Multidisciplinary optimisation and controller tuning: an analysis with multi-objective techniques ⋆

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Abstract: Multidisciplinary design optimisation (MDO) has shown to be a valuable tool for designers when different fields converge in the design phase. Where classical approaches perform a sequential optimisation procedure, it seeks to exploit synergies between interacting subsystems, with the aim of getting a better overall. In this paper, we analyse and compare three different MDO approaches considering the tuning of a Proportional-Integral (PI) controller and plant design simultaneously. As conflicting objectives might appear, we compare such approaches using multi-objective optimisation. With the provided example, advantages and drawbacks are highlighted, in order to provide an insight about the applicability of such approaches.

Keywords: Multidisciplinary optimisation, PI controller, multi-objective optimisation.

1. INTRODUCTION

As products, devices and processes increase their complexity, it is usually required the interaction and coordination of several engineering disciplines in their design phase. Mechatronic devices for example, have several subsystems and therefore different design phases converge: mechanical design, structural design, control design, among others (Avigad et al., 2003). Classically, sequential approaches have been used for such designs. From the control engineer's perspective for example, that means defining the process under consideration (mechanical design for instance) and afterwards, selecting the most suitable control structure (control design and controller tuning) in order to fulfil the desired specifications.

A different approach is suggested by the multidisciplinary design framework, where an integrated design procedure is carried on. With such an approach is expected to exploit synergies between mechanical and control subsystems (for example), in order to get a better overall performance of the whole system (Avigad et al., 2003; Martins and Lambe, 2013). From the control point of view again, it means that this design phase comprises not only the control selection and its tuning, but also incorporates the design of the plant itself *at the same time*.

Nowadays, commercial products as *modeFRONTIER* [1] exploit such multidisciplinary aspect in engineering design. With such a tool, it is possible to perform a multidisciplinary optimisation (MDO). Furthermore, as this problem has a multi-objective nature, it uses multi-objective optimisation (MOO) in order to provide a set of solutions (known as Pareto set) where it is possible to analyse trade-offs among design alternatives. As several subsystems are under consideration in MDO, MOO techniques might be valuable tools, in order to compare the overall performance, trade-offs and drawbacks of the whole system.

MDO and MOO have been identified as strategic points in the HORIZON 2020 path, of the European framework programme for research and innovation [2]. According to Roy et al. (2008) both of them are emerging tools for design, with potential but with challenges to overcome. As noticed in Reynoso-Meza et al. (2014b) there is an opportunity to merge MDO and MOO for the specific case of control systems design.

According to the above commented, new tools and procedures to deal with the multidisciplinary aspect of engineering design with multi-objective optimisation are valuable for designers. In this paper, we perform an analysis and comparison of three MDO approaches, in order to integrate plant design and the controller tuning process. Furthermore, they will be analysed and compared using multi-criteria decision making tools in order to perform an overall comparison between approaches. With this, it will be possible to provide an insight about their applicability, advantages and drawbacks.

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[1] `http://esteco.com/modefrontier`
[2] *Factories of the Future*, H2020-FoF-2014-2015

The remainder of this work is as follows: in Section 2 basic concepts on control systems, MDO and MOO are given. In Section 3 tools and methodologies used in this work are presented and explained. In Section 4 an example is provided in order to compare three MDO approaches. Finally, some concluding remarks and future directions on this work are commented.

2. BACKGROUND

In this paper, we will focus on the plant design and parameter's tuning of a given control structure. Analysing different control structures will lead to a design concepts comparison, out of the scope of this work. In order to provide a common framework for the analysis, basic concepts of control systems, MDO and MOO are presented below.

2.1 Control systems

A basic control loop is depicted in Figure 1, where $P(s)$ and $C(s)$ are the process and the controller, respectively. The objective of this control loop is to keep the desired output $Y(s)$ of the process $P(s)$ in the desired reference signal $R(s)$.

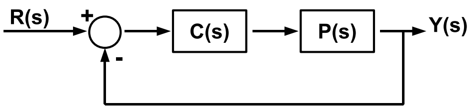


Fig. 1. Basic control loop.

