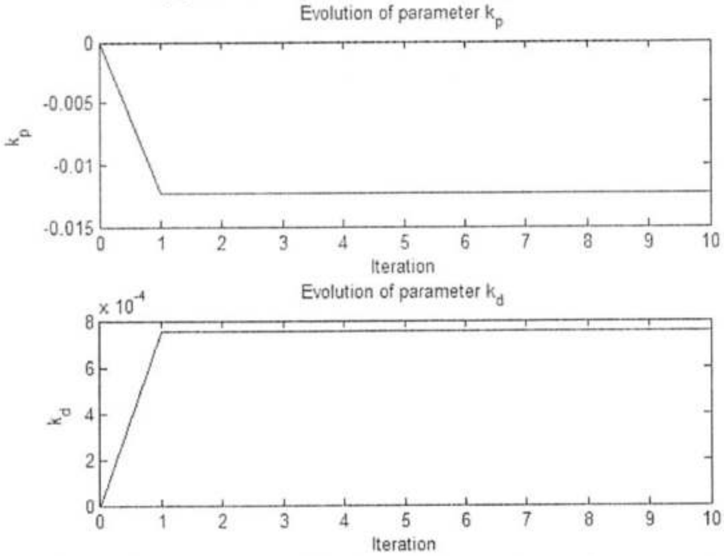


Fig. 10. Average values of parameters of indirect PD learning rule versus iteration number along 1 + 10 = 11 iterations of CSS algorithm.

**3.3.** The validation of new control structures with controllers designed using DDFC algorithms, through cooperation with private and external partners. Details on the validation at our private and external partners are presented in the followings.

Three of the controllers, which were in the validation stage starting with 2022, have been successfully validated in 2023, at the private partner 3.3.1 and the external partner 3.3.2. Due to privacy and non-competition reasons, the results obtained at both partners cannot be published. However, minimal information on the testing stands and the data-driven fuzzy control system behaviors will be given as follows.

Therefore, to privacy reasons, for protecting the algorithms proposed in this project, the design methodologies and the corresponding source programs of three Data-Driven Control, Fuzzy Control and Data-Driven Fuzzy Control algorithms, which were validated at our private and external partners, were registered successfully in 2023 in the National Register of Works handled by the Romanian Office of Copyright (Oficiul Român pentru Drepturile de Autor, ORDA). The three certificates are included in the positions [D47], [D48] and [D49], with appropriate links given on the webpage of the project, and they cover: the study of design and industrial implementation of a hybrid model-free fuzzy controller, the study of design and industrial implementation of a hybrid model-free adaptive fuzzy controller, and the study of design and industrial implementation of a fuzzy controller with proportional-derivative indirect iterative learning. The ORDA certificates [D47]–[D49] were and will be further used by our industrial partners mentioned in activity 2.4 and this activity to implement and validate the algorithms developed in the current project on their processes, but due to privacy and non-competition reasons, the results cannot be published and therefore they will not be published.

**3.3.1.** The private partner is Continental Automotive Timișoara. The partnership was created in 2008-2011 through the project PCCA "Real-time informatics technologies for embedded-system-control of power-train in automotive design and applications (SICONA)", project leader, Prof.Dr.Eng. Corneliu Lazăr, "Gheorghe Asachi" Technical University of Iaşi. As specified in the scientific report of the year 2022, the partnership was materialized in 2011, among others, with a testing stand.

The simplified structure of the valve-clutch system corresponding to a wet plate clutch actuated by a pressure reducing valve is presented in Fig. 11. The variables in Fig. 11 are: $P_S$ [Pa] is the line pressure, $P_T$ [Pa] is the tank pressure, $F_{mag}$ [N] is the magnetic force acting on the plunger, $x$ [m] is the plunger position, $P_R$ [Pa] is the controlled valve pressure, $x_p$ [m] is the clutch piston position, and $P_L$ [Pa] is the clutch piston pressure. The other variables and the parameters are described in [11]

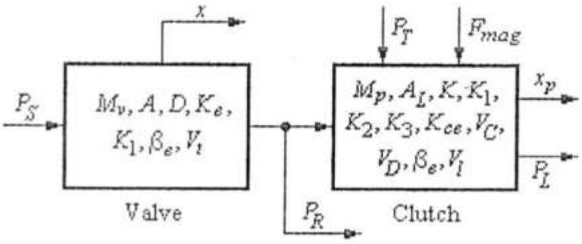


Fig. 11. Simplified valve-clutch system structure [11].

The following simplified linear state-space mathematical model of the valve-clutch system is derived from the first principle model resulted from the Pascal equations, the flow continuity equations, the force equilibrium, the pressure, and the flow dynamics equations:

$$\begin{aligned}\dot{\mathbf{x}}(t) &= \mathbf{A}\,\mathbf{x}(t) + \mathbf{B}\,\mathbf{u}(t),\\ \mathbf{y}(t) &= \mathbf{C}\,\mathbf{x}(t) + \mathbf{D}\,\mathbf{u}(t),\end{aligned} \tag{19}$$

where: $\mathbf{x}(t)$ is the state vector

$$\mathbf{x}(t) = [x_1(t) \quad x_2(t) \quad \ldots \quad x_8(t)]^T, \tag{20}$$

$x_1(t) = v(t)$[m/s] is the plunger speed, $x_2(t) = x(t)$, $x_3(t) = v_p(t)$[m/s] is the clutch position speed, $x_4(t) = x_p(t)$, $x_5(t) = P_C(t)$[Pa] and $x_6(t) = P_D(t)$[Pa] are the pressures of the left and right valve chamber, respectively, $x_7(t) = P_D(t)$, and $x_8(t) = P_L(t)$, $\mathbf{u}(t)$ is the input vector

$$\mathbf{u}(t) = [P_S(t) \quad P_T(t) \quad F_{mag}(t)]^T, \tag{21}$$

$F_{mag}(t)$ is employed usual as control signal, $\mathbf{y}(t)$ is the output vector

$$\mathbf{y}(t) = [x(t) \quad x_p(t) \quad P_R(t) \quad P_L(t)]^T, \tag{22}$$

the expressions of the matrices **A**, **C** and **D** are [12]

