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# An interactive decision-support system for multi-objective optimization of nonlinear dynamic processes with uncertainty

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ABSTRACT

The manufacturing industry is faced with the challenge to constantly improve its processes, e.g., due to lower profit margins, more strict environmental policies and increased societal awareness. These three aspects are considered as the pillars of *sustainable development* and typically give rise to multiple and conflicting objectives. Hence, any decision made will require trade-offs to be evaluated and compromises to be made. To support decision making an interactive multi-objective framework is presented to optimize dynamic processes based on mathematical models. The framework includes a numerically efficient strategy to account for parametric uncertainty in the models and it allows to directly minimize the operational risks arising from this uncertainty. Hence, for the first time expert knowledge on the trade-offs between traditional objective functions and operational risks is readily and interactively available for the practitioners in the field of dynamic systems. The introduced interactive framework for multi-objective dynamic optimization under uncertainty is successfully tested for a three and five-objective fed-batch reactor case study with uncertain feed temperature and heat transfer parameters.



## 1. Introduction

The increased awareness towards societal (e.g., increase safety and maintain/increase occupational level) and environmental aspects (e.g., decrease energy consumption and decrease emissions) of public institutions has indicated *sustainable development* as a main target for the whole global manufacturing industry. The priorities and targets of the EU growth strategy Europe-2020 confirmed this trend. An important aspect of *sustainable development* includes targeting a more *sustainable operation* of the existing technologies.

Dynamic mathematical models and model based optimization techniques have for more than 30 years contributed to improvements in economic sustainability (e.g., maximize profit or production) of industrial processes. However, much less effort has been spent on: (i) the inclusion of societal and environmental impact within optimization studies, (ii) the *trade-offs* arising between all objectives, (iii) the proposition of different optimal improvement alternatives (iv) the efficient visualization and analysis of proposed alternatives and (v) the making of well-informed decisions for operation under uncertainty.

### 1.1. Multi-objective and model based optimization as expert systems

For all these reasons, it is crucial to recognize the value of model based optimization and multi-objective optimization algorithms as powerful *expert systems*. In particular, one should consider how difficult it would be for a human-being to decide upon tens of degrees of freedom, subjected to (possibly) non-linear dynamic equations, constraints and objective functions. Adding to this mix, multiple and conflicting objectives, uncertainty and multi-dimensional data, makes the task of selecting an optimal operation policy extremely daunting. Hence, there is the need to develop advanced *expert systems* that draw from several different research directions (e.g., multi-objective optimization, model based dynamic optimization, interactive software design, information theory, decision-making and data visualization and analysis) to support experts in the field to make sound and reliable decisions in real-time.

With respect to multi-objective optimization (MOO), typically, a single solution that optimizes all conflicting objectives simultaneously is not possible, but there exists a set of mathematically equivalent solutions, known as the *Pareto set* (Miettinen, 1999). In order to select the best solution among this set of alternatives, an expert in the field of the investigated problem, i.e., a *decision-maker* (DM) is asked to express his/her *preferences*. To support decision-making in practice MOO can be exploited to help the DM generate different Pareto optimal alternatives according to

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his/her preferences and choose among them. Based on the way these preferences are taken into account, it is possible to categorize the different MOO methods in Marler and Arora (2004): (i) *a priori*; the DM expresses his/her preferences before generating the solution, (ii) *a posteriori*; the DM decides based on a set of previously generated alternatives and (iii) *interactive*; the DM directly participates in the solution procedure by consecutively refining the set of generated solutions according to his/her updated preferences.

### 1.2. Interactive multi-objective optimization

In the last decade the multi-objective optimization aspects in the operation of dynamic processes (resulting in so-called *multi-objective dynamic optimization* or *multi-objective optimal control problems* (MOOCPs)) have gained interest (see, e.g., Agrawal, Rangaiah, Ray, & Gupta, 2006; Deb, Mitra, Dewri, & Majumdar, 2004; Logist, Houska, Diehl, & Van Impe, 2010, 2012; Sarkar & Modak, 2004). It has to be mentioned that these infinite dimensional optimal control problems are typically discretized resulting into finite dimensional large-scale nonlinear optimization problems (NLPs).

Hence, in this context it may become computationally expensive to compute a well-distributed set of Pareto points over the entire feasible criteria space or it might be a non-trivial task for the DM to correctly condense his/her preferences in mathematical terms. One possible solution comes from *interactive multi-objective optimization* algorithms. These methods gradually explore the *Pareto set* based on a consecutive and repeated interaction with the DM. During the human-algorithm interaction the DM can gain valuable knowledge about the problem and adjust his/her preferences according to constantly updated and refined information. Often, interactive methods implement an achievement scalarization function (ASF) (Wierzbicki, 1980) in one of its variants to generate Pareto optimal alternatives (Luque, Lopez-Agudo, & Marcenaro-Gutierrez, 2015). As a consequence, it is possible to distinguish between methods according to the way the preference update is performed: (i) by updating the reference point (e.g. Eskelinen, Miettinen, Klamroth, & Hakanen, 2010; Hassanzadeh, Nemati, & Sun, 2014; Nikulin, Miettinen, & Mäkelä, 2012; Wierzbicki, 1982) or by assigning the different objectives to categories, e.g., to be improved and can be worsened. An example of the latter class is the NIMBUS method (Miettinen & Mäkelä, 1995). Recently, it has been extended to IND-NIMBUS with additional methods from the former class (Eskelinen et al., 2010; Hartikainen, Miettinen, & Wiecek, 2012) and it was linked to the dynamic process simulator APROS (Sindhya et al., 2014).