As commented before, here we focus on a specific control structure. In this case, a Proportional-Integral (PI) controller is used, due to its simplicity and practicality (Li et al., 2006; Stewart and Samad, 2011):

$$C(s) = kp\left(1 + \frac{1}{Ti\ s}\right) \tag{1}$$

where kp is the proportional gain and Ti the integral time. The control problem consists in selecting values for proportional gain kp and integral gain $ki = \frac{kp}{Ti}$ for the PI controller $C(s)$. The control engineer will select certain values for $C(s)$ in order to achieve a desirable performance of the overall process $P(s)$ as well as *reasonable* robust stability margins. This is an important issue, since the control engineer must consider uncertainties in the process modelling. This control problem is well known and it has been addressed with several techniques (Vilanova and Alfaro, 2011).

In Reynoso-Meza et al. (2013b, 2014b) it was noticed that evolutionary computation techniques have been useful for finding appropriate tuning parameters for PI controllers. Nevertheless, in spite of the efforts for defining useful and meaningful cost functions, bounding the search space has received less attention (Reynoso-Meza et al., 2014a, 2015). In Figure 2, the stabilizing parameters k_p, k_i (proportional and integral gains) using a PI controller in a simple process are depicted. As it can be noticed, the shape of the feasible parameters is irregular. Usually, for the optimisation statement, the search space is bounded using a hyperbox enclosing this feasible space (Bounding Box A in Figure 2) or one inside (Bounding Box B in same figure). In the former case, non feasible parameters are included in the search space; in the latter, the feasible search space is not fully considered.

When dealing with a MDO statement where decision variables concern the plant itself, the feasible set of parameters will change and with them control constraints. Therefore, a mechanism which enables sampling only the feasible space and (potentially) any feasible parameter combination could be valuable for the multidisciplinary optimisation stage. This is because the plant parameters are being optimised in the optimisation process and thus, the feasible set of parameters for a PI control are changing constantly.

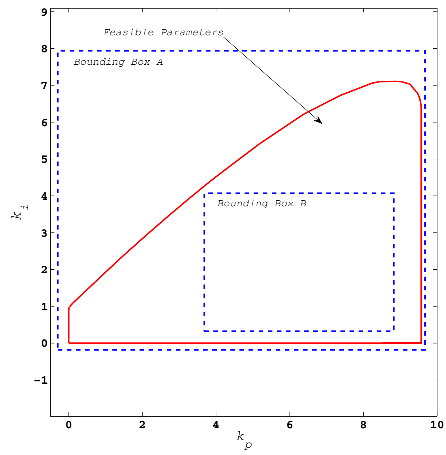


Fig. 2. Bounding boxes for feasible parameters of a PI controller and a first order plus delay time process.

2.2 Multidisciplinary optimisation

Multidisciplinary design might be carried out, under an optimisation framework, with three approaches: sequential, heuristic co-design and all-in-one optimisation. Hereafter, decision variables regarding the plant/process will be denoted as $\boldsymbol{x_\mathcal{P}}$ while tuneable parameters of the selected control structure as $\boldsymbol{x_\mathcal{C}}$; Design objectives regarding plant design as $\boldsymbol{J_\mathcal{P}}(\cdot)$ and control design objectives as $\boldsymbol{J_\mathcal{C}}(\cdot)$.

- Sequential design optimisation: the classical approach, where design objectives are optimised sequentially. That is:

$$\min \boldsymbol{J_\mathcal{C}}(\boldsymbol{x_\mathcal{C}}, \boldsymbol{x^*_\mathcal{P}}) \tag{2}$$

where

$$\boldsymbol{x^*_\mathcal{P}} = argmin \boldsymbol{J_\mathcal{P}}(\boldsymbol{x_\mathcal{P}}) \tag{3}$$

- Heuristic co-design optimisation: this is an approach where a bilevel optimisation approach is carried on (Sinha et al., 2017). That is:

$$\min \boldsymbol{J}(\boldsymbol{x_\mathcal{P}}, \boldsymbol{x^H_\mathcal{C}}) = [\boldsymbol{J_\mathcal{C}}(\boldsymbol{x_\mathcal{P}}, \boldsymbol{x^H_\mathcal{C}}), \boldsymbol{J_\mathcal{P}}(\boldsymbol{x_\mathcal{P}}, \boldsymbol{x^H_\mathcal{C}})] \tag{4}$$

where

$$\boldsymbol{x^H_\mathcal{C}} = f(\boldsymbol{x_\mathcal{P}}) \tag{5}$$

Usually $f(\boldsymbol{x_\mathcal{P}})$ is a given control tuning technique or rule, suitable to be used in the nested optimisation.

