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# Preference driven multi-objective optimization design procedure for industrial controller tuning

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ABSTRACT

Multi-objective optimization design procedures have shown to be a valuable tool for control engineers. These procedures could be used by designers when (1) it is difficult to find a reasonable trade-off for a controller tuning fulfilling several requirements; and (2) if it is worthwhile to analyze design objectives exchange among design alternatives. Despite the usefulness of such methods for describing trade-offs among design alternatives (tuning proposals) with the so called Pareto front, for some control problems finding a pertinent set of solutions could be a challenge. That is, some control problems are complex in the sense of finding the required trade-off among design objectives. In order to improve the performance of MOOD procedures for such situations, preference handling mechanisms could be used to improve pertinency of solutions in the approximated Pareto front. In this paper an overall MOOD procedure focusing in controller tuning applications using designer's preferences is proposed. In order to validate such procedure, a benchmark control problem is used and reformulated into a multi-objective problem statement, where different preference handling mechanisms in the optimization process are evaluated and compared. The obtained results validate the overall proposal as a potential tool for industrial controller tuning.



## 1. Introduction

Multi-objective Optimization Design (MOOD) procedures using Evolutionary Multi-objective Optimization (EMO) have shown to be a valuable tool for controller tuning applications [41]. They enable the designer or decision maker (DM) having a close embedment into the design process; since it is possible to take into account each design objective individually; they also enable comparing design alternatives (*i.e.* tuning proposals), in order to select a controller fulfilling the expected trade-off among conflicting objectives. This MOOD procedure comprises at least, three fundamental steps: the multi-objective problem (MOP) definition, the EMO process and the multicriteria decision making (MCDM) step.

Such procedures have been used with success when (1) it is difficult to find a reasonable trade-off for a controller tuning fulfilling several requirements; and (2) if it is worthwhile analyzing design objectives exchange among design alternatives. Despite the usefulness of such methods for describing trade-offs among design alternatives by the so called Pareto front,

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for some control problems finding a pertinent set of solutions could be a challenge. In such instances, finding pertinent solutions could be difficult due to complexity of the process and/or complexity of the MOP statement.

The former case refers when the process complexity makes difficult finding desirable solutions, even for 2 or 3 design objectives. That is, the region in the decision (search) space which fulfils designer's preferences could be difficult to find. In the latter case, designer commonly face the problem of fulfilling several performance objectives and requirements. If the number of design objectives is more than 3, it is said that the designer is dealing with a many-objective optimization instance. This could increase the complexity of the EMO process and the MCDM step, since diversity and convergence properties of a given algorithm usually conflict each other in the Pareto front approximation.

An alternative to overcome the above mentioned issues, is the inclusion of preferences in the EMO process. The inclusion of preferences is exploited by algorithms in order to provide an interesting (useful) Pareto front approximation for designers [7]. This information could be used in the same way to deal effectively with many-objective optimization instances [21], since the algorithm could be able to focus in the interesting regions of the objective space. Furthermore, preferences could be used to bridge any gap between problems definition, optimization and decision making process [34,41] leading to a holistic design procedure. With this tool, designer could address more effectively with complex processes, in the sense of complex to find a desirable trade-off among conflicting objectives.

The aim of this paper is twofold. On the one hand, proposing a MOOD procedure taking into account preference handling for controller tuning, in order to improve pertinency of solutions when it is difficult to find a desirable (required) trade-off. On the other hand, through the example provided, stating a controller tuning benchmark in the multi-objective optimization context. The lack of formal benchmarks definitions for multi-objective optimization in the control context was noticed in [41]; the statement of such benchmark will enable the comparison among techniques, methodologies and algorithms in the MOOD procedure context. This situation can motivate further developments of the MOOD procedure in controller tuning applications.

The remainder of this paper is as follows: in Section 2 a brief background on MOOD procedures and preference handling is commented; in Section 3 the proposal of this paper is presented; Section 4 is devoted to validate the MOOD procedure with preferences for controller tuning; with this aim, two different instances are stated using the Boiler Control benchmark problem of [28]: a univariable and a multivariable statement. Finally, some concluding remarks are given.

## 2. Theorical background on multi-objective optimization: A controller tuning context

Some notions on multi-objective optimization and preference handling techniques are required. They are provided below, within the controller tuning framework.

### 2.1. Multi-objective optimization statement

As referred in [26], a MOP[1], can be stated as follows:

$$\min_{\boldsymbol{x}} \boldsymbol{J}(x) = [J_1(\boldsymbol{x}), \ldots, J_m(\boldsymbol{x})] \tag{1}$$

subject to:

$$\boldsymbol{K}(\boldsymbol{x}) \le 0 \tag{2}$$

$$\boldsymbol{L}(\boldsymbol{x}) = 0 \tag{3}$$

$$\underline{x_i} \le x_i \le \overline{x_i}, i = [1, \ldots, n] \tag{4}$$

where $\boldsymbol{x} = [x_1, x_2, \ldots, x_n]$ is defined as the decision vector; $\boldsymbol{J}(\boldsymbol{x})$ 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 upper bounds in the decision space.

It has been pointed out 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 $\boldsymbol{\Theta}_P$, is defined. Each solution in the Pareto set defines an objective vector in the Pareto front $\boldsymbol{J}_P$. All the solutions in the Pareto front conforms a set of Pareto optimal and non-dominated solutions (Fig. 1):

**Definition 1** (Pareto optimality [26]). An objective vector $\boldsymbol{J}(\boldsymbol{x}^1)$ is Pareto optimal if there is not another objective vector $\boldsymbol{J}(\boldsymbol{x}^2)$ such that $J_i(\boldsymbol{x}^2) \le J_i(\boldsymbol{x}^1)$ for all $i \in [1, 2, \ldots, m]$ and $J_j(\boldsymbol{x}^2) < J_j(\boldsymbol{x}^1)$ for at least one j, $j \in [1, 2, \ldots, m]$.

**Definition 2** (Dominance [8]). An objective vector $\boldsymbol{J}(\boldsymbol{x}^1)$ is dominated by another objective vector $\boldsymbol{J}(\boldsymbol{x}^2)$ iff $J_i(\boldsymbol{x}^2) \le J_i(\boldsymbol{x}^1)$ for all $i \in [1, 2, \ldots, m]$ and $J_j(\boldsymbol{x}^2) < J_j(\boldsymbol{x}^1)$ for at least one j, $j \in [1, 2, \ldots, m]$.

It is important to notice that the Pareto front is usually unknown, and the DM can only rely on a Pareto front approximation $\boldsymbol{J}_P^*$. In order to successfully embed the multi-objective optimization concept into a design process, three fundamental

[1] A maximization problem can be converted to a minimization one. For each of the objectives that has to be maximized, the transformation: $\max J_i(\boldsymbol{x}) = -min(-J_i(\boldsymbol{x}))$ could be applied.