$$\begin{aligned}
&\mathbf{A} = [a_{ij}]_{i,j=\overline{1,8}}, a_{12} = -K_e / M_v, a_{15} = -A / M_v, a_{16} = D / M_v, a_{21} = 1, a_{34} = K / M_p, a_{38} = A_L / M_p, \\
&a_{43} = 1, a_{51} = C\beta_e / V_C, a_{55} = -K_1\beta_e / V_C, a_{57} = K_1\beta_e / V_C, a_{61} = -D\beta_e / V_D, a_{66} = -K_2\beta_e / V_D, \\
&a_{67} = K_2\beta_e / V_D, a_{72} = K_q\beta_e / V_t, a_{75} = K_1\beta_e / V_t, a_{76} = K_2\beta_e / V_t, a_{77} = -(K_{ce} + K_1 + K_2 + K_3)\beta_e / V_t, \\
&a_{78} = K_3\beta_e / V_t, a_{83} = A_L\beta_e / V_t, a_{87} = K_3\beta_e / V_t, a_{88} = -K_3\beta_e / V_t, \\
&a_{ij} = 0, (i,j) \neq (1,2), (i,j) \neq (1,5), (i,j) \neq (1,6), (i,j) \neq (2,1), (i,j) \neq (3,4), (i,j) \neq (3,8), \\
&(i,j) \neq (4,3),, (i,j) \neq (5,5), (i,j) \neq (5,7), (i,j) \neq (6,1), (i,j) \neq (6,6), (i,j) \neq (6,7), \\
&(i,j) \neq (7,2), (i,j) \neq (7,5), (i,j) \neq (7,6), (i,j) \neq (7,7), (i,j) \neq (7,8), (i,j) \neq (8,3), \\
&(i,j) \neq (8,7), (i,j) \neq (8,8), i = \overline{1,8}, j = \overline{1,8},
\end{aligned} \tag{23}$$

and the matrix **B** takes the expression $\mathbf{B}_c$ for the charging phase of the valve (for $x_2 = x > 0$) or the expression $\mathbf{B}_d$ for the discharging phase of the valve (for $x_2 = x \leq 0$):

$$\begin{aligned}
\mathbf{B}_c &= \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 & K_c\beta_e / V_t & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 1/M_v & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}^T, \\
\mathbf{B}_d &= \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & K_c\beta_e / V_t & 0 \\ 1/M_v & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}^T.
\end{aligned} \tag{24}$$

The real-world process data are acquired in the field at the industrial in terms of the testing stand with the schematic diagram presented in Fig. 12. A sampling period of 1 ms has been used in the acquisition.

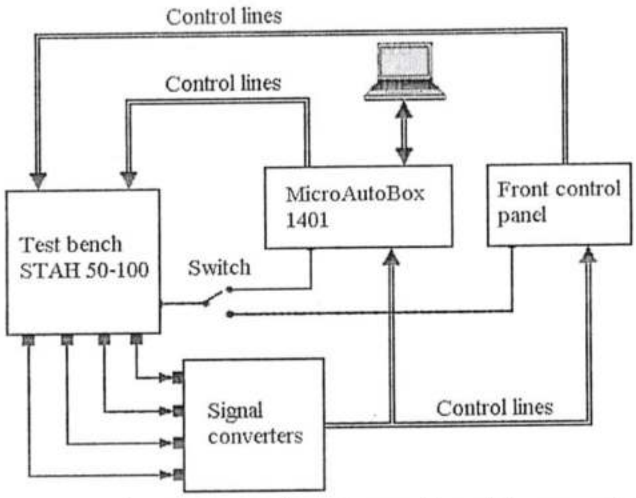


Fig. 12. Structure of testing stand used as real-world process benchmark.

The convenient design of the data-driven controllers is enabled by the usage of Tensor Product (TP)-based models, which are similar to fuzzy controllers. Such models were derived in [11], and they are similar to fuzzy models. The differences between these two types of models are the usage of weighting functions instead of membership functions, the weighting functions being fired for all values of the inputs (which are usually one or more process parameters), and the shapes of the weighting functions, which may be convex or not; nevertheless, the number of rules is much smaller in the TP case compared to the fuzzy one.

The responses of the TP model are presented in Fig. 13 in terms of the variations of all system outputs, $x$ (in Fig. 13 (a)), $x_p$ (in Fig. 13 (b)), $P_R$ (in Fig. 13 (c)) and $P_L$ (in Fig. 13 (d)) versus time.

As illustrated in Fig. 13, these models exhibit very good performance. The fuzzy controller design is next carried out in a similar way to the TP-based controller one, and both controllers are actually nonlinear state feedback controllers. The combination of Parallel Distributed Compensation (PDC) and Linear Matrix Inequalities (LMIs) leads to the state feedback controller model

$$F_{emag}(t) = r(t) - [\sum_{i=1}^{2} w_{1,i}(M_v(t))\mathbf{F}_i]\mathbf{x}(t). \tag{25}$$

The state feedback control system represents the inner control loop in a cascade control system structure. The inner loop is characterized by the equivalent sate feedback matrix **F** [11]