- Simultaneous optimisation: the also known as *all in one* optimisation approach. that is:

$$\min \boldsymbol{J}(\boldsymbol{x_\mathcal{P}}, \boldsymbol{x_\mathcal{C}}) = [\boldsymbol{J_\mathcal{C}}(\boldsymbol{x_\mathcal{P}}, \boldsymbol{x_\mathcal{C}}), \boldsymbol{J_\mathcal{P}}(\boldsymbol{x_\mathcal{P}}, \boldsymbol{x_\mathcal{C}})] \tag{6}$$

2.3 Evolutionary multiobjective optimisation

As referred in Miettinen (1998), a multi-objective problem (MOP) with m objectives [3], can be stated as follows:

$$\min_{\boldsymbol{x}} \boldsymbol{J}(\boldsymbol{x}) = [J_1(\boldsymbol{x}), \ldots, J_m(\boldsymbol{x})] \tag{7}$$

subject to:

$$\boldsymbol{K}(\boldsymbol{x}) \leq 0 \tag{8}$$

$$\boldsymbol{L}(\boldsymbol{x}) = 0 \tag{9}$$

$$\underline{x_i} \leq x_i \leq \overline{x_i}, i = [1, \ldots, n] \tag{10}$$

where $\boldsymbol{x} = [x_1, x_2, \ldots, x_n]$ is defined as the decision vector with $\dim(\boldsymbol{x}) = n$; $\boldsymbol{J}(\boldsymbol{x})$ as the objective vector and $\boldsymbol{K}(\boldsymbol{x})$, $\boldsymbol{L}(\boldsymbol{x})$ as the inequality and equality constraint vectors respectively; $\underline{x_i}, \overline{x_i}$ are the lower and the upper bounds in the decision space. It has been noticed that there is not a single solution in MOPs, because there is not generally a better solution in all the objectives. Therefore, a set of solutions, the Pareto set, is defined. Each solution in the Pareto set defines an objective vector in the Pareto front. All the solutions in the Pareto front are a set of Pareto optimal and non-dominated solutions (See Figure 3):

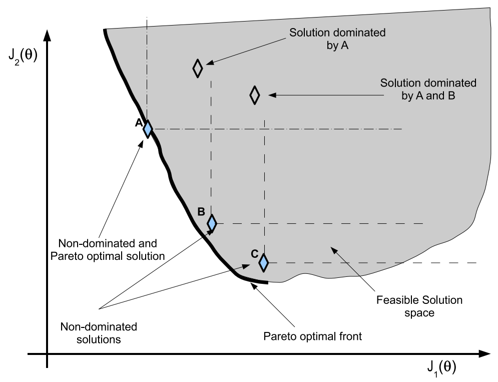


Fig. 3. Pareto optimality and dominance concepts.

- Pareto optimality (Miettinen, 1998): An objective vector $\boldsymbol{J}(\boldsymbol{x}^1)$ is Pareto optimal if there does not exist another objective vector $\boldsymbol{J}(\boldsymbol{x}^2)$ such that $J_i(\boldsymbol{x}^2) \leq J_i(\boldsymbol{x}^1)$ for all $i \in [1, 2, \ldots, m]$ and $J_j(\boldsymbol{x}^2) < J_j(\boldsymbol{x}^1)$ for at least one j, $j \in [1, 2, \ldots, m]$.
- Dominance (Coello and Lamont, 2004): An objective vector $\boldsymbol{J}(\boldsymbol{x}^1)$ is dominated by another objective vector $\boldsymbol{J}(\boldsymbol{x}^2)$ iff $J_i(\boldsymbol{x}^2) \leq J_i(\boldsymbol{x}^1)$ for all $i \in [1, 2, \ldots, m]$ and $J_j(\boldsymbol{x}^2) < J_j(\boldsymbol{x}^1)$ for at least one j, $j \in [1, 2, \ldots, m]$. This is denoted as $\boldsymbol{J}(\boldsymbol{x}^2) \preceq \boldsymbol{J}(\boldsymbol{x}^1)$.

3. APPROACHES UNDER ANALYSIS

In this section, we will describe two different approaches for multidisciplinary design: a heuristic co-design approach and a simultaneous optimisation.

