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Injecting problem-dependent knowledge to improve evolutionary optimization search ability

Joaquín Izquierdo [a,*], Enrique Campbell [a], Idel Montalvo [b], Rafael Pérez-García [a]

[a] FluIng-IMM, Universitat Politècnica de València, Cno. de Vera s/n, 46022 Valencia, Spain

[b] Ingeniousware GmbH, Bahnhofstraße 4a, 76137 Karlsruhe, Germany

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ABSTRACT

The flexibility introduced by evolutionary algorithms (EAs) has allowed the use of virtually arbitrary objective functions and constraints—even when evaluations require, as for real-world problems, running complex mathematical and/or procedural simulations of the systems under analysis. Even so, EAs are not a panacea. Traditionally, the solution search process has been totally oblivious of the specific problem being solved, and optimization processes have been applied regardless of the size, complexity, and domain of the problem. In this paper, we justify our claim that far-reaching benefits may be obtained from more directly influencing how searches are performed. We propose using data mining techniques as a step for dynamically generating knowledge that can be used to improve the efficiency of solution search processes. In this paper, we use Kohonen SOMs and show an application for a well-known benchmark problem in the water distribution system design literature. The result crystallizes the conceptual rules for the EA to apply at certain stages of the evolution, which reduces the search space and accelerates convergence.

1. Introduction

Optimization permeates every human endeavor, in particular, science and technology. The main interest is usually placed in solving real-world problems. However, the closer a problem is to reality, the more complex it becomes. Complexity derives from a number of facts: coexistence of various (in general, conflicting) objectives; objectives defined by complex mechanisms (not only functions, but also procedures); sensitive constraints that are difficult to meet (perhaps needing simulation to be represented); nonlinear expressions (frequently associated with lack of smoothness and even continuity); dependence of many decision variables (multi-dimensionality); coexistence of various types of decision variables (mixed Boolean-integer-real); uncertainty (both for the model and the problem data); multi-modality (coexistence of many good non-optimal solutions), etc. Classical optimization techniques (including classical numerical methods for optimization) have shown an obvious inability to meet their objectives. During the last two decades a plethora of new derivative-free approaches based on various natural (social, biological, etc.) principles have shown better performances when tackling some categories of real-world problems. Sometimes they are grouped together under the general umbrella of evolutionary algorithms (EAs) and include: genetic algorithms (GA) [1]; ant colony optimization (ACO) [2]; particle swarm optimization (PSO) [3]; simulated annealing [4,5]; shuffled complex evolution [6]; harmony search [7]; and memetic algorithms [8].

* Corresponding author. Tel.: +34 628 028 804.
E-mail addresses: jizquier@upv.es (J. Izquierdo), encamgo1@upv.es (E. Campbell), rperez@upv.es (I. Montalvo), imontalvo@ingeniousware.net (R. Pérez-García).

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Unlike most of the classical optimization algorithms, evolutionary algorithms enable the use of any form of quantitative (numerical) assessment of the desired objectives without conditioning the approach to the problem [9,10]. The flexibility introduced by EAs has allowed the use of virtually any objective function, even when evaluations require, as is the case of many real-world problems, running complex mathematical and/or procedural simulations of the systems under analysis. There is an extensive literature of examples within all fields of engineering and science, and more specifically in the water industry, and in particular urban hydraulics (the field of expertise of the authors) regarding design, calibration, energy saving, etc. See, among many other references in the water industry [11,7,12–19].

Typically, an EA considers a population of candidate solutions and applies algorithm-specific rules that are iterated through generations in an attempt to improve the fitness of at least one individual (which will hopefully hit the optimum). Despite its virtues, each EA has its own drawbacks and is better adapted to some problems than to others. The heuristics behind a certain evolutionary algorithm endow its elements with specific capabilities for efficiently solving some types of problems, while being clearly inefficient with problems of a different nature. This fact indicates that, firstly, their rules apply better to certain problems than to others; and, secondly, that even if the population of solutions does evolve, the way it evolves is somehow static and does not dynamically adapt to the specific search process. This is one of the reasons why many researchers develop variants of the basic forms of some EAs that adapt better to different problems. Another reason derives from the parameters on which every EA is based. These parameters condition the way an EA works. Fine-tuning those parameters to obtain better results from evolutionary algorithms is, in many cases, part of a hand-made meta-process where specialists, using their experience or recommendations from the literature, start changing parameters, testing algorithm performances, perhaps performing sensitivity analyses, and eventually keeping the best parameter set of values. There are methods that skip these cumbersome processes by using adaptive and self-adaptive parameters; for example, algorithms ASO [20] and TRIBES [21] are based on free-parameter versions of PSO; in [22], a support vector machine was trained to generate PSO parameters while the solution space of a problem was explored. Other self-tuning algorithms have also been developed [23–26]. Despite these attempts, many recent optimization methods (including their variants) still use parameters that are adjusted a priori, frequently undergoing very expensive processes.

However, better adjustments to the parameters of an EA is not the final solution. We suggest that this solution will come from influencing more directly the way a search is performed. In effect, EAs have been frequently accused of using solution search processes that completely ignore the specificities of the problem being solved. As a result, optimization processes have been insensitively applied and ignore the size, complexity, and domain of the problem.

In this paper, we justify our claim that far-reaching benefits will be obtained from more directly influencing the way the search is performed, since algorithms that adapt their behavior to the problems they are intended to solve will have more chances to succeed. This can be achieved by combining EA performances with the introduction of knowledge based on the domain of the problem being solved. Specifically, this paper proposes using Kohonen self-organizing feature maps (SOMs) [27] on sets of solutions evaluated after batches of generations from a single run of an EA in order to extract knowledge intended initially to be used by the following generations. This approach is applied to a very important optimization problem in hydraulics, namely, the optimum design of water distribution networks (WDNs).

The paper is organized as follows. After this introduction we present the problem of the optimum design of a WDN, emphasizing its inherent complexities, which are used to exemplify the approach we propose. A short description of the evolutionary approach used is then presented. We then motivate and describe our approach. Finally, we demonstrate the approach performance on a very well-known benchmark of the WDN design literature, namely the Hanoi problem. The paper concludes with conclusions and references.

2. Model problem: optimum design of a water distribution network

A mathematical description of a general simulation-based multi-objective optimization problem, considering uncertainties derived from changing environmental and operating conditions (see [28] for an overview of the state of the art in the field of robust optimization) may take the following form:

$$\text{Optimize } F(x,\varepsilon) = (f_1(x,\varepsilon), \ldots, f_m(x,\varepsilon))^{\mathrm{t}}$$

subject to

$$g_i(x,\varepsilon) > 0, \quad i = 1, 2, \ldots, k$$
$$h_j(x,\varepsilon) = 0, \quad j = 1, 2, \ldots, l$$

where $f_i,\ i = 1, \ldots, m$, are the objectives, and g_j and h_j are k and l inequality and equality constraints, respectively, which depend on the vector x of decision variables and ε, the uncertainty state vector. Decision vectors belong to the decision or search space $S \subseteq \mathbb{R}^d$ of decision variables, $x_1, \ldots, x_d$, and the uncertainty state vector belongs to certain state uncertainty set, U_s. The vector function, $F(x,\varepsilon)$ takes its values on the objective space $F(S, U_s) \subset \mathbb{R}^m$, its m components representing the various objective functions considered. The symbol $^{\mathrm{t}}$ is the matrix transposition operator. Both the optimization criteria f_k, and the constraint functions g_i and h_j may require multi-level computer simulations.

To gain specificity we now present the specific problem addressed in the case study of this paper.