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# Multiobjective Robust PI Synthesis in Plants with Uncertain Poles

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Abstract: The use of multiobjective optimization procedures for control tuning has been constantly explored, presenting satisfactory results, and generating significant contributions to control engineering. In this way, the field of robust control can benefit significantly from the integration of multiobjective optimization design procedures for robust Proportional-Integral-Derivative (RPID) controller synthesis, enabling innovative solutions to complex control challenges. Due to this fact, this paper explores an approach to utilize multiobjective optimization algorithms in a simplified procedure, considering uncertain systems in the form of interval plants with uncertain poles, the Kharitonov theorem is used to obtain a region of stability as search space for the multiobjective algorithm, being the optimization process performed over a nominal system model. Two numerical cases and a flexible actuator model were used to demonstrate the procedure for RPI synthesis, resulting in robustly stable controllers with optimized performance over error and control signal effort measures.

*Keywords:* Robust control, multiobjective optimization, robust stability, Kharitonov theorem, PI controller.

## 1. INTRODUCTION

Robust synthesis of Proportional-Integral-Derivative (PID) controllers is an important task in control engineering practices. This arises from the inherent reliance upon nominal models, used in the process of controller design, which is susceptible to uncertainties, inaccuracies, and modelling errors (Fortuna, Frasca, & Buscarino, 2022).

Considering that, many recent contributions were presented in diverse applications related to robust PID (RPID) synthesis, where the robustness of the solutions was tested by the inclusion of disturbances in the model, Miranda-Colorado and Aguilar (2020) presented an application where the control position of a quadrotor vehicle was performed by a PID and the orientation through a model-based controller, tuned by a cuckoo search algorithm.

In the paper of Khamies et al. (2021) an RPID controller was presented, and tested for frequency stabilization of power systems, being the combination of a PID and a linear quadratic Gaussian controller, and the parameters optimal setting obtained by the metaheuristic Improved lightning attachment procedure optimization. Santos et al. (2023) showed a topology for the design of robust autopilots with application on autonomous surface vessels and an optimization based on the Interior Points Algorithm was proposed to tune the RPID.

Other interesting results are from Fiuzy and Shamaghdari (2023) where an RPID $H_\infty$ strategy is presented and an optimization process employed to obtain the stabilization region for a type of uncertain fractional order system, and Mourtas et al. (2023) where a modified metaheuristic, based on the beetle antennae search algorithm, is presented to fine-tune the RPID, minimizing the mean square error of the simulated closed-loop system.

While prior studies have effectively utilized optimization strategies for the synthesis of RPID-like controllers, incorporating the use of multiobjective optimization design procedures can be an interesting contribution to the field of robust control.

Some advantages of using multiobjective optimization algorithms are related to the possibility of obtaining multiple optimal solutions in a single step (Coello et al., 2007), and the use of multiobjective optimization strategies in the controllers tuning process, was explored in many applications, e.g., in didactic experiments for control engineering education (Kagami, Kovalski da Costa, Mendes, & Freire, 2019); for automatic drugs administration in anaesthesia procedures (Kagami et al., 2021); magnetic levitation systems (Reznichenko & Podržaj, 2023); water treatment plants (Lúcio, Mariani, & Coelho, 2023); among others.

In this work, a general procedure of multiobjective optimization for robust PI synthesis is presented, considering the nominal plant representation and the Kharitonov theorem as key tools of the analysis.

In the next section the robust stability concept, based on Kharitonov's theorem is presented. Section 3 presents the proposed strategy and adopted in the section 4 simulations, followed by a conclusion and future works in section 5.

## 2. ROBUST STABILITY

Robustness can be defined as the system's insensitivity to uncertainties or the ability to maintain its performance under undesirable effects and is therefore related to system reliability (Tsui, 2022).

Common sources of uncertainties include parameter variations, unmodeled dynamics, and environmental disturbances, and the performance and stability of the closed-loop system can be adversely affected by the presence of such discrepancies between the assumed model and the actual dynamics of the plant (Yedavalli, 2014).

Instead of attempting a replica, a transfer function aims to represent the key dynamics of a system, which can be used to evaluate controllers and simulate behaviours. An interesting approach consists of the use of interval representations to describe parametric uncertainties in the plant (Bhattacharyya, Datta, & Keel, 2009).

