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Interactive evolutionary computation in process engineering

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Abstract

In practical system identification, process optimization and controller design, it is often desirable to simultaneously handle several objectives and constraints. In some cases, these objectives and constraints are non-commensurable and they are not explicitly/mathematically available. This paper proposes a new subjective optimization method based on interactive evolutionary computation (IEC) to handle these problems. IEC is an evolutionary algorithm whose fitness function is provided by human users. The whole approach has been implemented in MATLAB (EAsy-IEC Toolbox) and applied to two case-studies: tuning a Model Predictive Controller and temperature profile design of a batch beer fermenter. The results show that IEC is an efficient and comfortable method to incorporate the prior knowledge of the user into optimization problems. The developed EASy-IEC Toolbox (for MATLAB) can be downloaded from the website of the authors: http://www.fmt.vein.hu/softcomp/EAsy.

Keywords: Interactive evolutionary computation; Process engineering; Process optimization; Creativity supporting tools

1. Introduction

Process engineering deals with modelling, control and design of process systems. All of these tasks can be formulated as optimization problems. Usually, the objectives of these optimization problems are often non-commensurable and are frequently in conflict with each another (Johansen, 2000). Therefore most of process engineers meet with multi-objective optimization problems and they should define the cost functions and the constraints based on their prior knowledge. This requires in-depth information concerning various trade-offs and valuation of individual objectives. Hence, there is a need for tools which allow process engineers to effectively handle their background knowledge during the optimization procedure.

The idea of using human knowledge or intuition as part of an optimization process appeared in Parmee, Cvetkovic, Bonham, and Packham (2001). This *subjective optimization approach* means that, instead of defining a mathematical cost function, the human user directly evaluates the potential solutions and makes a decision which solutions are good and which are bad.

The subjective optimization approach requires a special optimization algorithm. Most optimization techniques which work by improving a single solution step by step are not suited for this technique. Evolutionary algorithms (EAs) and other population based optimization procedures are better suited for subjective optimization. EA is an optimization method which uses the computational model of natural selection. EA has proved particularly successful in problems that are difficult to formalize mathematically, and which are therefore not conducive to classical analysis based engineering tools. The EAs lack of reliance on domain-specific heuristics makes it attractive for systems that are highly nonlinear, that are stochastic and that are poorly understood, because very little a priori information is required, but this can be incorporated if so desired. EA works with a population of potential solutions, where each individual within the population represents a particular solution, generally represented in some form of genetic code. The fitness value of the individuals expresses how good the solution is at solving the problem. Better solutions are assigned higher values of fitness than worse performing solutions. The key of EA is that the fitness also determines how successfully the individual will be at propa-

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gating its genes (its code) to the subsequent generations. As this description suggests, this optimization approach is ideal for subjective optimization since the human user can directly evaluate the fitness of the solutions by ordering the solutions or by the selection of the best ones. This approach become known as *interactive evolutionary computation* (IEC) (Takagi, 2001). IEC has been already applied in computer graphics (McCormack, 1993), animation, creating forms, textures, and motion (Aoki, Takagi, & Fujimura, 1996). Potential applications of interactive evolution include development of components of biological nature (Furuta, Maeda, & Watanabe, 1995; Smith, 1991)and engineering construction design (Ohsaki & Takagi, 1998). The applications of IEC to control problems have been recently increased (Kamihira, Yamaguchi, & Kita, 1999; Lund & Miglino, 1998).

Contrary to the high number of IEC application examples, this approach has not been applied in chemical process engineering. The aim of this paper is to show how this tool can be tailored and applied in this area. Two examples will be shown: tuning an MPC controller and a temperature profile design of a batch beer fermentation process. These examples demonstrate the applicability of the MATLAB EAsy-IEC Toolbox developed for solving process engineering problems by IEC. With the application of this toolbox the users can simultaneously analyze the numerical performance indices along with the plotted concentration profiles and modify the design variables suggested by the evolutionary algorithm.

2. IEC framework for process engineering problems

2.1. IEC as a subjective optimization tool

Evolutionary algorithm (EA) is a widely used population based iterative optimization technique, that mimics the process of natural selection, see Fig. 1 (Eiben & Schoenauer, 2002). The population is evolved over generations to produce better solutions to the problem. The evolution is performed using a set of stochastic genetic operators, which manipulate the representation of the potential solutions. Most evolutionary algorithms include operators that select individuals for reproduction, produce new individuals based on those selected, and determine the composition of the population at the subsequent generation.

Interactive evolutionary computation (IEC) is simply an EA in which the selection of the best individuals for reproduction is performed by a human user, see Fig. 1B). In the field of process engineering, this means that the user should simultaneously analyze the numerical results and the plotted trajectories used to represent the solution of a control, system identification, or process optimization problem, e.g. concentration and temperature profiles, and select the best solutions which approach his/her requirements. These selected individuals will constitute the next generation.

George A. Miller discussed some limits of the human brain with respect to information processing. In particular, his research had found that people are unable to keep up with more than five to nine different chunks of information at a time (Miller, 1956). Since a human user cooperates with a tireless computer and evaluates the potential solutions, the IEC process cannot be continued after many generations prohibiting the practical use of the IEC. Due to the limitation of the individuals simultaneously displayed on the monitor, the limitation of human capability to memorize the time-sequentially displayed individuals and the requirement to minimize the human fatigue, the main problem of the effective realization of IEC is the development of an evolutionary algorithm that is able to search for a goal with a small population size within a few number of searching generations. The good news is that thanks to a good initial convergence of evolutionary algorithms, unlike gradient methods, the human fatigue problem may be less tiring than from gradient searches (Takagi, 2001).

2.2. Evolution strategy

Among the wide range of EAs we found that evolution strategy (ES) (Schwefel, 1965) is the best suited for IEC applications. The design variables in ES are represented by n-dimensional vector $\mathbf{x}_j = [x_{j,1}, \ldots, x_{j,n}]^T \in R^n$, where $\mathbf{x}_j$ represents the jth potential solution, i.e. the jth the member of the population. The mutation operator adds $z_{j,i}$ normal distributed random numbers to the design variables:

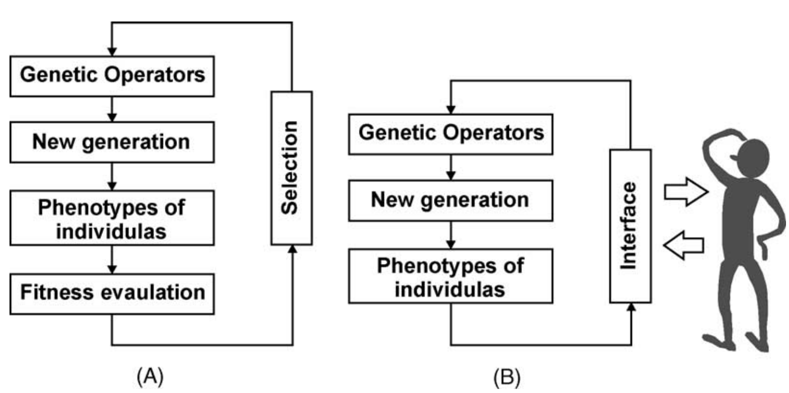

Fig. 1. Scheme of IEC. (A) Evolutionary algorithm; (B) interactive evolutionary algorithm.