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An archive-based multi-objective evolutionary algorithm with adaptive search space partitioning to deal with expensive optimization problems: Application to process eco-design

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ABSTRACT

In eco-design, the integration of environmental aspects into the earliest stage of design is considered with the aim of reducing adverse environmental impacts throughout a product's life cycle. An eco-design problem is therefore multi-objective, where several objectives (environmental, economic, and technological) are to be simultaneously optimized.

The optimization of industrial processes usually requires solving expensive multi-objective optimization problems (MOPs). Aiming to solve efficiently MOPs, with a limited computational budget, this paper proposes a new framework called AMOEA-MAP. The framework relies on the structure of the NSGAII algorithm and possesses two novel operators: a memory-based adaptive partitioning strategy, which provides an adaptive reticulation of the search space for a quick identification of optimal zones with less computational effort; and a bi-population evolutionary algorithm, tailored for expensive optimization problems.

To ascertain its generality, the framework is first tested on several tough benchmarks. Its performance is subsequently validated on a real-world eco-design problem.

1. Introduction

1.1. Motivation

In many engineering optimization fields, multi-objective problems (MOPs) require high fidelity prediction of the economic, technical and environmental performance of processes. This increasingly rigorous modelling of different behaviours and performances in a given process leads to time consuming (or computationally expensive) black-box simulations and hence to expensive function evaluations. As an example for the eco-design of a conventional potable water production plant, illustrated in Ahmadi and Tiruta-Barna (2015), a MOP incorporated:

- Rigorous modelling of multiple unit operations and their corresponding simulations.
- Complete integration of the Life Cycle Assessment (LCA) as an independent software and methodology.
- Water quality databases and the water chemistry calculations.
- Evaluations of other efficiencies, costs, and performance indicators.

All these features are to be handled simultaneously within an integrated platform, where both simulations and data transfer between different modules are usually time consuming. Similar difficulties have been widely identified and discussed in the literature on various environmental and LCA-based optimization problems (Garcia and You, 2015; Capitanescu et al., 2015a,b; Capon-Garcia et al., 2014; You et al., 2012; Guillen-Gosalbez and Grossmann, 2010; Gerber et al., 2011). Therefore, the development of an efficient optimization method to deal with expensive simulation-based MOPs, by simultaneously providing good accuracy

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and fewer function evaluations is an essential contemporary challenge.

1.2. Basic notions of computationally expensive MOP

A MOP describes conflicting trade-offs (where the improvement in one objective function results in the deterioration of another) and can be mathematically stated as,

$$\begin{aligned} &\text{Minimize} \quad F(x) = (f_1(x), \ldots, f_m(x)) \\ &\text{Subject to} \quad x \in \Lambda \end{aligned} \tag{1}$$

where, m is the number of objectives, x the vector of decision variables, $f_i(x)$ the objective functions, and Λ the multi-dimensional search space. Given a population of solutions, the concept of domination is defined to discriminate solutions one against another. For two solutions x_1 and x_2, the solution x_1 is said to dominate x_2 (which is denoted by $x_1 < x_2$) if and only if $f_i(x_1) \leq f_i(x_2)$ for all objective functions and $f_i(x_1) < f_i(x_2)$ on at least one objective function. The Pareto front comprises all optimal solutions belonging to the set of non-dominated optimal solutions known as the Pareto Set (PS) and its image on the objective space is called the Pareto Front (PF).

A computationally expensive MOP can exhibit one or more of the following general features:

(a) One function evaluation demands a computational time ranging from several minutes to several hours.
(b) Running multiple evaluations simultaneously is difficult or impossible (parallelism).
(c) The total number of function evaluations is restricted by different constraints.
(d) A simplified approximation of problem modelling does not provide realistic predictions (complex black-box models).
(e) The search space is locally smooth but multimodal.

In order to deal with these characteristics, the optimization method must be able to produce reasonable solutions within a limited computational budget; in other words, with a limited number of function evaluations.