An interval polynomial $\mathfrak{P}(s)$ with degree $n$, described in the form:

$$\mathfrak{P}(s) = [a_0] + [a_1]s + [a_2]s^2 + \cdots + [a_n]s^n, \qquad (1)$$

where $[a_i] \in \left[\underline{a_i}, \overline{a_i}\right], i = 0, \ldots, n$ are the interval coefficients with lower $(\underline{a_i})$ and upper $(\overline{a_i})$ bounds, is assumed the degree of all polynomials are invariant over the uncertainty set ($0 \notin [\underline{a_i}, \overline{a_i}]$), and the set of all possible polynomials is named the interval family, being a transfer function that uses this representation called interval plant (Bhattacharyya et al., 2009).

Considering an interval plant, Kharitonov's theorem (Kharitonov, 1978) allows to verify the asymptotic stability of the entire interval family, checking the Hurwitz stability of four polynomials, also named Kharitonov polynomials:

$$\begin{aligned} K^1(s) &= \underline{a_0} + \underline{a_1}s + \overline{a_2}s^2 + \overline{a_3}s^3 + \underline{a_4}s^4 \ldots; \\ K^2(s) &= \underline{a_0} + \overline{a_1}s + \overline{a_2}s^2 + \underline{a_3}s^3 + \underline{a_4}s^4 \ldots; \\ K^3(s) &= \overline{a_0} + \underline{a_1}s + \underline{a_2}s^2 + \overline{a_3}s^3 + \overline{a_4}s^4 \ldots; \\ K^4(s) &= \overline{a_0} + \overline{a_1}s + \underline{a_2}s^2 + \underline{a_3}s^3 + \overline{a_4}s^4 + \cdots. \end{aligned} \qquad (2)$$

A controller that stabilizes the four Kharitonov polynomials is considered a controller robustly stable (Polyak & Shcherbakov, 2021).

## 3. PROCEDURES FOR ROBUST PID TUNING EMPLOYING MULTIOBJECTIVE OPTIMIZATION

This section describes the PID tuning strategy proposed, which was adopted to obtain the results presented in the next section. The procedure is based on the Multiobjective Optimization Design procedure for controller tuning presented by Reynoso-Meza et al. (2017) and consists of three main steps: (*i*) identify the interval plant and use it to obtain the four Kharitonov polynomials, and the stability region of the interval family that will be used as the search space during the optimization process; (*ii*) the multiobjective problem statement; and (*iii*) the multiobjective optimization and decision-making stage.

### *3.1 Interval and Kharitonov Plants*

Since the system's behaviours were modelled and the uncertainties among poles location established, or in the characteristic equation coefficients, the four Kharitonov polynomials (2) can be obtained (2) and used to represent the four Kharitonov plants.

For each Kharitonov plant it is necessary to identify its stability region of the controller gains, e.g. the strategy presented by Guan, Li, & Dong (2023), where the interval of controller gains are obtained through an optimization process.

The strategy adopted in this paper is based in the presented by Reynoso-Meza & Sánchez (2018), here the ultimate gain ($k_u$), a frequency range $\omega$, and two pseudo-decision variables $\widehat{k_p} \in [0, 1]$ and $\widehat{k_i} \in [0, 1]$, are used to obtain the proportional ($k_p$) and integral ($k_i$) gains:

$$k_p = (\widehat{k_p})k_u, \text{ and} \qquad (3)$$

$$k_i = k_{i_{min}} + (\widehat{k_i})k_{i_{max}}, \qquad (4)$$

where $k_{i_{min}}$ and $k_{i_{max}}$ are the bounds of stability for a specific value of $k_p$. In this approach, the pseudo-decision variables ($\widehat{k_p}$ and $\widehat{k_i}$) are used by the optimization algorithm to map the feasible search space limited by the ultimate gain ($k_u$), being $\widehat{k_p}$ interpreted as a ratio of $k_u$ which is assigned to $k_p$, and $\widehat{k_i}$ a ratio in the interval $[k_{i_{min}}, k_{i_{max}}]$ assigned to $k_i$ for the related $k_p$.