$$\mathbf{F} = \sum_{i=1}^{2} w_{1,i}(M_v(t))\mathbf{F}_i. \tag{26}$$

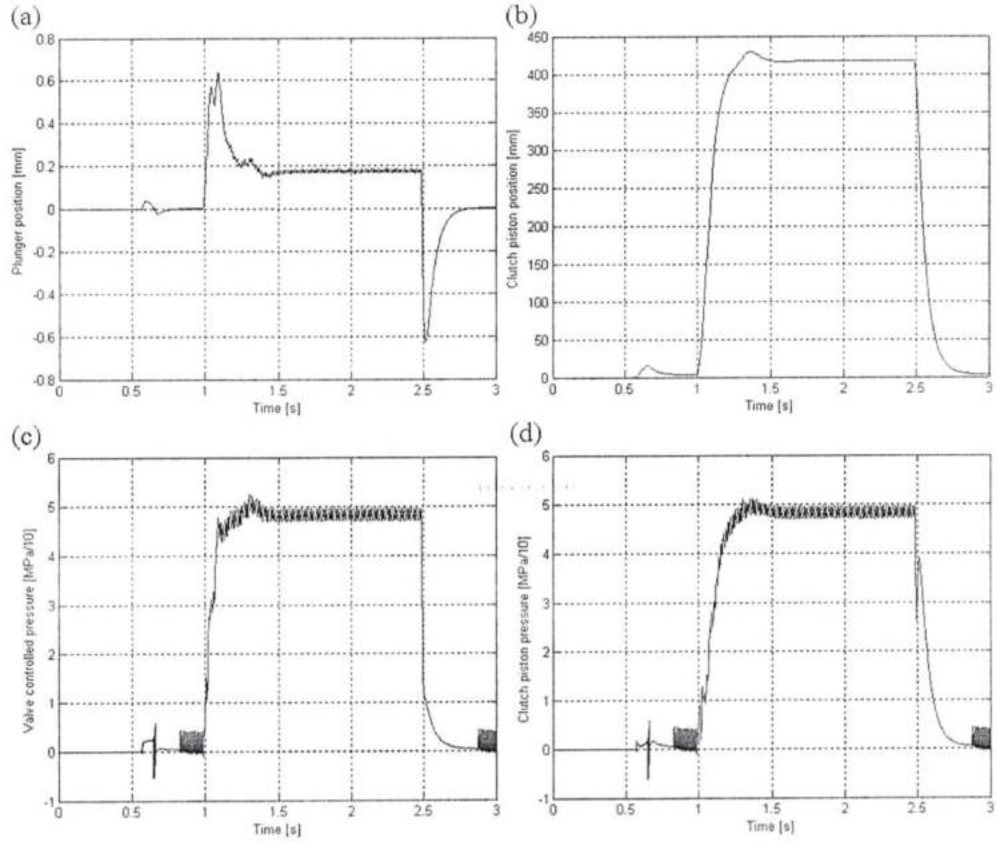


Fig. 13. Plunger position $x$ (a), clutch piton position $x_p$ (b), valve controlled pressure $P_R$ (c) and clutch piston pressure $P_L$ (d) versus time for the TP model of the valve-clutch system.

3.3.2. The external partner is the company ATS Automation (Cambridge, ON, Canada), where the partner and co-author Dr. Ali Safaei has worked since October 2022 till March 2023. The non-holonomic autonomous ground rover has been considered, which is a ground wheeled mobile robot moving on a plane environment with the non-holonomic constraint; i.e. a constraint on its velocity vector, where the rover can have only velocity in its forward direction and the component of velocity in a perpendicular direction to its centerline would be always zero. The dynamic system of such robot (Fig. 14), which is also known as a differential-drive robot, is viewed as a double integrator Multi-Input-Multi-Output (MIMO) system and defined as follows [13]:

$$\begin{aligned}
\dot{x} &= v\cos\psi, \\
\dot{y} &= v\sin\psi, \\
\dot{\psi} &= \omega, \\
\dot{v} &= \frac{1}{m}(f - k_f v + f_d), \\
\dot{\omega} &= \frac{1}{J}(\tau - k_\tau \omega + \tau_d),
\end{aligned} \tag{27}$$

where $x$ and $y$ are the 2D positions of the rover, $v$ is the forward velocity of the rover, $\psi$ is its heading (or yaw) angle, $\omega$ is the angular velocity of the rover, $f$ and $\tau$ are the input force and torque of the rover, respectively, while $f_d$ and $\tau_d$ are the corresponding external translational and rotational external disturbances. In addition, $m$ is mass of the rover, $J$ is its moment of inertia, and $k_f$ and $k_\tau$

are the constant coefficients for resistive drag force and torque acting on the rover, respectively. As it can be observed, the dynamic system in (27) has three outputs (i.e. $x$, $y$ and $\theta$) and two inputs (i.e. $f$ and $\tau$). Moreover, by assuming that the rover has two drive wheels, the expressions of the inputs become [D6]

$$\begin{aligned} f &= k_v(\omega_l + \omega_r)/r, \\ \tau &= d\,k_v(\omega_r - \omega_l)/r, \end{aligned} \tag{28}$$

where $\omega_l$ and $\omega_r$ are the angular speed of the left and right wheels of the rover respectively, $d$ is the constant distance between the two wheels, $r$ is the radius of each wheel and $k_v$ is a coefficient for motors attached to the wheels that relates each motor angular speed to the generated traction force at the wheel.

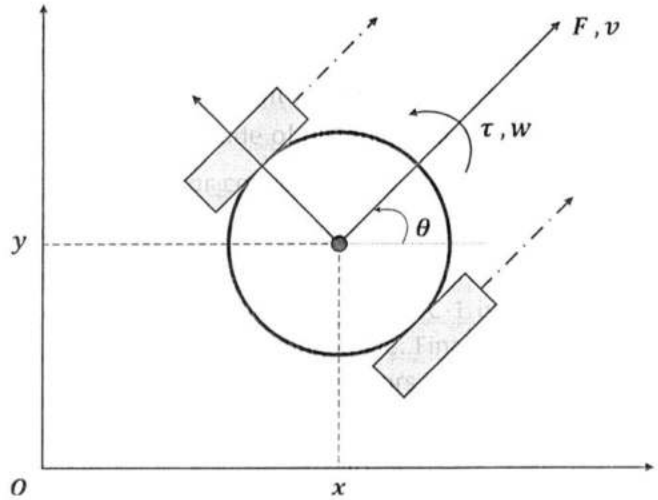


Fig. 14. Schematic of a non-holonomic autonomous ground mobile robot [13].

The presented ground rover robot was used in the industrial implementation and validation of a representative data-driven controller, namely a model-free adaptive controller, also referred to as adaptive model-free controller (AMFC). In this regard, a cascade control scheme is utilized as depicted in Fig. 15 . According to this figure, a switching controller is used for triggering either the distance controller or heading controller, based on the magnitude of distance tracking error $e_{dis}$ and heading tracking error $e_{hed}$. Then, two P controllers are used for converting the distance and heading tracking errors into the desired linear and angular velocities of the robot (i.e. $v_{des}$ and $\omega_{des}$), respectively. After that two AMFC modules are implemented to determine the desired force and torque at the robot, by considering the tracking errors for linear and angular velocities. Here, AMFC-1 is dedicated for the distance controller and AMFC-2 unit is used for controlling the heading angle. Finally, an allocation unit is used for defining the desired rotational speed of right and left electric motors on the robot.