3.1 Heuristic co-design for process and control

For the co-design optimisation, the SIMC tuning rule (Skogestad, 2003) for PI control is used:

$$kp = \frac{1}{k} \cdot \frac{T}{Tc + L} \tag{11}$$

$$Ti = \min(T, 4(Tc + L)) \tag{12}$$

Where $k\frac{e^{-Ls}}{Ts+1}$ is a first order plus delay time approximation of $P(s)$, with gain k, lag L and time constant T. The variable Tc is a tuneable parameter of the SIMC-rule, providing a trade-off between performance and robustness. The bigger the value, the more the robustness in the closed loop. Recommended value is $Tc = L$, nevertheless it is possible also to use the SIMC tuning rule with the tuneable parameter Tc as a design variable where $Tc \in [L, 2L]$.

3.2 Simultaneous optimisation for process and control

In order to overcome the above commented issue regarding the stochastic search process in the feasible space of a PI controller, an *ad-hoc* coding is used. Some works have focused in determining the feasible set of PI parameters for a given plant (Silva et al., 2002; Tan et al., 2006); It is important to remark that whilst such computation is useful, in this instance acquires an additional advantage. Since process parameters (plant) are also optimised in the optimisation stage, the set of feasible parameters changes with the optimised plant; thus, it will be valuable to know, in each iteration, the available set of feasible parameters. Here we will use a coding based of the work of Tan et al. (2006) where kp and ki for a given process $P(s) = \frac{N(s)}{D(s)}$ are calculated, for a frequency range ω, as follows:

$$kp = \frac{X(\omega)U(\omega) - Y(\omega)R(\omega)}{Q(\omega)U(\omega) - R(\omega)S(\omega)} \tag{13}$$

$$ki = \frac{Y(\omega)Q(\omega) - X(\omega)S(\omega)}{Q(\omega)U(\omega) - R(\omega)S(\omega)} \tag{14}$$

where

$$Q(\omega) = -\omega^2 N_o(-\omega^2) \tag{15}$$

$$R(\omega) = N_e(-\omega^2) \tag{16}$$

$$S(\omega) = \omega N_e(-\omega^2) \tag{17}$$

$$U(\omega) = \omega N_o(-\omega^2) \tag{18}$$

$$X(\omega) = -\omega^2 D_o(-\omega^2) \tag{19}$$

$$Y(\omega) = -\omega^2 D_e(-\omega^2) \tag{20}$$

and $N_o(-\omega^2), N_e(-\omega^2), D_o(-\omega^2), D_e(-\omega^2)$ are the odd and even part of numerator and denominator of $P(s)$ respectively. Therefore, it is possible to define the following coding, in order to sample stabilizing PI controllers for a given (stable) process $P(s)$, with the following pseudo-decision variables $\hat{kp} \in [0, 1]$, $\hat{ki} \in [0, 1]$:

$$kp = \hat{kp} \cdot ku \tag{21}$$

and

$$ki = ki_{min} + \hat{ki} \cdot ki_{max} \tag{22}$$

where ku is the ultimate gain, ki_{min}, ki_{max} are the solutions of (14), with $\hat{\omega}$ the roots of (13) for the obtained value of kp in (3.2).

[3] A maximisation problem can be converted to a minimisation problem. For each of the objectives that have to be maximised, the transformation: $\max J_i(\boldsymbol{x}) = -min(-J_i(\boldsymbol{x}))$ could be applied.

3.3 Multiobjective tools

The Multi-objective Differential Evolution Algorithm with spherical pruning (sp-MODE) [4] is used (with default parameters). It uses Differential Evolution as evolutionary algorithm (Storn and Price, 1997; Das and Suganthan, 2011); as diversity mechanism it uses a spherical pruning technique. With such an approach, it is possible to attain a good distribution along the Pareto front (Reynoso-Meza et al., 2010). The algorithm selects one solution for each spherical sector, according to a given norm or measure. It has shown a good performance for controller tuning purposes (Reynoso-Meza et al., 2016).
In order to evaluate the obtained Pareto front and set, Level diagrams [5] are used (Blasco et al., 2008; Reynoso-Meza et al., 2013a), since they provide a framework useful for design concepts comparisons in m-dimensional spaces. Such feature will be used in order to compare the Pareto front approximations for each one of the design approaches.