Since each Kharitonov plant has its own stability region, the search space, to obtain suitable values of $k_p$ and $k_i$, need to consider the simultaneous stability of each Kharitonov plant, that can be obtained by the intersection of all regions, however we used the following approach:

$$k_u = \min(k_{u,K^1}, k_{u,K^2}, k_{u,K^3}, k_{u,K^4}), \qquad (5)$$

$$k_i = \min(k_{i,K^1}, k_{i,K^2}, k_{i,K^3}, k_{i,K^4}), \qquad (6)$$

where $k_{u,K^1}, k_{u,K^2}, k_{u,K^3}, k_{u,K^4}$ are the ultimate gains of the Kharitonov plants and $k_{i,K^1}, k_{i,K^2}, k_{i,K^3}, k_{i,K^4}$ the integral gains calculated by their respective $k_{u,K}$. The minimum values assigned to $k_u$ and $k_i$ ensures that both gains are inner the stability region. The same process can be used to obtain the derivative gain.

### *3.2 Multiobjective Problem Statement*

A multiobjective optimization problem (MOP), represented by $k \geq 2$ cost functions $J_{1\ldots k}(\boldsymbol{\theta})$, without loss of generality, can be written as:

$$\min_{\boldsymbol{\theta}} \boldsymbol{J}(\boldsymbol{\theta}), \qquad \boldsymbol{J}(\boldsymbol{\theta}) = [J_1(\boldsymbol{\theta}), \dots, J_k(\boldsymbol{\theta})] \qquad (7)$$

subject to:

$$g_i(\boldsymbol{\theta}) \leq 0, i = [1, \dots, m]$$
$$h_j(\boldsymbol{\theta}) = 0, j = [1, \dots, n], \qquad (8)$$

with $m$ inequality and $n$ equality restriction, where $\boldsymbol{\theta}$ is the decision vector $p$-dimensional, from a set U of feasible solutions:

$$\boldsymbol{\theta} = [\theta_1, \dots, \theta_p] \mid \boldsymbol{\theta} \in \text{U}. \qquad (9)$$

The existence of $k \geq 2$ cost functions in control tuning problems allow us to include possible conflicting objectives, e.g. errors and control signal effort measures, that enrich information regarding the problem.

### *3.3 Multiobjective Optimization and Decision-Making Stage*

In the macro stage of the multiobjective optimization processes, a multiobjective algorithm is addressed, aiming to approximate the Pareto front, providing a set of non-dominated solutions, and representing the optimal trade-offs between the conflicting objectives.

Obtaining the Pareto front during the multiobjective optimization process causes the existence of multiple potential solutions, optimal in their context. Therefore, the use of a Multicriteria Decision Making Method (MCDM) is necessary to select a single feasible solution to solve the original problem (Ojha, Singh, Chakraborty, & Verma, 2019).

The MCDMs differ mainly due to how the problem is structured to select the most preferable solution, in this work we used the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) (Hwang & Yoon, 1981; Lai, Liu, & Hwang, 1994), its strategy is based on selecting the alternative with best cost ($B_C$), considering its distance ($D_W(\boldsymbol{\theta})$) from an undesirable solution ($J_W(\boldsymbol{\theta})$) and proximity ($D_B(\boldsymbol{\theta})$) to an ideal solution ($J_B(\boldsymbol{\theta})$), the TOPSIS concept is presented in Fig. 1, where $D_B(\boldsymbol{\theta})$ and $D_W(\boldsymbol{\theta})$ are related to a potential solution of the Pareto front:

$$D_B(\boldsymbol{\theta}) = \sqrt{\sum_{i=1}^{n} \left(J_i(\boldsymbol{\theta}) - J_B(\boldsymbol{\theta})\right)^2}, \qquad (10)$$

$$D_W(\boldsymbol{\theta}) = \sqrt{\sum_{i=1}^{n} \left(J_i(\boldsymbol{\theta}) - J_W(\boldsymbol{\theta})\right)^2}, \qquad (11)$$

$$B_C = argmin\left\{\frac{D_W + D_B}{D_W}\right\}. \qquad (12)$$

## 4. SIMULATIONS AND RESULTS

In this section, to illustrate the strategy outlined in the previous section, we present three examples: two numerical cases and one involving the robust stabilization of a flexible actuator. These examples highlight the benefits of employing multiobjective optimization in robust control synthesis.