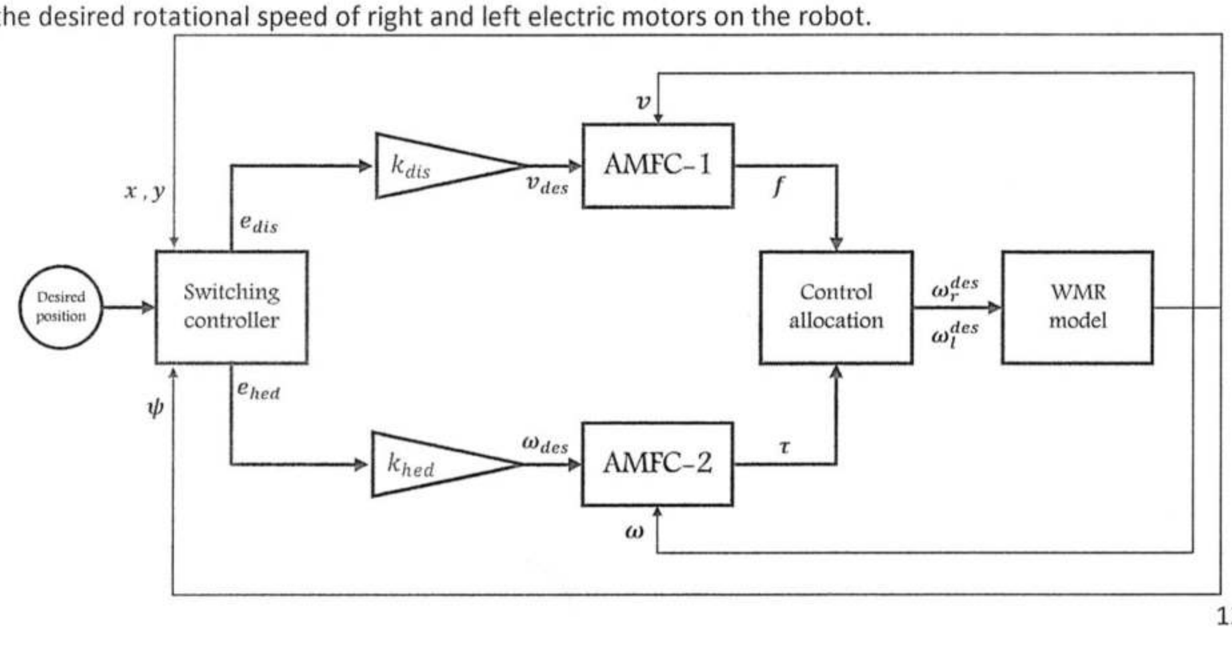

Fig. 15. Control scheme for position tracking of a non-holonomic wheeled mobile robot [D6].

A sample of experimental results obtained for is illustrated in Fig. 16. These system responses show the very good control system performance.

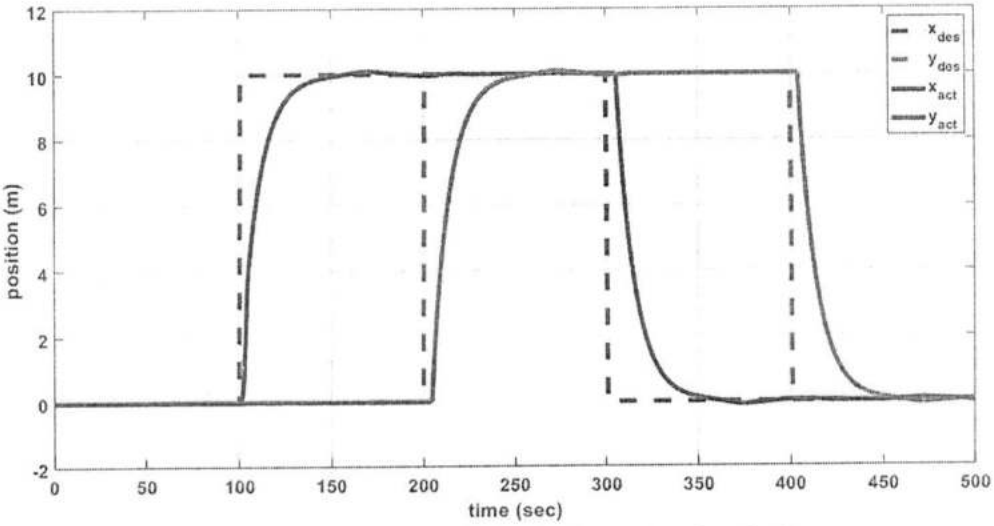


Fig. 16. Position versus time of wheeled mobile robot in 2D space.

**3.4.** Continuing and improving cooperation with external industrial partners.

This cooperation is fourfold. First, the authors continued the cooperation with Prof. Emil M. Petriu, our partner of the University of Ottawa, ON, Canada. The most recent joint papers (2023) are [D31], [D35], [D37], [D38], [D40]–[D43]. Prof. Petriu has very good links to Ontario Centre of Excellence, which will be used after alleviating the long-term economic effects of the COVID-19 pandemic.

Second, the cooperation with Dr. Ali Safaei from Canada, which started in 2021 in terms of publishing the joint book [D6] in 2021 in CRC Press, Taylor & Francis, continued in terms of the industrial validation of a part of the controllers. Dr. Ali Safaei moved in May 2023 to an automotive company, which brings new opportunities for cooperation.

Third, the research team started the cooperation with a research team of the University of Craiova for developing new fuzzy controllers for discrete events systems. The cooperation started with the published paper [D30]. The team from Craiova has good connections with external partners in the region.

Fourth, the project leader started recently the cooperation with Acad. Gheorghe Duca, Acad. Serbey M. Abramov, Acad. Sergey Travin and Dr. Inga Zinicovscaia of Moldova and Russian Federation on modeling, optimization and control of chemical processes and environmental processes. Three papers have been published as first results of this cooperation: [D33], [D34] plus one that is not related to this project. Although their links to the local industries are not strong, this cooperation has the potential to lead to good research results because of the strong theoretical background of these fresh partners.

## B. ESTIMATED AND OBTAINED RESULTS

The estimated results are:

- Minimum three papers in high impact leading journals.
- Six conference papers presented at visible international conferences.
- Three data-driven fuzzy controllers ready to implement in industry.

The obtained results are much higher compared to the estimated ones:

- 16 papers published in Clarivate Analytics Web of Science (formerly ISI Web of Knowledge) journals with impact factors, **cumulated impact factor according to 2021 Journal Citation Reports (JCR) released by Clarivate Analytics in 2022 = 69.118.**
- 11 papers published in conference proceedings and book chapters indexed in Clarivate Analytics Web of Science (formerly ISI Web of Knowledge or ISI Proceedings).
- 14 papers published in conference proceedings indexed in international databases (IEEE Xplore, INSPEC, Scopus, sciencedirect, Springer Link, DBLP).

- 2 books published in CRC Press, Taylor & Francis, and Editura Politehnica.
- 3 book chapters published in Springer and World Scientific books.
- **Two Highly Cited Papers according to Clarivate Analytics Web of Science** (IEEE Transactions on Fuzzy Systems, 2022 [D8]; Information Sciences, 2022 [D10]) as of May/June 2023.
- **One Hot Paper according to Clarivate Analytics Web of Science** (IEEE Transactions on Fuzzy Systems, 2022 [D8]) as of May/June 2023.
- One **book voted by the Editorial Board of CRC Press as 2021 Outstanding Title in STEM** [D6].
- 3 certificates that register to the Romanian Office of Copyright (Oficiul Român pentru Drepturile de Autor, ORDA) the works "Study of design and industrial implementation of a hybrid model-free fuzzy controller", no. RGII/INT/1838/02.05.2023 - RGII/IES/1838/08.05.2023 [D47], "Study of design and industrial implementation of a hybrid model-free adaptive fuzzy controller", no. RGII/INT/2607/23.06.2023 - RGII/IES/2607/20.07.2023 [D48], "Study of design and industrial implementation of a fuzzy controller with proportional-derivative indirect iterative learning", no. RGII/INT/3514/29.08.2023 - RGII/IES/3514/28.09.2023 [D49].
- 1 PhD thesis [D29]

## C. ESTIMATED IMPACT OF OBAINED RESULTS AND MOST SIGNIFICANT OBTAINED RESULT

The **cumulated impact factor** of the 16 papers published in Clarivate Analytics Web of Science (formerly ISI Web of Knowledge) journals with impact factors **according to 2021 Journal Citation Reports (JCR) released by Clarivate Analytics in 2022 is 69.118**.