4. EVALUATION

In order to evaluate the efficiency of the commented approaches, the following process is under consideration:

$$P(s) = \frac{-s+1}{(\tau_1 s+1)(\tau_2 s+1)} \quad (23)$$

where design variables in order to modify the plant (process) are (a,b), such that:

$$\tau_1 = \frac{a}{b} \quad (24)$$

$$\tau_2 = a + b \quad (25)$$

$$a \in [0.1, 1] \quad (26)$$

$$b \in [1, 2] \quad (27)$$

In Figure 4 a comparison of the feasible set of PI controller parameters for three different achievable plants is depicted. As expected, this shape is modified due to the plant selected.

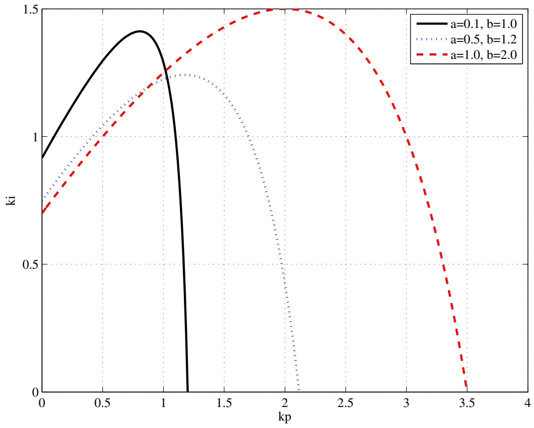
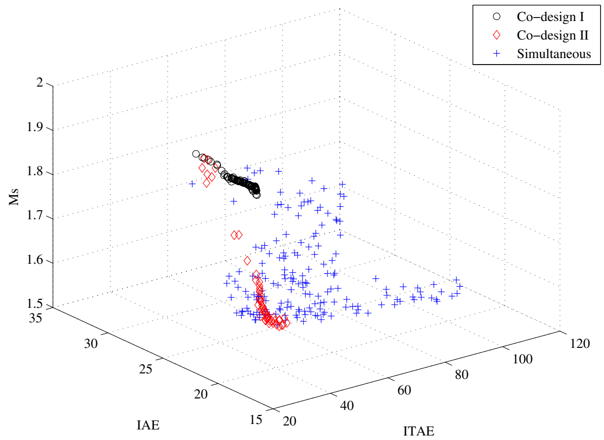
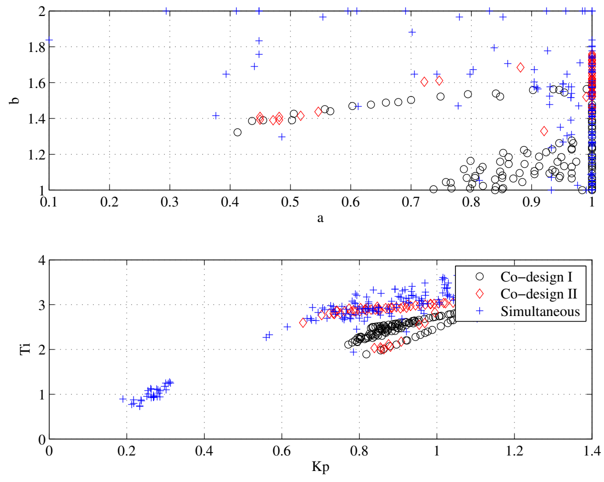


Fig. 4. Set of feasible PI controller parameters for the process $P(s)$ under consideration.

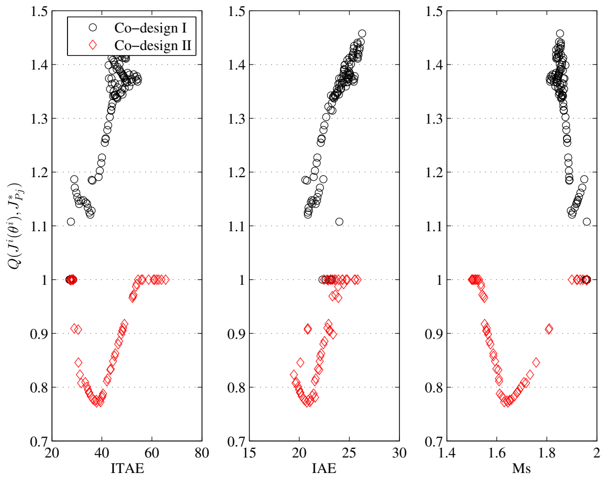
Three instances will be evaluated:



(a) Pareto front



(b) Pareto set



(c) Pareto front comparision

Fig. 5. MOP-1 results.