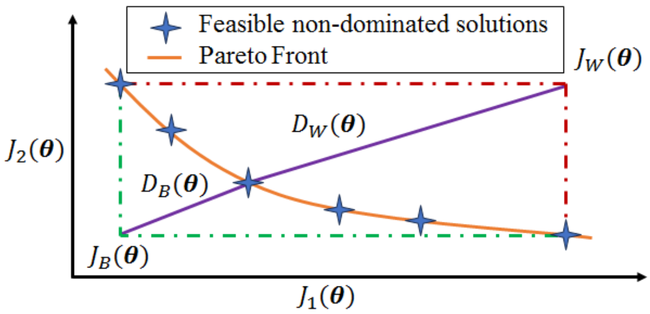


*Fig. 1. TOPSIS concept.*

In the simulations, the Nondominated Sorting Genetic Algorithm II (NSGA-II) (Deb et al., 2002), was employed, considering a population of 100 individuals and 100 generations, in addition to a 90% crossover and a 10% mutation probability.

For the examples in the sequence, the cost functions are $J_1(\boldsymbol{\theta})$ the Integral Absolute Error (IAE) and $J_2(\boldsymbol{\theta})$ the Integral Absolute Variation of Control signal (IAVU):

$$J_1(\boldsymbol{\theta}) = \int_{t=t_0}^{t_f} |e(t)| dt, \quad J_2(\boldsymbol{\theta}) = \int_{t=t_0}^{t_f} \left|\frac{du(t)}{dt}\right| dt, \qquad (13)$$

and $\boldsymbol{\theta} = [k_p, k_i]$, considering $\widehat{k_p}$ and $\widehat{k_i}$ and (3-6) as the search space in the joint stability of Kharitonov polynomials.

To provide statistical consistency of the results, we performed 51 repetitions of the optimization process, normalized the cost function in the interval [1,10] and selected the Pareto front with median hypervolume (Shang et al., 2021).

### *4.1 Example 1*

Consider the high-order interval plant:

$$\mathfrak{G}(s) = \frac{1.7s^2 + 2.8s + 2.3s}{[a_5]s^5 + [a_4]s^4 + [a_3]s^3 + [a_2]s^2 + [a_1]s + [a_0]}; \qquad (14)$$

where $[a_5] = [1.2, 2.0]$, $[a_4] = [13.4, 18.6]$, $[a_3] = [53.0, 60.9]$, $[a_2] = [77.5, 83.0]$, $[a_1] = [55.0, 58.5]$, and $[a_0] = [0.8, 1.3]$.

Using the Kharitonov theorem (2), the four plants are:

$$G_{K^1}(s) = \frac{1.7s^2 + 2.8s + 2.3s}{1.2s^5 + 13.4s^4 + 60.9s^3 + 83.0s^2 + 55.0s + 0.8};$$

$$G_{K^2}(s) = \frac{1.7s^2 + 2.8s + 2.3s}{2.0s^5 + 13.4s^4 + 53.0s^3 + 83.0s^2 + 58.5s + 0.8}; \qquad (15)$$

$$G_{K^3}(s) = \frac{1.7s^2 + 2.8s + 2.3s}{1.2s^5 + 18.6s^4 + 60.9s^3 + 77.5s^2 + 55.0s + 1.3};$$

$$G_{K^4}(s) = \frac{1.7s^2 + 2.8s + 2.3s}{2.0s^5 + 18.6s^4 + 53.0s^3 + 77.5s^2 + 58.5s + 1.3}.$$

The stability region for each transfer function is presented in Fig. 2, where is possible to identify the intersection set, the desired search space for the $k_p$ and $k_i$ gains.

