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Controller tuning using evolutionary multi-objective optimisation: Current trends and applications

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ABSTRACT

Control engineering problems are generally multi-objective problems; meaning that there are several specifications and requirements that must be fulfilled. A traditional approach for calculating a solution with the desired trade-off is to define an optimisation statement. Multi-objective optimisation techniques deal with this problem from a particular perspective and search for a set of potentially preferable solutions; the designer may then analyse the trade-offs among them, and select the best solution according to his/her preferences. In this paper, this design procedure based on evolutionary multiobjective optimisation (EMO) is presented and significant applications on controller tuning are discussed. Throughout this paper it is noticeable that EMO research has been developing towards different optimisation statements, but these statements are not commonly used in controller tuning. Gaps between EMO research and EMO applications on controller tuning are therefore detected and suggested as potential trends for research.

1. Introduction

Satisfying a set of specifications and constraints required by real-control engineering problems is often a challenge. For parametric controller tuning, for example, these range from time-domain specifications to frequency-domain requirements. Problems in which the designer must deal with the fulfillment of multiple objectives are known as multi-objective problems (MOPs).

It is common to define an optimisation statement to deal with MOPs and calculate a solution with the desired balance among (usually conflictive) objectives. When dealing with an MOP, we usually seek a Pareto optimal solution (Miettinen, 1998) in which the objectives have been improved as much as possible without giving anything in exchange. According to Mattson and Messac (2005), there are two main approaches to solving an optimisation statement for an MOP: the *aggregate objective function* (AOF) and the *generate-first choose-later* (GFCL) approach.

In the AOF context a single-index optimisation statement that merges the design objectives is defined. In such cases, the decision maker (DM or simply the designer) needs to describe all the trade-offs at once and at the beginning of the optimisation process. In the GFCL approach, the main goal is to generate many potentially desirable Pareto optimal solutions, and then select the most preferable alternative. This is due to the impossibility of obtaining a solution that is good for all objectives, and therefore several solutions with different trade-off levels may appear. The selection takes place in a *multi-criteria decision-making* (MCDM) step, where the task of the DM is to analyse the trade-offs among the objectives, and select the best solution according to his/her preferences.

One way to generate such sets of potential solutions in the GFCL approach is by means of multi-objective optimisation. This optimisation approach seeks for a set of Pareto optimal solutions to approximate what is known as the Pareto set (Marler & Arora, 2004; Miettinen, 1998). A Pareto set approximation may provide a preliminary idea of the objective space, and according to Bonissone, Subbu, and Lizzi (2009) it could be helpful when it is necessary to explain and justify the MCDM procedure. As drawbacks, more time and embedment of the DM in the overall process are necessary.

In order to approximate this Pareto set, classic optimisation techniques (Miettinen, 1998) and *evolutionary multi-objective optimisation* (EMO) approaches have been used. In the latter case, *multi-objective evolutionary algorithms* (MOEAs) have become a valuable tool to approximate the Pareto front for non-convex, non-linear and constrained optimisation instances (Coello & Lamont, 2004; Coello, Veldhuizen, & Lamont, 2002). They have been used with success in several control systems (Fleming & Purshouse, 2002) and engineering design (Saridakis & Dentsoras, 2008) areas.

Regarding the GFCL framework, when the multi-objective optimisation process is merged with the MCDM step for a given

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MOP statement, it is possible to define a multi-objective optimisation design (MOOD) procedure (Reynoso-Meza, Blasco, & Sanchis, 2012). This MOOD procedure cannot substitute, in all instances, an AOF approach; nevertheless, it could be helpful in complex design problems, where a close embedment of the designer is necessary. For example, when an analysis of trade-offs would be valuable for the DM before implementing a desired solution.

In this paper, an overview of different applications and examples of MOOD procedures in control system engineering is provided. The paper is focused on this MOOD procedure since from a practical point of view, it is necessary to perform the optimisation as well as the MCDM stage. Likewise, only instances where the EMO is used in the optimisation process are discussed. Therefore this means that optimisation statements using AOF approaches for MOPs are outside the scope of this paper. This work is not intended to present an exhaustive review of the literature, but to identify promising and potential areas of EMO in control systems. The rest of this paper is organised as follows: in Section 2 some definitions regarding MOP are given together with the MOOD procedure. In Section 3, several applications of MOOD for PID, fuzzy, predictive and state space feedback controllers are discussed. Finally, some concluding remarks and possible trends for research are indicated.

2. Multi-objective optimisation design procedure

An MOP, without loss of generality,[1] can be stated as follows:

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

subject to

$$\boldsymbol{g}(\boldsymbol{\theta}) \leq 0 \tag{2}$$

$$\boldsymbol{h}(\boldsymbol{\theta}) = 0 \tag{3}$$

$$\underline{\theta_i} \leq \theta_i \leq \overline{\theta_i}, \quad i = [1, \ldots, n] \tag{4}$$

where $\boldsymbol{\theta} \in \Re^n$ is defined as the decision vector, $\boldsymbol{J}(\boldsymbol{\theta}) \in \Re^m$ as the objective vector, $\boldsymbol{g}(\boldsymbol{\theta})$, $\boldsymbol{h}(\boldsymbol{\theta})$ as the inequality and equality constraint vectors respectively; $\underline{\theta_i}, \overline{\theta_i}$ are the lower and upper bounds in the decision space for θ_i variable.