(1) Heuristic co-design I: design variables are a, b while PI controller will be tuned using the SIMC-rule with the above commented approximation and $Tc = L$.
(2) Heuristic co-design II: design variables are a, b and $Tc \in [L, 2L]$ for the SIMC-rule.
(3) Simultaneous design: design variables are a, b and kp, Ti.

[4] http://www.mathworks.com/matlabcentral/fileexchange/39215.
[5] http://www.mathworks.com/matlabcentral/fileexchange/39458.

The MDO approach will use the coding presented in Section 3.2, with the model of Equation (23). In order to use the SIMC-rule in the co-design approaches, the following approximation is used ($\tau_1 < \tau_2$):

$$P(s) = \frac{-s+1}{(\tau_1 s+1)(\tau_2 s+1)} \approx \frac{e^{\tau_1/2+1}}{(\tau_2+\tau_1/2)s+1} \quad (28)$$

Two different multi-objective problems (MOPs) will be used in order to compare the proposed approaches. In both cases it is evaluated the set-point response.

4.1 MOP-1

The first MOP statement under consideration is:

$$\min_{\boldsymbol{x}} \boldsymbol{J(x)} = [J_{ITAE}(\boldsymbol{x}), J_{IAE}(\boldsymbol{x}), J_{Ms}(\boldsymbol{x})] \quad (29)$$

where $J_{ITAE}(\boldsymbol{x})$ is the integral of the time weighted absolute value of the error; $J_{IAE}(\boldsymbol{x})$ is the integral of the absolute value of the error and $J_{Ms}(\boldsymbol{x})$ the maximum value of the sensitivity function of the closed loop. Last objective is bounded within the limits $1.5 \leq J_{Ms}(\boldsymbol{x}) \leq 1.9$ in order to analyse a pertinent region of the objective space. That is, too avoid too sensitive values that will lead to unexpected behaviour (due to modelling error) or unacceptable performance in practice.

In Figures 5a and 5b, the approximated Pareto front and set (respectively) are depicted. As it can be noticed, the first co-design approach is able to reach a small portion of the third design objective. The second co-design and simultaneous approaches have a better covering on the third design objective and therefore, a better approximation of the Pareto frontier. Nevertheless, the last one gets an overall better coverage of the objective space. In Figure 5c, a Pareto front comparison using level diagrams is depicted for the co-design approaches [6] . With such visualisation, it is possible to appreciate the advantages of using the tuneable parameter of the SIMC tuning rule within. Regarding the simultaneous approach, further analysis would be required in order to determine if the additional covering is really valuable for the designer.

4.2 MOP-2

The second MOP statement is defined using the same process, but with meaningful design objectives:

$$\min_{\boldsymbol{x}} \boldsymbol{J(x)} = [J_{st}(\boldsymbol{x}), J_{os}(\boldsymbol{x}), J_{Ms}(\boldsymbol{x})] \quad (30)$$

where $J_{st}(\boldsymbol{x})$ is the settling time (at 98%); $J_{os}(\boldsymbol{x})$ is the percentage overshoot and $J_{Ms}(\boldsymbol{x})$ the maximum value of the sensitivity function of the closed loop. Once again, last objective is bounded within the limits $1.5 \leq J_{Ms}(\boldsymbol{x}) \leq 1.9$.

In Figures 6a and 6b, the approximated Pareto front and set (respectively) are shown. Main difference with the previous example is the covering of the second co-design and simultaneous approaches: the latter dominates a portion of the former. In Figure 6c, a Pareto front comparison using level diagrams is depicted for both of them in order to appreciate such behaviour. As it can be noticed, when different design objectives are stated, tendencies are different when compared with the previous example. While in MOP-1 there was no conclusive advantage between them in this example the simultaneous approach dominates the second co-design statement, indicating that for those design objectives, it is a clear advantage to use as decision variables both PI controller parameters, instead the tuneable parameter of the SIMC tuning rule and its simplification of the process model.

[6] In such visualisation, values above 1 are design alternatives of a Pareto front which are dominated by the remainder Pareto front; values below 1 are design alternatives of a Pareto front which dominates at least a portion of the remainder Pareto front. That is, the further away from 1, the more design alternatives are dominated by or dominate others.

