DESIGNING FDI OBSERVERS BY IMPROVED EVOLUTIONARY MULTI-OBJECTIVE OPTIMIZATION

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Abstract: The paper considers using evolutionary multi-objective optimization (EMO) for solving FDI design problems. In order to prevent genetic procedures from premature convergence and to increase the effectiveness of searching for sought optimal solutions, different types of niching allow taking care of their diversity in consecutive generations. Another problem results from considering design objectives of high dimensions, when the conception of Pareto-domination is not effective. The paper discusses the characteristics of several innovative mechanisms concerning the methods of selection and parental crossover, based on concepts of niches and genders.

Keywords: FDI design, diagnostic observers, multi-objective optimization, Pareto-optimality, genetic algorithms (GA), evolutionary computations (EC)

1. INTRODUCTION

Most engineering system design problems are based on optimization of multiple objectives at the same time (Goldberg, 1989; Michalewicz, 1996; Man, *et al.*, 1997). To integrate those objectives, it is vital to determine the relations among the partial objectives. Otherwise the notion of optimality is not obvious. To solve this problem, various methods are applied, *e.g.*, weighted profits, distances, sequential inequalities, or ranking w.r.t. Pareto-optimality (Michalewicz, 1996; Man *et al.*, 1997; Kowalczuk *et al.*, 1999; Kowalczuk and Białaszewski, 2000a; 2000b). These methods are workable, but they have the disadvantage of relaying on a choice of the decisive vectors of weights or demands, or limit values for the objective function. A different approach is applied in ranking based on the notion of Pareto-optimality that allows a taxonomy of solutions that takes into account all the objectives.

In this paper we reflect on methods of improving the performance of (EMO) evolutionary multi-objective optimization methods of designing involved systems. In particular, different techniques of niching, which are isolated with respect to the object of a niching manipulation (Kowalczuk and Białaszewski, 2000b; 2004a; 2004b) by considering: niching of the fitness (NF) and the ranks (NR) of all the individuals, and niching of the fitness (NFP) and the ranks (NRP) of the parents solely. The four types of niching can also be considered in two versions with respect to the frequency of their application within a GA/EC cycle.

Another improvement presents a genetic-gender (GGA) method (Kowalczuk and Białaszewski, 2002; 2003) of solving the EMO problems, in which the information about a degree of membership to a given gender is attributed to each obtained solution. This information is utilized in the process of parental crossover, in which only individuals of different genders are allowed to create their offspring.

2. MULTI-OBJECTIVE OPTIMIZATION

Consider an *n*-dimensional vector of objectives

$$\boldsymbol{f}(\boldsymbol{x}) = \left[f_1(\boldsymbol{x}) \quad f_2(\boldsymbol{x}) \quad \dots \quad f_m(\boldsymbol{x})\right]^{\mathrm{T}} \in \Re^m \quad (1)$$

$$\boldsymbol{x} = [x_1 \quad x_2 \quad \ldots \quad x_n]^{\mathrm{T}} \in \Re^n \qquad (2)$$

denotes n-dimensional vector of searched parameters, while $f_j(\boldsymbol{x})$, $j = 1,2,...,m$, is the j-th partial objective function. Assuming that all the co-ordinates are profit functions, the multi-objective optimization task without constrains can be formulated as follows

$$\max_{\boldsymbol{x}} \boldsymbol{f}(\boldsymbol{x}) \qquad (3)$$

Pareto-optimality. The terms of Pareto optimality (Goldberg, 1989) for the maximization task (3) can be formulated as follows. Let $\boldsymbol{f}(\boldsymbol{x}_p), \boldsymbol{f}(\boldsymbol{x}_r) \in \Re^m$, where $\boldsymbol{x}_p$ and $\boldsymbol{x}_r$ are two individuals (solutions). Vector $\boldsymbol{f}(\boldsymbol{x}_p)$ is partially smaller than vector $\boldsymbol{f}(\boldsymbol{x}_r)$ if and only if for all their co-ordinates j=1,2,..., m

$$\left(\forall_j f_j(\boldsymbol{x}_p) \le f_j(\boldsymbol{x}_r)\right) \wedge \left(\exists_j f_j(\boldsymbol{x}_p) < f_j(\boldsymbol{x}_r)\right) \qquad (4)$$

Thus, in the Pareto sense, $\boldsymbol{x}_p$ is dominated, if there is $\boldsymbol{x}_r$ partially 'better' than $\boldsymbol{x}_p$ in terms of definition (4). Not dominated entities are taken as P-optimal.

