UNIVERSITE LIBRE DE BRUXELLES

FACULTE DES SCIENCES

SERVICE TELEMATIQUE ET COMMUNICATION

Crowding Factor in Evolutionary Multi-Agent System for Multiobjective Optimization

Paper to be presented at the IC-AI'01 Conference, June 25th -28th , 2001, Las Vegas (USA)

Marek Kisiel-Dorohinicki
Krzysztof Socha

Faculté des Sciences
Service Télématique et Communication
CP 230 - Blvd du Triomphe
B-1050 Bruxelles

ULB - Rapport STC
01-04
mai 2001

Crowding Factor in Evolutionary Multi-Agent System for Multiobjective Optimization

Marek Kisiel-Dorohinicki
Institute of Computer Science
University of Mining and Metallurgy
Kraków, Poland

Krzysztof Socha
Service Telematique et Communication
Free University of Brussels
Brussels, Belgium

Abstract *In the paper the idea of an evolutionary multi-agent system (EMAS) for multiobjective optimization is presented. Decentralized model of evolution employed in EMAS allows for effective approximation of the whole Pareto set, even if it consists of several disjoined parts. The introduced mechanism of crowd is described and its effects on the performance of the system are discussed. A control parameter called crowding factor indicates how the agents representing similar solutions behave in the system. Selected experimental results show the influence of the crowding factor on the quality of the solutions generated.*

Keywords: multiobjective optimization, evolutionary computation, multi-agent systems, crowding factor

1 Introduction

Decision making and lots of other tasks of human activity described by many non-comparable factors may be mathematically formulated as multiobjective optimization problems. The terms "multiobjective" or "multicriteria" indicate that classical notion of optimality becomes ambiguous since decisions, which optimize one criterion need not optimize the others.

The notion of Pareto-optimality is based on (non-)domination of solutions (which corresponds to the weak-order of vectors in the evaluation space) and leads to selection of multiple alternatives (the Pareto set). The relation of domination may be defined as follows: $\vec{x}^a$ is dominated by $\vec{x}^b$ if and only if:

$$\forall_{m=1,\ldots,M} \quad f_m(\vec{x}^a) \leq f_m(\vec{x}^b) \quad \text{and} \quad \exists_{m=1,\ldots,M} \quad f_m(\vec{x}^a) < f_m(\vec{x}^b) \qquad (1)$$

where $\vec{x} = [x_1, \ldots, x_N]^T \in \mathbf{R}^N$ denotes a feasible solution and $f_m : \mathbf{R}^N \rightarrow \mathbf{R}$ denote criteria functions $F = [f_1, \ldots, f_M]^T$.

In a general case (i.e. when no particular class of criteria and constraints functions is considered) effective approximation of the Pareto set is hard to obtain. For specific types of criteria and constraints (e.g. of linear type) some methods are known, but even in low-dimensional cases they need much computational effort. For complex problems, involving multimodal or discontinuous criteria, disjoined feasible spaces and noisy function evaluations, evolutionary approach (e.g. a genetic algorithm) may be applied [5, 4].

The proposed approach consists in an application of an evolutionary multi-agent system (EMAS) instead of classical evolutionary computation. Decentralization of the evolution process in EMAS allows for intensive exploration of the search space and effective approximation of the whole Pareto set, especially in case of the disjoined frontier [7]. The introduction of the mechanism of *crowd*, similar to the one proposed by De Jong [6, and later], may cause the system to produce better results in comparable or even shorter time.

Below the idea EMAS and its application to multiobjective optimization problems is described. In particular the parameter called