5. CONCLUSIONS

Multidisciplinary design optimisation (MDO) is a valuable tool for designers when different fields converge in the design phase. Where classical approaches perform a sequential optimisation procedure, it seeks to exploit synergies between interacting subsystems. In this paper, three different optimisation approaches for multidisciplinary design were compared for process and control design; such statements integrate plant (process) design and the PI controller tuning process. Such comparison was performed using multi-objective optimisation techniques, since conflictive objectives appear.

With the provided examples, co-design approaches are able to approximate the Pareto frontier for design objectives as IAE and ITAE. That is, simplifications required in the process model in order to apply the SIMC-rule might provide an acceptable Pareto front approximation for such design objectives. Nevertheless, with design objectives as settling time and overshoot, the simultaneous approach using the model process *as it is* provides better results. This means that, in spite of the usefulness of a tuning rule like SIMC, such tuning technique might reduce significantly the decision space of the design variables. Therefore more integrated approaches need to be considered for plant and control design simultaneously.

Further research on this direction, identifying the subset of design objectives where a tuning rule could provide acceptable performance within this framework might be valuable. On going work on this MDO approach includes comparing different co-design approaches for PI-PID controllers, as well as more complex control structures.

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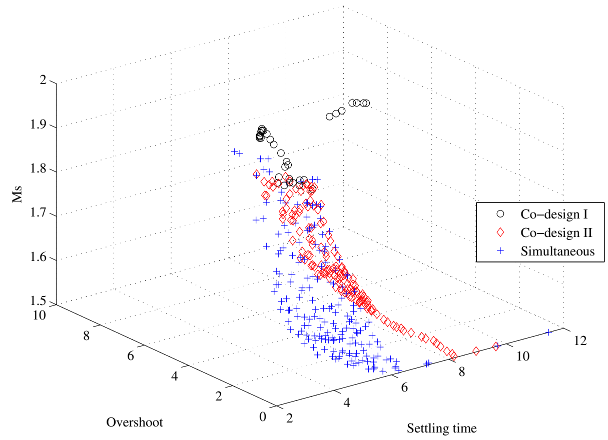
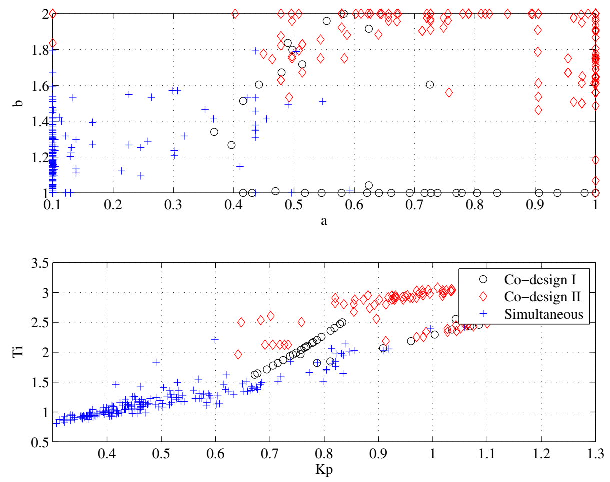
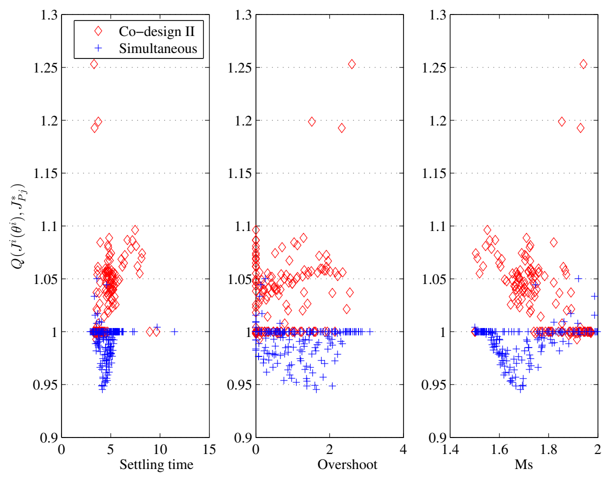


(a) Pareto front



(b) Pareto set



(c) Pareto front comparison

Fig. 6. MOP-2 results.

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