1.3. Literature survey

Zhou et al. (2011) conducted an interesting survey on the extensive developments of multi-objective evolutionary algorithms (MOEAs) during the past decade. Owing to their ability to evolve a population of solutions, their efficiency in approximating the set of global optimal solutions in a single run, and their derivative-free search strategy, MOEAs have been widely used and investigated in the literature (Fonseca and Fleming, 1993; Zitzler et al., 2001; Deb et al., 2002) to deal with MOPs with different degrees of complexity: non-linearity, stiffness, black-box, and multimodality. The key limitations of MOEAs, due to their evolutionary features, are the slow convergence near optimum solutions and the significant number of function evaluations needed to provide optimal solutions. These limitations make conventional MOEAs incompatible with expensive optimization problems, if they are used in their original form.

As regrouped in Table 1, several advanced strategies proposed so far to improve convergence performances and/or deal with expensive MOPs in different engineering fields can be classified into six groups. A few major works in each abovementioned classes are briefly reviewed hereafter.

1.3.1. Class A

The main research effort put in the enhancement of conventional MOEAs for demanding MOPs focuses on the improvement of the accuracy vs speed trade-off. The goal is to accelerate the speed of convergence while not deteriorating accuracy by the use of efficient metaheuristics. In this regard, special attention has been paid to hybrid and memetic MOEAs where, the global and local search algorithms are used together (Kim and Liou, 2014; Lara et al., 2010; Igel et al., 2007; Knowles and Corne, 2005), or search operators of different algorithms are combined (Alberto et al., 2014). Inspired by the gradient-free Hill Climber with Sidestep (HCS) local search operator of Lara et al. (2010), Kim and Liou (2014) introduced a novel directional local search operator for MOEAs, called efficient Local Search (eLS). The latter uses a hill climber method to improve convergence, but does not adopt the sidestepper in order to reduce the number of additional function evaluations. The eLS algorithm is among the most promising recent metaheuristics to deal with the improvement of the accuracy/speed ratio in the convergence of MOEAs. This work also investigates the hybrid eLS as a baseline for comparison, owing to its memory-based peculiarity providing directional local search through previously evaluated solutions in the neighbourhood without sidestep.

1.3.2. Class B

Zhang and Li (2007) proposed a decomposition-based strategy in MOEAs where MOPs are decomposed into a number of sub-problems, each sub-problem being optimized in a collaborative manner by using information provided from their neighbouring sub-problems. Because the objective for each sub-problem is defined as a weighted aggregation of the individual objectives, it can result in a prior ordering of objectives, where realistic interactions among objectives and their importance are susceptible to misevaluation or loss.

1.3.3. Class C

The micro genetic algorithms (Coello Coello and Pulido, 2001; Pulido and Coello Coello, 2003) aim to provide a very fast converging algorithm with low computational costs by using either a small population and a re-initialization process (Coello Coello and Pulido, 2001), or by adaptive readjustment of evolutionary parameters such as crossover rate, population size and the number of subdivisions of the grid to control clustering (Pulido and Coello Coello, 2003). The algorithm was outperformed by the state-of-the-art NSGAII on certain test functions; however, several features such as

Table 1
Literature on advanced strategies for the enhancement of convergence performance in multi-objective optimization.

Multi-objective optimization strategies		Literature
A	Hybrid/memetic multi-objective evolutionary algorithms	Kim and Liou (2014), Alberto et al. (2014), Lara et al. (2010), Igel et al. (2007), Knowles and Corne (2005)
B	Interactive scalarization methods based on decomposition	Alhindi and Zhang (2014), Zhang and Li (2007)
C	Micro Genetic Algorithms	Pulido and Coello Coello (2003), Coello Coello and Pulido (2001)
D	Efficient evolutionary algorithms	Aittokoski and Miettinen (2008)
E	Interactive and surrogate problem construction techniques	Ojalehto et al. (2015), Capitanescu et al. (2015)
F	Gaussian stochastic process modelling for multi-objective optimization problems	Zhang et al. (2010), Ponweiser et al. (2008), Knowles (2006)