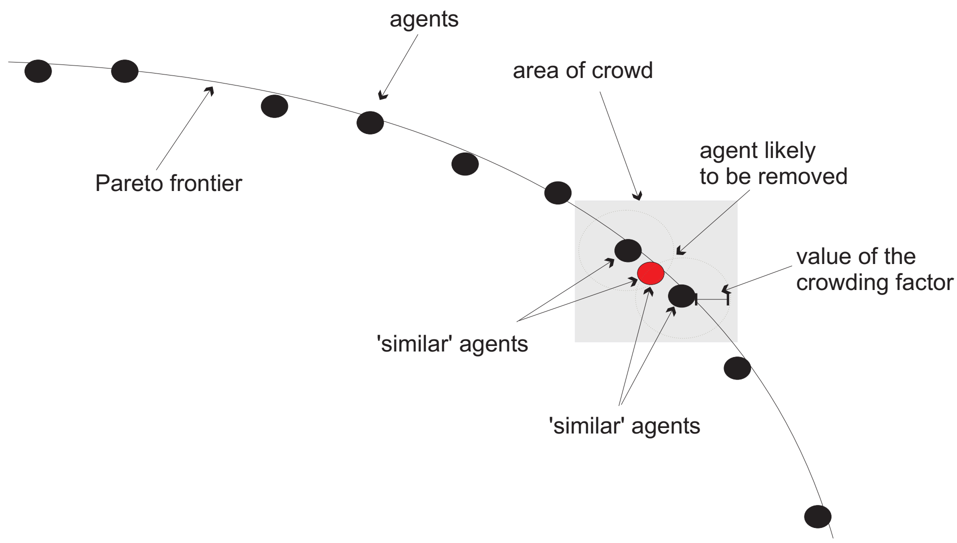

Figure 1: Overview of the mechanism of crowd

crowding factor is presented and its influence on on the operation of the EMAS for multiobjective optimization discussed. There are selected experimental results presented and conclusions drawn.

2 Evolutionary Multi-Agent Systems

The key idea of EMAS is the incorporation of evolutionary processes into a multi-agent system (MAS) at a population level. It means that besides interaction mechanisms typical for MAS (such as communication) the agents are able to reproduce (generate new agents with the use of variation operators, i.e. mutation or recombination) and may die (be eliminated from the system).

A decisive factor of agent's activity is its fitness, expressed by amount of the possessed non-renewable resource called life energy. The energy is gained and lost when the agent executes actions in the environment. Increase in energy is a reward for 'good' behavior of the agent, decrease – penalty for 'bad' behavior. Selection is then realized as agents with high energy are more likely to reproduce, while low energy increases possibility of death.

Evolutionary multi-agent system may be regarded as a new class of adaptive MAS, where evolutionary processes help to accomplish population-level goals [2]. At the same time it may be used as a novel computational technique utilizing a *decentralized* model of evolution. Such approach may help to overcome some of the shortcomings of classical evolutionary algorithms, which employ much simplified model of evolution [1].

In general EMAS enables the following [3]:

- local selection allows for intensive exploration of the search space, like in parallel evolutionary algorithms,
- the way fenotype (behavior of the agent) is developed from genotype (inherited information) depends on its interaction with the environment,
- self-adaptation of the population size is possible when appropriate selection mechanisms are used.

What is more, explicitly defined living space should facilitate implementation in a distributed computational environment.