The proposed interactive method differs from the previously mentioned approaches both from a theoretical and from a practical point of view. First of all, the proposed method is based on an interactive adaptation of the Normal Boundary Intersection (NBI, Das & Dennis, 1998) and Enhanced Normalized Normal Constraint (ENNC, Messac & Mattson, 2004; Sanchis, Martinez, Blasco, & Salcedo, 2008) methods. Hence, the DM does not express his/her preferences via a reference point or by assigning objectives to categories but via the *browsing* of the scalarization parameters, i.e., *weights*, space. This represents the first difference in respect to other interactive methods since there is a fundamental shift in paradigm during the interaction between the DM and the algorithm. A second difference is given by the active use of the Graphical User Interface (GUI) as a learning tool for the DM, when solving dynamic optimization problems. The proposed GUI allows the DM to grasp the underlying system dynamics and to identify possible process bottlenecks and critical constraints via the interactive visualization of the state and control profiles. After this first learning step the DM can decide either to refine the entire Pareto set or to add an additional point in a specific location of interest on the Pareto set. The use of the GUI to explore in depth the obtained dynamic optimization solutions represents a novelty with respect to algorithm implementation which is necessary when dealing with dynamic systems. A similar approach to the one presented here was presented by Bortz et al. (2014). There an interactive implementation of the Pascoletti–Serafini scalarization method (Pascoletti & Serafini, 1984, i.e., the general case of NBI and ENNC) was used and it was connected to the steady-state flowsheet simulator CHEMASIM. Also there the DM updates his/her preference by selecting the scalarization parameters via sliders. Additionally, in this work a sandwich approach (i.e., calculation of outer and inner approximations was used) to estimate the accuracy of the Pareto front. The main difference in methodology between the two methods is that in the proposed implementation a simplicial grid is imposed on the Pareto front, where the Pareto points are the vertices of the multi-dimensional simplices. This allows a better understanding of the relationship between points and it is also used to provide decision support for problems with more than two objectives.

It has to be noted that all the interactive MOO methods discussed so far are based on deterministic scalarization methods, a separate discussion could be done for evolutionary strategies (e.g., Deb, 2001; Deb & Jain, 2014) and their interactive implementations (see e.g., Beiranvand, Mobasher-Kashani, & Bakar, 2014; Chaudhuri & Deb, 2010; Fowler et al., 2010; Gong, Ji, Sun, & Sun, 2014; Gong, Sun, & Ji, 2013; Hettenhausen, Lewis, & Kipouros, 2014; Kollat & Reed, 2007; Montoya, Manzano-Agugliaro, Lapez-Marquez, Hernandez-Escobedo, & Gil, 2014; Pedro & Takahashi, 2014; Sinha, Korhonen, Wallenius, & Deb, 2014). The reasons behind this is due to the differences between the way candidate Pareto solutions are generated and the fact that the DM interaction is mostly limited to the selection of a reference point. Hence, since the current work is based on deterministic and scalarization based approaches, for the sake of brevity, a detailed discussion on evolutionary based methods is not reported here.

Moreover, in order to exploit all the possible benefits and to limit the possible drawbacks coming from the deployment of human-algorithm interactions, a careful attention to the design of the interactivity features should be taken into account (Tarkkanen, Miettinen, Hakanen, & Isomäki (2013)). In this respect, it results crucial to avoid overloading the DM with too much information (Miller, 1956; Miettinen, 1999) which can undermine his/her decision capabilities, extend the time to reach a decision or even mislead him/her towards (possibly) wrong search directions. A possible solution to this problem as been recently introduced by Ojalehto, Podkopaev, and Miettinen (2015). There, the DM is assisted by *agents*, which help guiding the exploration process towards predetermined search directions. Another possibility comes from a wider and more systematic use of concepts and tools (e.g., Bostock, Ogievetsky, & Heer, 2011) from the field of visual analytics (i.e., analytic reasoning supported by tailored data visualizations). In this respect the work of Hettenhausen et al. (2014) can be considered a first starting point. In this work a step in this direction is done by allowing the DM to interactively select between different visualization methods both for the learning phase and for updating his/her preferences. In particular, for the latter case the proposed GUI makes use of dedicated support-decision windows that allow the DM to gain different insights and, therefore, build a stronger confidence in his/her decision in a shorter amount of time.

### 1.3. Quantify uncertainty to minimize operational risk

Additionally, another important contribution of this work is the possibility to directly consider operational risk related to uncertainty in the process parameters as an objective function.