The research team published **two Highly Cited Papers according to Clarivate Analytics Web of Science** (IEEE Transactions on Fuzzy Systems, 2022 [D8]; Information Sciences, 2022 [D10]) as of May/June 2023.

The research team published **one Hot Paper according to Clarivate Analytics Web of Science** (IEEE Transactions on Fuzzy Systems, 2022 [D8]) as of May/June 2023.

Ms. Eng. Elena-Lorena Hedrea, an important member of the research team, defended in September 1, 2022, the PhD Thesis "Tensor Product-based Model Transformation Used in Control System Modeling and Design", PhD supervisor: Prof.Dr.Eng. Radu-Emil Precup. The thesis contains chapters connected to the main objectives of this project. The PhD committee gave the thesis the Excellent (Summa cum Laude) qualification.

## D. RESEARCH TEAM'S PUBLICATIONS


[D1] E.-L. Hedrea, R.-E. Precup, R.-C. Roman, E. M. Petriu, C.-A. Bojan-Dragoş and C. Hedrea, Tensor Product-Based Model Transformation Technique Applied to Servo Systems Modeling, Proceedings of 30th International Symposium on Industrial Electronics ISIE 2021, Kyoto, Japan, pp. 1-6, 2021, indexed in Clarivate Analytics Web of Science.

[D2] A. Topîrceanu and R.-E. Precup, A novel geo-hierarchical population mobility model for spatial spreading of resurgent epidemics, Scientific Reports (Nature), vol. 11, paper 14341, pp. 1-12, 2021, impact factor (IF) = 4.996, IF according to 2021 Journal Citation Reports (JCR) released by Clarivate Analytics in 2022 = 4.996.

[D3] R.-E. Precup, C.-A. Bojan-Dragoş, E.-L. Hedrea, R.-C. Roman and E. M. Petriu, Evolving Fuzzy Models of Shape Memory Alloy Wire Actuators, Romanian Journal of Information Science and Technology (Romanian Academy, Section for Information Science and Technology), vol. 24, no. 4, pp. 353-365, 2021, impact factor (IF) = 0.852, IF according to 2021 Journal Citation Reports (JCR) released by Clarivate Analytics in 2022 = 0.852.

[D4] C.-V. Pop, R.-E. Precup and L. I. Cădariu-Brăiloiu, Analysis of Monetary Policy Decisions of the National Bank of Romania with Text Mining Techniques, Proceedings of 2021 IEEE 15th International Symposium on Applied Computational Intelligence and Informatics SACI 2021, Timisoara, Romania, pp. 21-26, 2021, indexed in Clarivate Analytics Web of Science.

[D5] C.-A. Bojan-Dragoş, R.-E. Precup, S. Preitl, R.-C. Roman, E.-L. Hedrea and A.-I. Szedlak-Stînean, GWO-Based Optimal Tuning of Type-1 and Type-2 Fuzzy Controllers for Electromagnetic Actuated Clutch Systems, Proceedings of 4th IFAC Conference on Embedded Systems, Computational Intelligence and Telematics in Control CESCIT 2021, Valenciennes, France, 2021, IFAC-PapersOnLine, vol. 54, no. 4, pp. 189-194, 2021, indexed in Clarivate Analytics Web of Science.

[D6] R.-E. Precup, R.-C. Roman and A. Safaei, Data-Driven Model-Free Controllers, 1st Ed., CRC Press, Taylor & Francis, Boca Raton, FL, USA, 289 pp., 2021, **voted by the Editorial Board of CRC Press as 2021 Outstanding Title in STEM**, indexed in Scopus.

[D7] R.-E. Precup, E.-I. Voişan, R.-C. David, E.-L. Hedrea, E. M. Petriu, R.-C. Roman and A.-I. Szedlak-Stînean, Nature-inspired optimization algorithms for path planning and fuzzy tracking control of mobile robots, in: Applied Optimization and Swarm Intelligence, E. Osaba and X.-S. Yang, Eds., Springer Tracts in Nature-Inspired Computing, Springer, Singapore, pp. 129-148, 2021.

[D8] C. Pozna, R.-E. Precup (corresponding author), E. Horvath and E. M. Petriu, Hybrid Particle Filter-Particle Swarm Optimization Algorithm and Application to Fuzzy Controlled Servo Systems, IEEE Transactions on Fuzzy Systems, vol. 30, no. 10, pp. 4286-4297, 2022, impact factor (IF) = 12.253, IF according to 2021 Journal Citation Reports (JCR) released by Clarivate Analytics in 2022 = 12.253, **Highly Cited Paper according to Clarivate Analytics Web of Science** as of May/June 2023, **Hot Paper according to Clarivate Analytics Web of Science** as of May/June 2023.

[D9] A.-I. Szedlak-Stînean, R.-E. Precup (corresponding author), E. M. Petriu, R.-C. Roman, E.-L. Hedrea and C.-A. Bojan-Dragoş, Extended Kalman filter and Takagi-Sugeno fuzzy observer for a strip winding system, Expert Systems with Applications (Elsevier), vol. 208, paper 118215, pp. 1-15, 2022, impact factor according to 2021 Journal Citation Reports (JCR) released by Clarivate Analytics in 2022 = 8.665.

[D10] I. A. Zamfirache, R.-E. Precup (corresponding author), R.-C. Roman and E. M. Petriu, Policy iteration reinforcement learning-based control using a grey wolf optimizer algorithm, Information Sciences (Elsevier), vol. 585, pp. 162-175, 2022, impact factor (IF) = 8.233, IF according to 2021 Journal Citation Reports (JCR) released by Clarivate Analytics in 2022 = 8.233, **Highly Cited Paper according to Clarivate Analytics Web of Science** as of May/June 2023.

[D11] R.-E. Precup, S. Preitl, C.-A. Bojan-Dragoş, E.-L. Hedrea, R.-C. Roman and E. M. Petriu, A low-cost approach to data-driven fuzzy control of servo systems, Facta Universitatis, Series: Mechanical Engineering (University of Nis), vol. 20, no. 1, pp. 21-36, 2022, impact factor according to 2021 Journal Citation Reports (JCR) released by Clarivate Analytics in 2022 = 4.622.