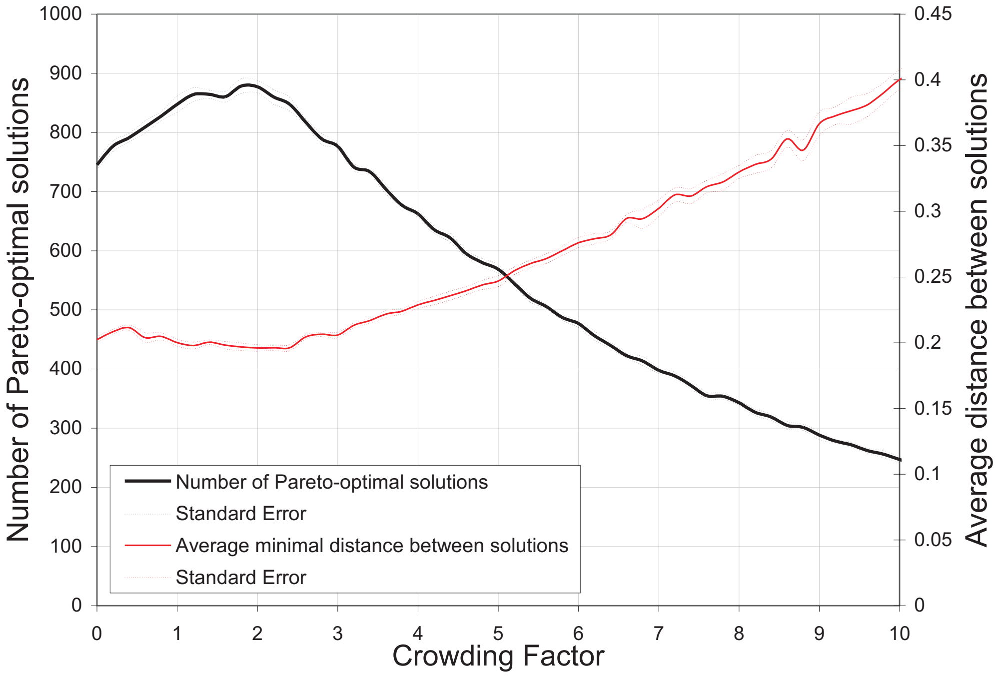

Figure 2: The influence of the crowding factor on the performance of the system in case of the coherent Pareto frontier

3 Crowd in EMAS for Multi-objective Optimization

In the particular case each agent represents feasible solution to the given multiobjective optimization problem. By means of communication the agents acquire information that allows for the determination of the domination relation with respect to the others. Dominated agents transfer a fixed amount of energy to their dominants. This way non-dominated agents represent subsequent approximations of the Pareto set.

The crowding factor describes how the agents representing similar solutions to the problem behave in the system. Crowd may be understood as a higher density of agents in the particular spot of the search space – this *density* is in fact the number of agents in some neighborhood that represent similar solutions (fig. 1). Larger crowding factor value indicates that there is less tolerance for the similar solutions, which is accomplished via reduction of life energy of the agents that have their solutions too close to the others. The smaller is the value of the crowding factor, the weaker becomes this tendency, up to its disappearance for crowding factor value equal to 0.

However, due to the general idea of EMAS, there is no particularly easy and straightforward way to measure the number of agents with similar solutions in the whole system. The system does not contain a centralized control unit, so there may be no central management of the crowd. A special way of self-management done by the agents was implemented to deal with this problem and to take advantage of the distributed qualities of EMAS. The only possibility of establishing that two given agents have similar solutions,

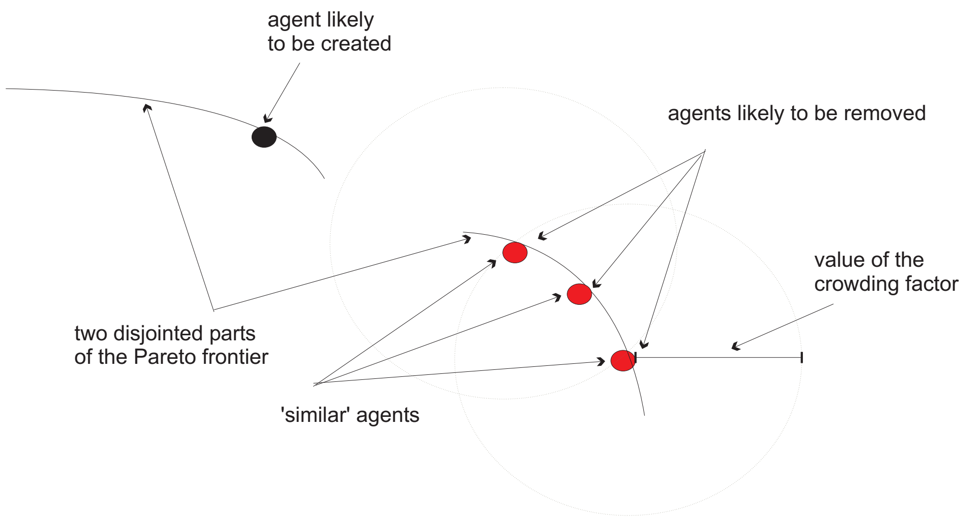

Figure 3: The effect of the mechanism of crowd in case of the Pareto frontier consisting of several disjoined parts

is when they meet and exchange information. When this happens, and the solutions of both agents are similar, one of the agents may take some energy from the other.

The idea behind introducing the mechanism of crowd, was to encourage agents to try not to create large bunches at some distinctive points on the Pareto frontier. Instead they should be able to fairly uniformly distribute over the whole frontier (fig. 1). Also in case of problems with Pareto frontier consisting of several disjoined parts, this mechanism should improve the ability of the agents to cover wide area of search space (fig. 3).