As remarked previously, there is no single solution because in general there is no solution that is best for all 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 solutions in the Pareto front are said to be a set of Pareto-optimal and non-dominated solutions.

Definition (*Pareto optimality, Miettinen, 1998*). An objective vector $\boldsymbol{J}(\boldsymbol{\theta}^1)$ is Pareto optimal if there is no other objective vector $\boldsymbol{J}(\boldsymbol{\theta}^2)$ such that $J_i(\boldsymbol{\theta}^2) \leq J_i(\boldsymbol{\theta}^1)$ for all $i \in [1, 2, \ldots, m]$ and $J_j(\boldsymbol{\theta}^2) < J_j(\boldsymbol{\theta}^1)$ for at least one j, $j \in [1, 2, \ldots, m]$.

Definition (*Dominance (Miettinen, 1998)*). An objective vector $\boldsymbol{J}(\boldsymbol{\theta}^1)$ is dominated by another objective vector $\boldsymbol{J}(\boldsymbol{\theta}^2)$ if $J_i(\boldsymbol{\theta}^2) < J_i(\boldsymbol{\theta}^1)$ for all $i \in [1, 2, \ldots, m]$.

For example, in Fig. 1, five different solutions ($\diamond$) are calculated to approximate a Pareto front (bold line). Solutions A, B, and C are non-dominated solutions, since there are no better solution vectors (in the calculated set) for all the objectives. Solutions B and C are not Pareto optimal, since some solutions (not found in this case) dominate them. Furthermore, solution A is also Pareto optimal, since it lies on the feasible Pareto front. The set of non-dominated solutions (A, B, and C) build the Pareto front approximation. It is important to notice that most of the times the Pareto front is unknown and we shall only rely on approximations.

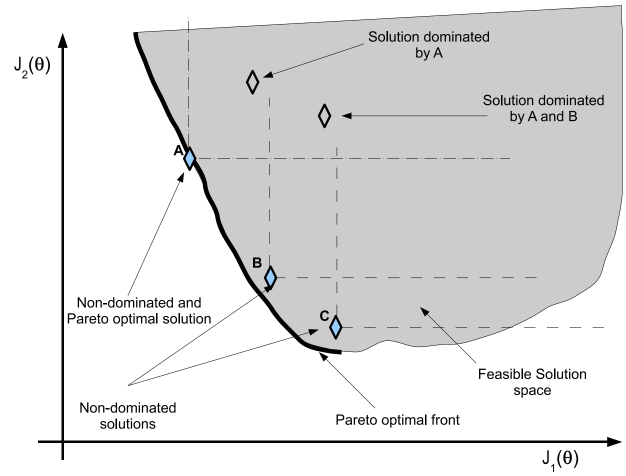

Fig. 1. Pareto optimality and dominance concepts.

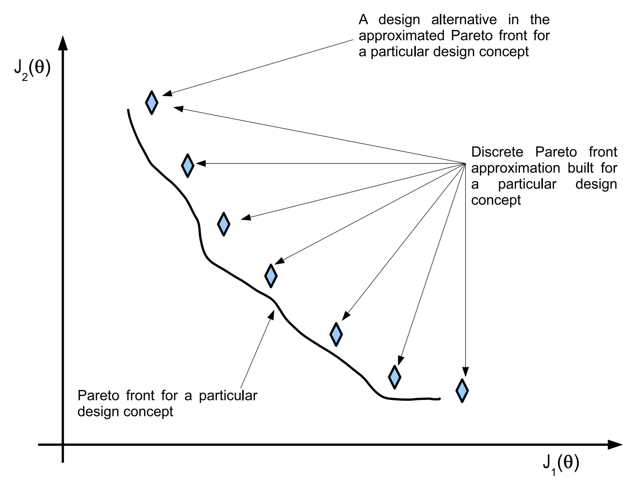

Fig. 2. Design concept and design alternative.

In Mattson and Messac (2005), an addendum is incorporated into the Pareto front notion to differentiate design concepts. A Pareto front is defined given a design concept (or simply, a concept) which is an idea about how to solve a given MOP. This design concept is built with a family of design alternatives (Pareto-optimal solutions) that are specific solutions in the design concept. For example, in Fig. 2, a Pareto front approximation (bold line) for a particular design concept is calculated with a set of Pareto-optimal design alternatives ($\diamond$); we can state, for example, a PID controller for a given MOP as a design concept, where a design alternative is a specific set of values for its parameters.

As remarked in Mattson and Messac (2005), a comparison between design concepts could be useful for the designer, because he will be able to identify the concept strengths, weaknesses, limitations and drawbacks. It is also important to visualise such comparisons, and to have a quantitative measure to evaluate strengths and weaknesses.

A general framework is required to successfully incorporate this approach into any engineering design process. A multi-objective optimisation design (MOOD) procedure is shown in Fig. 3. It consists of (at least) three main steps (Coello, Lamont, & Veldhuizen, 2007, 2002): the MOP definition (measurement); the multi-objective optimisation process (search); and the MCDM stage (decision making).

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