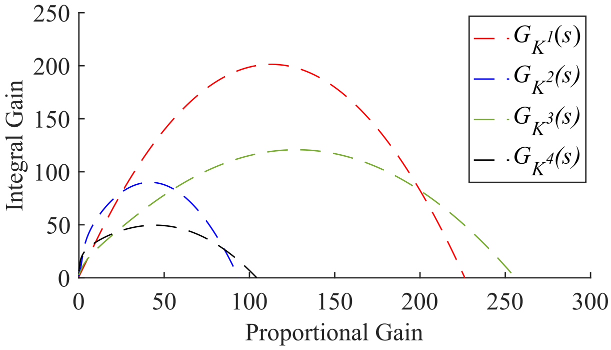


*Fig. 2. Stability regions – example 1.*

As result of the optimization process over a nominal model, obtained by the mean value of interval coefficients, with 51 repetitions and selection of the Pareto front with median hypervolume (Fig. 3), we applied the TOPSIS method, resulting in the PI controller:

$$C_{PI}(s) = \frac{13.2557s + 0.2530}{s}. \tag{16}$$

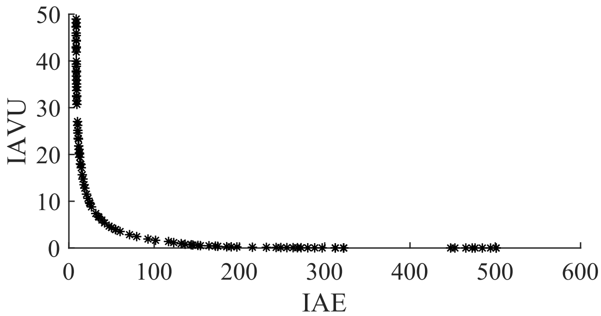


*Fig. 3. Pareto front – example 1.*

To verify the robust stability of the optimized controller, a Monte Carlo simulation with 5000 tests was performed, the step response and the control signal are presented in Fig. 4 and Fig. 5 as an interval family approximation.

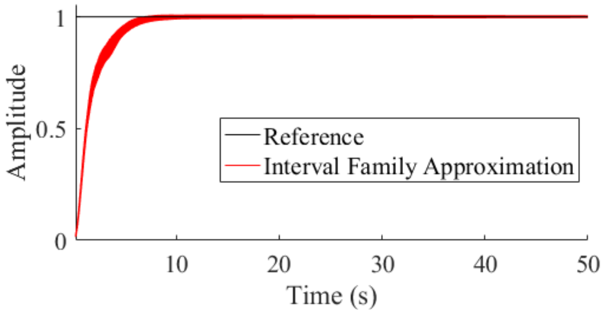


*Fig. 4. Step response – example 1.*

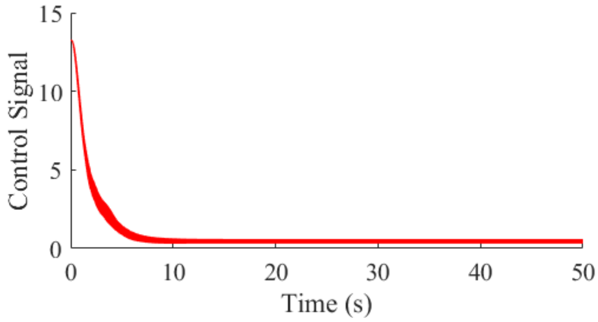


*Fig. 5. Control signal – example 1.*

### 4.2 Example 2

Consider a generic open-loop transfer function with interval coefficients:

$$\mathfrak{G}(s) = \frac{1}{[a_3]s^3 + [a_2]s^2 + [a_1]s + [a_0]}; \tag{17}$$

where $[a_3] = [1, 2]$, $[a_2] = [4, 6]$, $[a_1] = [2, 3]$, and $[a_0] = [1, 2]$.

Considering the process described in section 3, the stability region for the Kharitonov plants can be seen in Fig. 6, and the Pareto front with median hypervolume in Fig. 7.