4 Experimental Results

Several different tests were performed for different optimization problems. Various system parameters were checked in order to establish the influence of the crowding factor on system's performance. It has been established that there is a substantial relation between the factor and system's operation. During the testing, there were two distinctive types of influence of crowding factor found.

4.1 Influence of Small Values of the Crowding Factor

The first type of influence was the fact that small values of the crowding factor improved system's performance in case of virtually any test problem. It was best visible in case of problems with coherent Pareto frontier. The agents were able to find more points on the frontier, comparing to the cases with no crowd (i.e. when the crowding factor was equal to 0). An example of such a test problem is a set of four paraboloid shape functions with two dimensions each:

$$\begin{cases} f_1(x,y) = -[(x-5)^2 + (y-5)] + 5 \\ f_2(x,y) = -[(x+5)^2 + (y-5)] + 5 \\ f_3(x,y) = -[(x-5)^2 + (y+5)] + 5 \\ f_4(x,y) = -[(x+5)^2 + (y+5)] + 5 \end{cases} \tag{2}$$

This set of criteria functions for maximization problem give the Pareto set in a shape of a rectangle.

The results obtained for this test problem are presented on fig. 2. The units in which the crowding factor values are presented are the same as the search space is defined. It is thus clear that for this particular problem the optimal value of the crowding factor is $\frac{1}{5}$ of the

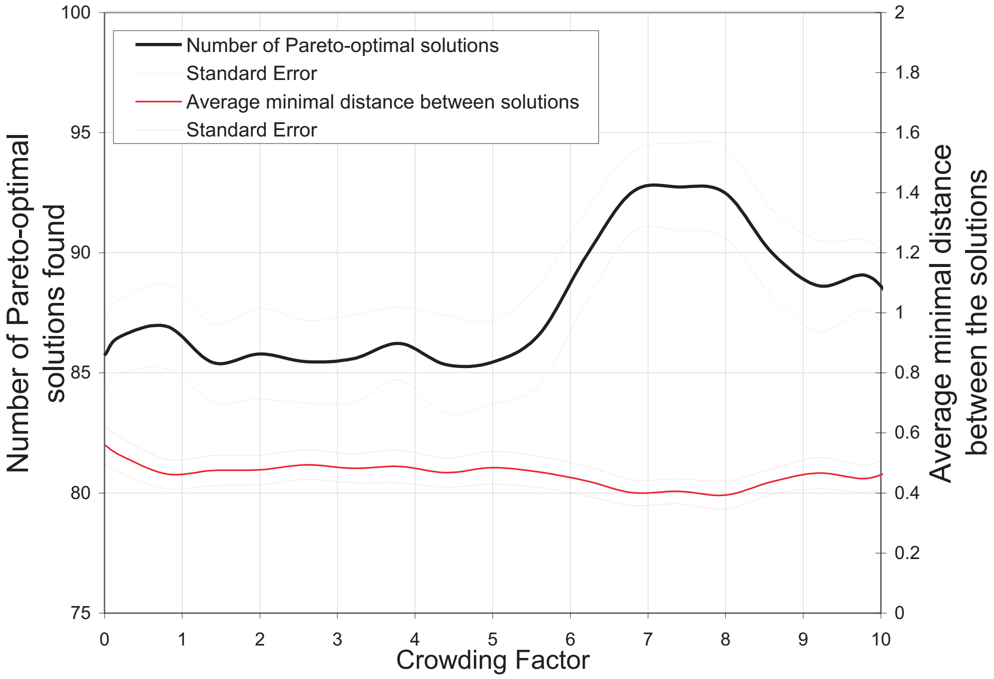

Figure 4: The influence of the crowding factor on the performance of the system in case of Pareto frontier consisting of several disjoined parts

average diameter of the Pareto frontier. For other test problems it varied, but the peak was never obtained for the value 0, and it usually was closer to 0 than diameter of Pareto frontier. The only exception from this rule were test problems described in the following subsection.

4.2 Influence of Large Values of the Crowding Factor

In addition to the expected influence of the crowding factor, another issue was found during the experiments. It became apparent that for specific types of problems, also larger values of the crowding factor – even larger than the average diameter of the Pareto frontier – were found beneficial.