Pareto-optimality ranking. The P-optimal assessment determines a P-optimal set. Each solution is assigned a certain scalar quantity called a rank (Goldberg, 1989; Man *et al*., 1997), which can have different definitions. In general, such a rank relates to the number of individuals by which the analyzed one is dominated in the sense of Pareto (Kowalczuk *et al*., 1999; Kowalczuk and Białaszewski, 2004a). Here, the rank $\rho(\boldsymbol{x}_i)$ of $\boldsymbol{x}_i$ is computed as follows:

$$r(\boldsymbol{x}_i) = \mu_{\max} - \mu(\boldsymbol{x}_i) + 1, \; \mu_{\max} = \max_{i=1,2,\ldots,N} \mu(\boldsymbol{x}_i) \qquad (5)$$

where $\mu(\boldsymbol{x}_i)$ is the degree of domination, *i.e.* the number of solutions by which $\boldsymbol{x}_i$ is dominated in the P-sense, while $\mu_{\max}$ stands for the maximum value amongst all $\mu(\boldsymbol{x}_i)$, $i = 1, 2, \ldots, N$, in the population.

Global optimality. To utilize the freedom of the P-optimality, an idea was proposed (Kowalczuk and Białaszewski, 2000a; 2004a) to map the profit vector of each solution to a global optimality level GOL, which equals a minimal co-ordinate of the vector.

3. NICHES IN THE PARAMETER SPACE

Niching in GAs allows balancing the population by preserving weak individuals and giving them a chance to relay their genetic codes into offspring (Goldberg, 1989; Kowalczuk *et al*., 1999; Kowalczuk and Białaszewski, 2004a).

The degree of kinship between two individuals can be represented by a closeness function (Kowalczuk and Białaszewski, 2004a), also called a sharing one. Formally, the niche identifying a species of 'bred' individuals is defined as a hyper-ellipsoid defined by a set of radii $\{\phi_k, k = 1,2,...,n\}$ in the parameter space. The closeness function δ_{ij} for two individuals $\boldsymbol{x}_i$ and $\boldsymbol{x}_j \in \Re^n$, $(i, j = 1,2,\ldots,N)$, can be computed as a measure of the geometrical distance between them (Kowalczuk and Białaszewski, 2004a) and takes its values from the range [0, 1]. The unity value of the closeness function means that the individuals are identical or closely related.

The niching can be performed with respect to the fitness vector or the rank of individuals in their niches according to the following (Goldberg, 1989; Michalewicz, 1996; Kowalczuk *et al*., 1999; Kowalczuk and Białaszewski, 2004a):

$$\tilde{\boldsymbol{f}}(\boldsymbol{x}_i) = \boldsymbol{f}(\boldsymbol{x}_i) \Big/ \sum_{j=1}^{N} \delta_{ij} \qquad (6)$$

$$\tilde{\rho}(\boldsymbol{x}_i) = \rho(\boldsymbol{x}_i) \Big/ \sum_{j=1}^{N} \delta_{ij} \qquad (7)$$

where $\boldsymbol{f}(\boldsymbol{x}_i)$ is the vector fitness and $\rho(\boldsymbol{x}_i)$ is the scalar rank of the i-th individual, while $\tilde{\boldsymbol{f}}(\boldsymbol{x}_i)$ and $\tilde{\rho}(\boldsymbol{x}_i)$ denote niche-adjusted functions.

From the experience (Kowalczuk and Białaszewski, 2000b; 2004a; 2004b) one can characterize the niching of ranks as a 'stronger' mechanism. Analogous types of the niching can be considered with respect to the parental pools (*ibid.*). It is important that in spite of such a uniform breeding policy, a global effect is observed which consists in constant densities sustained in certain niches. This can eventually be interpreted in terms of their robustness to changes in the fitness measure.

Niching should also be studied in terms of their time conditioning within the evolutionary cycles. Taking into account the fact that niching proofs to be useful (Kowalczuk and Białaszewski, 2000b; 2004a), though time-consuming, one can also consider its periodic version (Kowalczuk and Białaszewski, 2004b) as an alternative to the classical continuous implementation. With the periodic approach, niching is limited to a fixed number of cycles, and next is switched off until the subsequent period of niching.

4. GENETIC GENDERS

While considering EMO problems one has always to be aware of the issues of dimensionality: When the space of the objectives has a higher dimension many individuals fall within the category of being P-optimal, *i.e.* mutually equivalent in the Pareto sense.