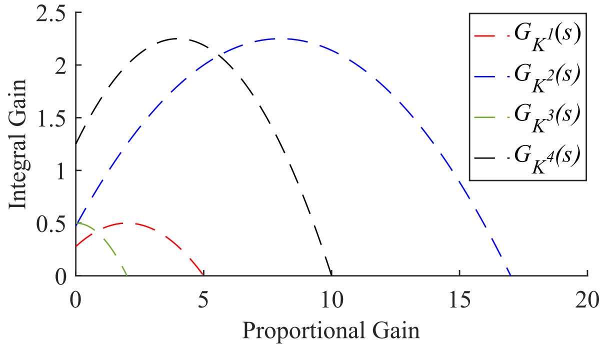


*Fig. 6. Stability regions – example 2.*

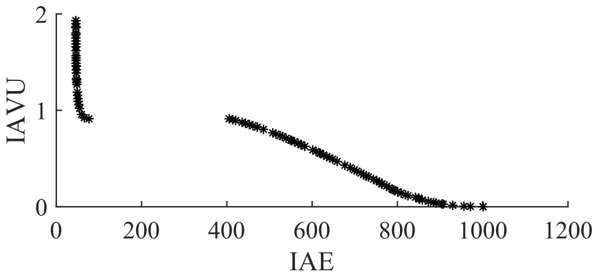


*Fig. 7. Pareto front – example 2.*

The obtained PI controller (18) by the employ of TOPSIS MCDM was tested in a Monte Carlo simulation, with 5000 samples, which can be seen in Fig. 8 and Fig. 9, for the step response and the control signal, respectively. The variations observed in the Monte Carlo simulation are caused by the unknow location of the poles, near the unstable region, in the interval family approximation.

$$C_{PI}(s) = \frac{0.7501s + 0.3539}{s} \tag{18}$$

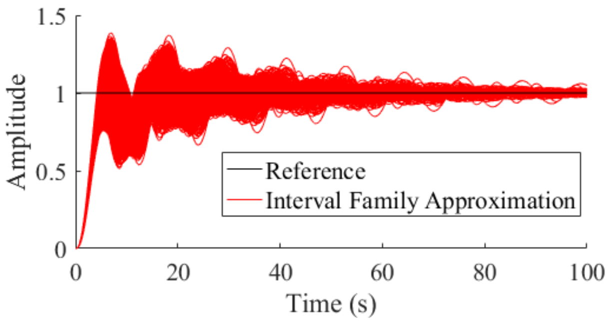


*Fig. 8. Step response – example 2.*

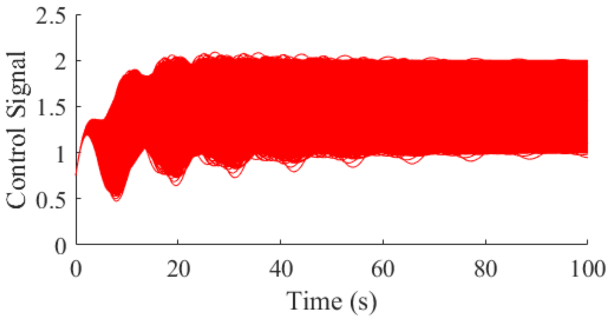


*Fig. 9. Control signal – example 2.*

### 4.2 Example 3

Consider an Ionic Polymer-Metal Composite (IPMC) actuator, an electroactive polymer also called "artificial muscles" with applications as flexible sensors and actuators in industrial environments, robotics, and biomedicine (Hao et al., 2019).

An interval plant for IPMC actuators was presented by Sano et al. (2010) made by Nafion NE-1110 (DuPont) through five times gold plating process and sodium counter-ion, with dimensions 40(mm)×5(mm)×0,28(mm), voltage as control signal $[-2.5, 2.5]$ V, with open-loop transfer function:

$$\mathfrak{G}(s) = \frac{F(s)}{V(s)} = \frac{s}{[a_3]s^3 + [a_2]s^2 + [a_1]s + [a_0]}, \quad (19)$$

where $[a_0]$=$[2.658, 5.674]10^{-3}$, $[a_1]$=$[1.395, 2.704]10^{-1}$, $[a_2]$=$[4.944, 7.410]10^{-1}$, and $[a_3]$=$[4.888, 8.011]10^{-2}$.