[D12] R.-E. Precup, R.-C. Roman, E.-L. Hedrea, C.-A. Bojan-Dragoş, M.-M. Damian and M.-L. Nedelcea, Performance Improvement of Low-Cost Iterative Learning-Based Fuzzy Control Systems for Tower Crane Systems, International Journal of Computers Communications & Control, vol. 17, no. 1, 4623, pp. 1-18, 2022, impact factor according to 2021 Journal Citation Reports (JCR) released by Clarivate Analytics in 2022 = 2.635.

[D13] I.-D. Borlea, R.-E. Precup (corresponding author) and A.-B. Borlea, Improvement of K-means Cluster Quality by Post Processing Resulted Clusters, Proceedings of 8th International Conference on Information Technology and Quantitative Management ITQM 2020 & 2021, Chengdu, China, 2021, Procedia Computer Science (Elsevier), vol. 199, pp. 63-70, 2022, indexed in Clarivate Analytics Web of Science.

[D14] R.-C. Roman, R.-E. Precup, E.-L. Hedrea, S. Preitl, I. A. Zamfirache, C.-A. Bojan-Dragoş and E. M. Petriu, Iterative Feedback Tuning Algorithm for Tower Crane Systems, Proceedings of 8th International Conference on Information Technology and Quantitative Management ITQM 2020 & 2021, Chengdu, China, 2021, Procedia Computer Science (Elsevier), vol. 199, pp. 157-165, 2022, indexed in Clarivate Analytics Web of Science.

[D15] R.-E. Precup, E.-L. Hedrea, R.-C. Roman, E. M. Petriu, C.-A. Bojan-Dragoş and A.-I. Szedlak-Stînean, GWO-Based Performance Improvement of PD-Type Iterative Learning Fuzzy Control of Tower Crane Systems, Proceedings of 2022 IEEE 31st International Symposium on Industrial Electronics ISIE 2022, Anchorage, AK, USA, pp. 1041-1046, 2022, indexed in Clarivate Analytics Web of Science.

[D16] R.-E. Precup, E.-L. Hedrea, R.-C. Roman, E.-M. Petriu, C.-A. Bojan-Dragoş, A.-I. Szedlak-Stînean and F.-C. Paulescu, AVOA-Based Tuning of Low-Cost Fuzzy Controllers for Tower Crane Systems, Proceedings of 2022 IEEE International Conference on Fuzzy Systems FUZZ-IEEE 2022, Padova, Italy, pp. 1-8, 2022, indexed in Clarivate Analytics Web of Science.

[D17] C.-A. Bojan-Dragoş, R.-E. Precup, E. M. Petriu, R.-C. Roman, E.-L. Hedrea and A.-I. Szedlak-Stînean, GWO-Based Optimal Tuning of Controllers for Shape Memory Alloy Wire Actuators, Proceedings of 6th IFAC International Conference on Intelligent Control and Automation Sciences ICONS'22, Cluj-Napoca, Romania, 2022, IFAC-PapersOnLine, vol. 55, no. 15, pp. 39-44, 2022, indexed in Clarivate Analytics Web of Science.

[D18] R.-E. Roman, R.-E. Precup, S. Preitl, C.-A. Bojan-Dragoş, A.-I. Szedlak-Stînean and E.-L. Hedrea, Data-Driven Control Algorithms for Shape Memory Alloys, Proceedings of 2022 IEEE Conference on Control Technology and Applications CCTA 2022, Trieste, Italy, pp. 1306-1312, 2022, indexed in INSPEC and Scopus.

[D19] R.-E. Precup, E.-L. Hedrea, R.-C. Roman, E. M. Petriu, C.-A. Bojan-Dragoş, A.-I. Szedlak-Stînean and C. Hedrea, Evolving Fuzzy and Tensor Product-based Models for Tower Crane Systems, Proceedings of 48th Annual Conference of the IEEE Industrial Electronics Society IECON 2022, Brussels, Belgium, pp. 1-6, 2022, indexed in INSPEC and Scopus.

[D20] A.-I. Szedlak-Stînean, R.-E. Precup, R.-C. Roman, E. M. Petriu, C.-A. Bojan-Dragoş and E.-L. Hedrea, Discrete-time Linear and Nonlinear Observers for an Electromechanical Plant with State Feedback Control, Proceedings of 2022 IEEE Symposium Series on Computational Intelligence SSCI 2022, Singapore, pp. 700-707, 2022, indexed in Clarivate Analytics Web of Science.

[D21] C.-B. Gale-Cazan, C.-A. Bojan-Dragoş, R.-E. Precup (corresponding author), R.-C. Roman, E. M. Petriu and A.-I. Szedlak-Stînean, GWO-based Modeling of an Unstable Transport System, Proceedings of 9th International Conference on Information Technology and Quantitative Management ITQM 2022, Beijing and Zhangjiakou, China, 2022, Procedia Computer Science (Elsevier), vol. 214, pp. 195-202, 2022, indexed in sciencedirect.

[D22] E.-L. Hedrea, R.-E. Precup, R.-C. Roman, C.-A. Bojan-Dragoş, A.-I. Szedlak-Stînean and C. Hedrea, Tensor Product-based and State Feedback Structures for Level Control of Vertical Three Tank Systems, Proceedings of 26th International Conference on System Theory, Control and Computing ICSTCC 2022, Sinaia, Romania, pp. 195-200, 2022, indexed in Clarivate Analytics Web of Science.

[D23] M.-M. Damian and R.-E. Precup, Signal Preprocessing and Artifact Removal for Brain-Computer Interfaces, Proceedings of IEEE 16th International Symposium on Applied Computational Intelligence and Informatics SACI 2022, Timisoara, Romania, pp. 51-54, 2022, indexed in IEEE Xplore.

[D24] F.-C. Paulescu and R.-E. Precup, Fuzzy Models for a Two-Wheeled Self-Balancing Robot, Proceedings of IEEE 16th International Symposium on Applied Computational Intelligence and Informatics SACI 2022, Timisoara, Romania, pp. 277-282, 2022, indexed in IEEE Xplore.

[D25] C.-A. Bojan-Dragoş, R.-E. Precup and E.-L. Hedrea, Fuzzy Control Systems with Mechatronics Applications (in Romanian: Sisteme de reglare fuzzy cu aplicații mecatronice), Editura Politehnica, Timisoara, 162 pp., 2022.