This second effect that was observed concerning only cases of problems having a fairly large number of distinctive disjoined parts of Pareto frontier. In that case a larger value of the crowding factor (compared with the distance between the separate parts of the Pareto set) allowed the system to find those disjointed parts more efficiently.

Most likely the following mechanism is responsible for such an effect. Large values of the crowding factor cause that *all* agents in one Pareto-optimal area tend to take energy from all the others. The agents that actually gain the energy will be very likely to reproduce. Thanks to various reproduction operators (several types of crossover and mutation) new agents that will be created may end up quite far away from their parents (but of course they do not have to). Their energy may be lost if they are too close to their parents, and it may be lost even faster if they are dominated (they leave Pareto set). However, if they appear in the other part of the frontier they will be safe (fig. 3).

Such situation is presented on (fig. 4). The values presented here were obtained for the following set of criteria functions:

$$\begin{cases} f_1(x) = \sin x \\ f_2(x) = \sin(x+1) \end{cases} \tag{3}$$

For such criteria functions, the Pareto set X_{opt} is defined as:

$$\begin{aligned} & x \in X_{opt} \quad \Leftrightarrow \\ & \frac{\pi}{2} + 2k\pi \leq x \leq \frac{\pi}{2} + 2k\pi + 1; \qquad k \in \mathbf{Z} \end{aligned} \tag{4}$$

For the purpose of the experiment the domain was limited to $x \in <-100, 100>$. For the given problem there were over 30 distinctive disjoined parts of the Pareto set in that domain.

5 Conclusions

Although it was possible to obtain some interesting results, and improve general system performance through the use of the mechanism of crowd, it is clear that further research in this area is necessary. For any given problem there is some optimal value of the crowding factor that improves results obtained by the system. This value is unfortunately different for various types of optimization problems. Based on the experience gathered so far, it is possible to estimate that small values of the crowding factor usually give better results than disabling the mechanism of crowd. Yet for some problems it may be the case that actually larger values would give even better results.

Additionally, currently the crowding factor is expressed in absolute values, which depends heavily on the problem definition. Future goal would be to work out certain relations between the value of the crowding factor and the quality of the results obtained. Also other parameters of the simulation system have influence on the effectiveness of the crowding factor. For instance the level of life energy, applied variation operators and many others. They all have to be taken into account in order to have more measurable and comparable results.

References

[1] T. Bäck, U. Hammel, and H.-P. Schwefel. Evolutionary computation: Comments on the history and current state. *IEEE Transactions on Evolutionary Computation*, 1(1), 1997.

[2] K. Cetnarowicz. Evolution in multi-agent world = genetic algorithms + aggregation + escape. In *Position Papers of MAAMAW'96*, Tech. Rep. 96-1. Vrije Universiteit Brussel, Artificial Intelligence Laboratory, 1996.

[3] K. Cetnarowicz, M. Kisiel-Dorohinicki, and E. Nawarecki. The application of evolution process in multi-agent world (MAW) to the prediction system. In M. Tokoro, editor, *Proc. of the 2nd Int. Conf. on Multi-Agent Systems (ICMAS'96)*. AAAI Press, 1996.

[4] C. A. Coello Coello. An updated survey of evolutionary multiobjective optimization techniques: State of the art and future trends. In P. J. Angeline, Z. Michalewicz, M. Schoenauer, X. Yao, and A. Zalzala, editors, *Proceedings of the Congress on Evolutionary Computation*, volume 1. IEEE Press, 1999.

[5] C. M. Fonseca and P. J. Fleming. An overview of evolutionary algorithms in multiobjective optimization. *Evolutionary Computation*, 3(1):1–16, 1995.

[6] K. A. De Jong. *An analysis of the behaviour of a class of genetic systems.* PhD thesis, University of Michigan, 1975.

[7] M. Kisiel-Dorohinicki, G. Dobrowolski, and E. Nawarecki. Evolutionary multiagent system in multiobjective optimisation. In M. Hamza, editor, *Proc. of the IASTED Int. Symp.: Applied Informatics.* IASTED/ACTA Press, 2001.