The controller proposed by Sano et al. (2010) is the RPID:

$$C_{Ref}(s) = \frac{0.03s^2 + 1.78s + 11.3}{s}. \quad (20)$$

Considering the interval plant (19), the Kharitonov plants were used to obtain the stabilization set, being the multiobjective optimization problem the minimization of IAE and IAVU, through the use of NSGA-II algorithm, the Pareto front with median hypervolume for the 51 repetitions is presented in Fig. 10, with the TOPSIS selected controller as:

$$C_{PI}(s) = \frac{2.2614s + 0.8771}{s}. \quad (21)$$

We compared the obtained controller with the one presented in the reference, which step response and control signal are presented in Fig. 10 and Fig. 11, also the performance of the proposed controller was tested in the four Kharitonov plants, being presented in Fig. 13 and Fig. 14 the step response and the control signal, respectively.

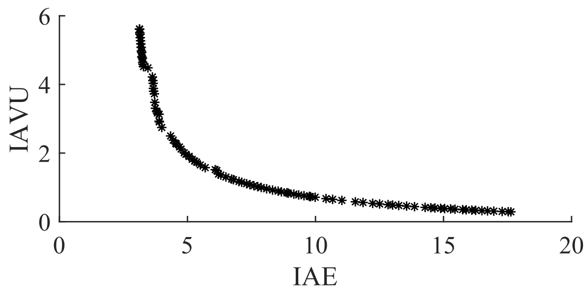


*Fig. 10. Pareto front – IPMC.*

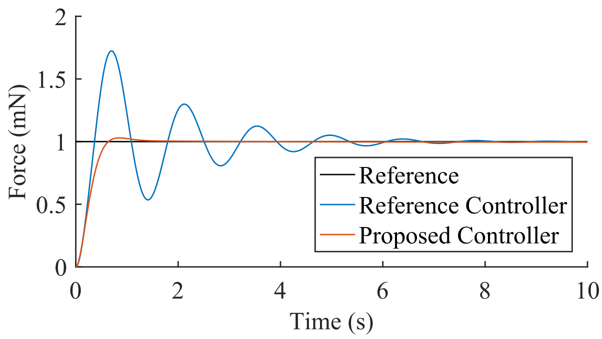


*Fig. 11. Step response – IPMC.*

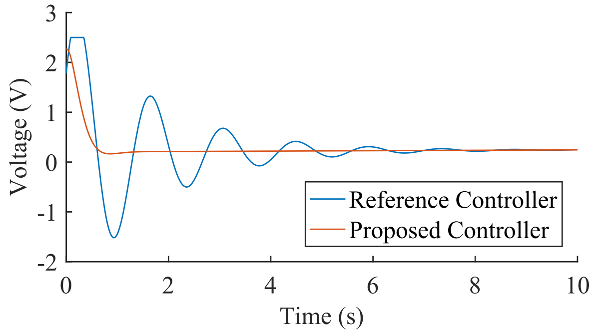


*Fig. 12. Control signal – IPMC.*

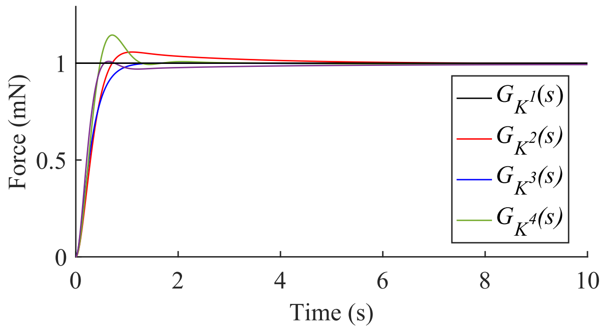


*Fig. 13. Step response – IPMC Kharitonov plants.*

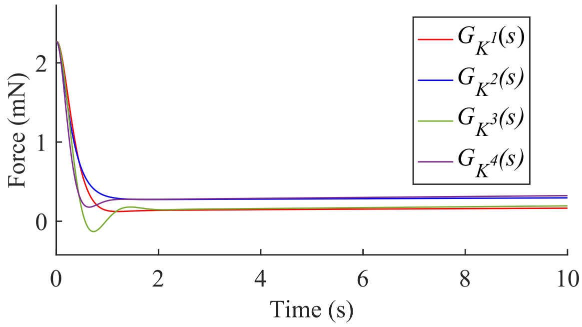


*Fig. 14. Control signal – IPMC Kharitonov plants.*

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