[D26] A. Albu, R.-E. Precup and T.-A. Teban, Intelligent Paradigms for Diagnosis, Prediction and Control in Healthcare Applications, in: Handbook of Artificial Intelligence in Healthcare, Vol. 2: Practicalities and Prospects, C.-P. Lim, Y.-W. Chen, A. Vaidya, C. Mahorkar and L. C. Jain, Eds., Springer, Cham, Intelligent Systems Reference Library, vol. 212, pp. 3-41, 2022, indexed in Scopus.

[D27] R.-E. Precup and R.-C. David, Nature-Inspired Optimal Tuning of Fuzzy Controllers, Chapter 20 in Handbook on Computer Learning and Intelligence, 2nd Edition, P. P. Angelov, Ed., World Scientific, Singapore, Volume 2: Deep Learning, Intelligent Control and Evolutionary Computation, pp. 775-808, 2022.

[D28] R.-C. Roman, R.-E. Precup, S. Preitl, A.-I. Szedlak-Stînean, C.-A. Bojan-Dragoş, E.-L. Hedrea and E. M. Petriu, PI Controller Tuning via Data-Driven Algorithms for Shape Memory Alloy Systems, Proceedings of 1st IFAC Workshop on Control of Complex Systems COSY 2022, Bologna, Italy, 2022, IFAC-PapersOnLine, vol. 55, no. 40, pp. 181-186, 2022, indexed in Clarivate Analytics Web of Science.

[D29] E.-L. Hedrea, Tensor Product-based Model Transformation Used in Control System Modeling and Design, PhD thesis, Politehnica University of Timisoara, Timisoara, Romania, Sept. 2022, thesis grade Excellent (Summa cum Laude).

[D30] M. Brezovan, R.-E. Precup (corresponding author), D. Selişteanu and L. Stănescu, Colored Petri nets-based control and experimental validation on three-tank system level control, International Journal of General Systems (Taylor & Francis), vol. 51, no. 1, pp. 1-47, 2023, impact factor (IF) = 2.435, IF according to 2021 Journal Citation Reports (JCR) released by Clarivate Analytics in 2022

= 2.435.

[D31] I. A. Zamfirache, R.-E. Precup (corresponding author), R.-C. Roman and E. M. Petriu, Neural Network-based Control Using Actor-Critic Reinforcement Learning and Grey Wolf Optimizer with Experimental Servo System Validation, Expert Systems with Applications (Elsevier), vol. 225, paper 120112, pp. 1-15, 2023, impact factor (IF) = 8.665, IF according to 2021 Journal Citation Reports (JCR) released by Clarivate Analytics in 2022 = 8.665.

[D32] A.-I. Borlea, R.-E. Precup (corresponding author) and R.-C. Roman, Discrete-time model-based sliding mode controllers for tower crane systems, Facta Universitatis, Series: Mechanical Engineering (University of Nis), vol. 21, no. 1, pp. 1-20, 2023, impact factor (IF) = 4.622, IF according to 2021 Journal Citation Reports (JCR) released by Clarivate Analytics in 2022 = 4.622.

[D33] G. Duca, S. Travin, I. Zinicovscaia and R.-E. Precup (corresponding author), Approach to Evaluate the Data of Moss Biomonitoring Studies: Preprocessing and Preliminary Ranking, Romanian Journal of Information Science and Technology (Romanian Academy, Section for Information Science and Technology), vol. 26, no. 3-4, pp. 276-288, 2023, impact factor (IF) = 3.5, IF according to 2022 Journal Citation Reports (JCR) released by Clarivate Analytics in 2023 = 3.5.

[D34] S. M. Abramov, S. Travin, G. Duca and R.-E. Precup (corresponding author), New Opportunities Model for Monitoring, Analyzing and Forecasting the Official Statistics on Coronavirus Disease Pandemic, Romanian Journal of Information Science and Technology (Romanian Academy, Section for Information Science and Technology), vol. 26, no. 1, pp. 49-64, 2023, impact factor (IF) = 3.5, IF according to 2022 Journal Citation Reports (JCR) released by Clarivate Analytics in 2023 = 3.5.

[D35] R.-C. Roman, R.-E. Precup (corresponding author), E. M. Petriu and M. Muntyan, Fictitious Reference Iterative Tuning of Discrete-Time Model-Free Control for Tower Crane Systems, Studies in Informatics and Control (ICI Bucharest), vol. 32, no. 1, pp. 5-14, 2023, impact factor (IF) = 1.6, IF according to 2022 Journal Citation Reports (JCR) released by Clarivate Analytics in 2023 = 1.6.

[D36] C. Pozna and R.-E. Precup, On the Use of Quaternions, in the Translated Reference Frame Formalism, Acta Polytechnica Hungarica, vol. 20, no. 6, pp. 195-214, 2023, impact factor (IF) = 1.806, IF according to 2020 Journal Citation Reports (JCR) released by Clarivate Analytics in 2021 = 1.806.

[D37] R.-E. Precup, R.-C. Roman, E.-L. Hedrea, E. M. Petriu, C.-A. Bojan-Dragoş and A.-I. Szedlak-Stînean, Slime Mold Algorithm-Based Performance Improvement of PD-Type Indirect Iterative Learning Fuzzy Control of Tower Crane Systems, Proceedings of 57th Annual Conference on Information Sciences and Systems CISS 2023, Baltimore, MD, USA, pp. 1-6, 2023, indexed in Scopus.

[D38] C.-A. Bojan-Dragoş, R.-E. Precup, A.-I. Szedlak-Stînean, R.-C. Roman, E.-L. Hedrea and E. M. Petriu, Sliding Mode and Super-Twisting Sliding Mode Control Structures for SMA Actuators, Proceedings of 2023 European Control Conference ECC 2023, Bucharest, Romania, pp. 1-6, 2023, indexed in Clarivate Analytics Web of Science.

[D39] R.-C. Roman, R.-E. Precup and E.-L. Hedrea, Intelligent Proportional Controller Tuned by Virtual Reference Feedback Tuning and Fictitious Reference Iterative Tuning, Proceedings of 10th International Conference on Information Technology and Quantitative Management ITQM 2023, Oxford, UK, 2023, Procedia Computer Science (Elsevier), vol. 221, pp. 86-93, 2023, indexed in Scopus.

[D40] R.-C. Roman, R.-E. Precup, E. M. Petriu, M. Muntyan and E.-L. Hedrea, Fictitious Reference Iterative Tuning of Intelligent Proportional-Integral Controllers for Tower Crane Systems, Proceedings of 31st Mediterranean Conference on Control & Automation MED'23, Limassol, Cyprus, pp. 740-746, 2023, indexed in Clarivate Analytics Web of Science.

[D41] C.-A. Bojan-Dragoş, R.-E. Precup, R.-C. Roman, E. M. Petriu and M. Muntyan, PI and Super Twisting Sliding Mode with Smith Predictor Control Structures for SMA Actuators, Proceedings of 32nd International Symposium on Industrial Electronics ISIE 2023, Helsinki-Espoo, Finland, pp. 1-7, 2023, indexed in Scopus.

[D42] A.-I. Szedlak-Stînean, R.-E. Precup, R.-C. Roman and E. M. Petriu, Discrete-time Observers for a Mechatronics System with PID Controllers Tuned Using SMA, Proceedings of 32nd International Symposium on Industrial Electronics ISIE 2023, Helsinki-Espoo, Finland, pp. 1-8, 2023, indexed in

Scopus.

[D43] A.-I. Szedlak-Stînean, R.-E. Precup, R.-C. Roman, E. M. Petriu and E.-L. Hedrea, SMA-Based Tuning of PI Controller Using Takagi Sugeno Fuzzy Observers for an Electromechanical System with Variable Parameters, Proceedings of 9th International Conference on Control, Decision and Information Technologies CoDiT 2023, Rome, Italy, pp. 1761-1768, 2023, indexed in ieeexplore.

[D44] E.-L. Hedrea, R.-E. Precup, R.-C. Roman and C. Hedrea, Tensor Product-based and State Feedback Control Solutions for Cart Position Control of Pendulum-Cart Systems, Proceedings of 27th International Conference on System Theory, Control and Computing ICSTCC 2023, Timisoara, Romania, pp. 12-17, 2023, indexed in ieeexplore.

[D45] A.-I. Borlea, R.-E. Precup and R.-C. Roman, Two Discrete-Time Data-Driven Sliding Mode Controllers for Tower Crane Systems, Proceedings of 27th International Conference on System Theory, Control and Computing ICSTCC 2023, Timisoara, Romania, pp. 239-244, 2023, indexed in ieeexplore.

[D46] A.-I. Szedlak-Stînean, R.-E. Precup and R.-C. Roman, Linear and Nonlinear Observers Developed for Direct Current Electric Drive Systems, in: Intelligent Methods Systems and Applications in Computing, Communications and Control, 9th International Conference on Computers Communications and Control (ICCCC) 2022, Baile Felix, Romania, 2022, S. Dzitac, D. Dzitac, F. G. Filip, J. Kacprzyk, M. J. Manolescu and H. Oros (Eds.), Advances in Intelligent Systems and Computing, vol. 1435, Springer, Cham, pp. 107-119, 2023, indexed in Springer Link.

[D47] Certificates that registers to the Romanian Office of Copyright (Oficiul Român pentru Drepturile de Autor, ORDA) the work "Study of design and industrial implementation of a hybrid model-free fuzzy controller", nr. RGII/INT/1838/02.05.2023 - RGII/IES/1838/08.05.2023.

[D48] Certificates that registers to the Romanian Office of Copyright (Oficiul Român pentru Drepturile de Autor, ORDA) the work "Study of design and industrial implementation of a hybrid model-free adaptive fuzzy controller", nr. RGII/INT/2607/23.06.2023 - RGII/IES/2607/20.07.2023.

[D49] Certificates that registers to the Romanian Office of Copyright (Oficiul Român pentru Drepturile de Autor, ORDA) the work "Study of design and industrial implementation of a fuzzy controller with proportional-derivative indirect iterative learning", nr. RGII/INT/3514/29.08.2023 - RGII/IES/3514/28.09.2023.

**REFERENCES**


[1] R.-E. Precup, S. Preitl, I. J. Rudas, and J. K. Tar, "On the use of iterative learning control in fuzzy control system structures," in *Proc. 7th Int. Symp. Hung. Res. Comput. Intell.*, Budapest, Hungary, 2006, pp. 69–82.

[2] S. Preitl and R.-E. Precup, "On the algorithmic design of a class of control systems based on providing the symmetry of open-loop Bode plots," Sci. Bull. UPT Trans. Autom. Control Comput. Sci., vol. 41, no. 2, pp. 47–55, Dec. 1996.

[3] S. Preitl and R.-E. Precup, "An extension of tuning relations after symmetrical optimum method for PI and PID controllers," Autom., vol. 35, no. 10, pp. 1731–1736, Oct. 1999.

[4] R.-E. Precup, S. Preitl, E. M. Petriu, J. K. Tar, and J. Fodor, "Iterative learning-based fuzzy control system," in *Proc. 6th IEEE Int. Worksh. Rob. Sensor Env.*, Ottawa, ON, Canada, 2008, pp. 25–28.

[5] R.-E. Precup, R.-C. David, and E. M. Petriu, "Grey wolf optimizer algorithm-based tuning of fuzzy control systems with reduced parametric sensitivity," *IEEE Trans. Ind. Electron.*, vol. 64, no. 1, pp. 527–534, Jan. 2017.

[6] S. Galichet and L. Foulloy, "Fuzzy controllers: Synthesis and equivalences," *IEEE Trans. Fuzzy Syst.*, vol. 3, no. 2, pp. 140–148, May 1995.

[7] Q.-X. Yu and Z.-S. Hou, "Adaptive fuzzy iterative learning control for high-speed trains with both randomly varying operation lengths and system constraints," *IEEE Trans. Fuzzy Syst.*, vol. 29, no. 8, pp. 2408–2418, Aug. 2021.

[8] F. Bouakrif, T. Bensidhoum, and M. Zasadzinski, "Iterative learning fuzzy control for nonlinear systems with adaptive gain and without resetting condition," *Cybern. Syst.*, vol. 53, no. 1, pp. 23–43, Jan. 2022.

[9] R.-E. Precup and R.-C. David, *Nature-Inspired Optimization Algorithms for Fuzzy Controlled Servo Systems*. Oxford: Butterworth-Heinemann, Elsevier, 2019.

[10] Inteco, *Tower Crane, User's Manual*. Krakow: Inteco Ltd, 2012.

[11] R.-E. Precup, C.-A. Dragoş, S. Preitl, M.-B. Rădac, and E. M. Petriu, "Novel tensor product models for automatic transmission system control," *IEEE Syst. J.*, vol. 6, no. 3, pp. 488–498, Sep. 2012.

[12] C. Lazăr et al., "Real-time informatics technologies for embedded-system-control of power-train in automotive design and applications," Research Report 2.2 of the SICONA CNMP Grant, "Gh. Asachi" Technical University of Iasi, Iasi, Romania, 2010 (in Romanian).

[13] A. Safaei and M. N. Mahyuddin, "Optimal model-free control for a generic MIMO nonlinear system with application to autonomous mobile robots," *Int. J. Adapt. Control Signal Proc.*, vol. 32, no. 6, pp. 792–815, Jun. 2018.

Project leader,

Prof.Dr.Eng. Radu-Emil Precup