Multi-Objective Optimization Using Co-Evolutionary Multi-Agent System with Host-Parasite Mechanism

Rafał Dreżewski, Leszek Siwik

Department of Computer Science
AGH University of Science and Technology, Kraków, Poland
{drezew,siwik}@agh.edu.pl

Abstract. Co-evolutionary techniques for evolutionary algorithms are aimed at overcoming their limited adaptive capabilities and allow for the application of such algorithms to problems for which it is difficult or even impossible to formulate explicit fitness function. In this paper the idea of *co-evolutionary multi-agent system with host-parasite mechanism for multi-objective optimization* is introduced. In presented system the Pareto frontier is located by the population of agents as a result of co-evolutionary interactions between species. Also, results from runs of presented system against test functions are presented.

1 Introduction

Evolutionary algorithms (EAs) are techniques for finding suboptimal solutions of global optimization and adaptation problems, which are based on analogies to biological evolutionary processes. Evolutionary algorithms, however, often suffer from premature loss of population diversity. This results in premature convergence and may lead to locating local optimum instead of a global one. In the case of multi-modal problem landscapes EA without any special mechanisms will inevitably locate basin of attraction of single optimum. The loss of diversity also limits the adaptive capabilities of EAs in dynamic environments.

In *co-evolutionary algorithms* the fitness of each individual depends not only on the quality of solution to the given problem but also (or solely) on other individuals' fitness. This makes such techniques applicable in the cases where the fitness function formulation is difficult (or even impossible). Co-evolutionary techniques, are aimed at improving adaptive capabilities and introducing open-ended evolution into EAs by maintaining population diversity [8].

High quality approximation of *Pareto frontier* should fulfill at least three distinguishing features: first of all it of course should be "located" as close to the ideal Pareto frontier as possible what is very natural and common condition for both single- and multi- objective optimization, secondly it should include as many alternatives as possible and, at last, all proposed non-dominated alternatives should be evenly distributed over the whole ideal Pareto set.

In consequence, in the case of multi-objective optimization, premature loss of population diversity can result not only in lack of drifting to the ideal Pareto frontier but also in obtaining approximation of Pareto set that is focused around its selected area(s)

— what of course is very undesirable assuming that preference-based multi-objective optimization is not considered in this place.

Evolutionary multi-agent systems (EMAS) have proved their grate usefulness for solving a lot of different discrete, continuous, combinatorial and non-combinatorial multi-objective optimization problems [12, 11]. Co-evolutionary mechanisms are aimed at maintaining population diversity and improving adaptive capabilities of EMAS systems — especially in dynamic environments. This paper introduces the idea of *co-evolutionary multi-agent system with host-parasite mechanism for multi-objective optimization*. The process of locating Pareto frontier in such system emerges as a result of co-evolutionary interactions between species of agents. The results from runs of co-evolutionary multi-agent system for multi-objective optimization against commonly used test functions are also presented and the comparison to classical multi-objective evolutionary algorithms is made.

2 Evolutionary and Co-Evolutionary Multi-Objective Optimization

During most real-life decision processes a lot of different (often contradictory) factors have to be considered, and the decision maker has to deal with an ambiguous situation: the solutions which optimize one criterion may prove insufficiently good considering the others. From the mathematical point of view such multi-objective (or multi-criteria) problem can be formulated as follows [13].

Let the problem variables be represented by a real-valued vector:

$$x = [x_1, x_2, \ldots, x_N]^T \in \mathrm{IR}^N \tag{1}$$

where N gives number of the variables. Then a subset of IR^N of all possible (feasible) decision alternatives (options) can be defined by a system of:

- inequalities (constraints): $g_k(x) \geq 0$ and $k = 1, 2, \ldots, K$,
- equalities (bounds): $h_l(x) = 0$, $l = 1, 2, \ldots, L$

and denoted by $\mathcal{D}$. The alternatives are evaluated by a system of M functions (objectives) denoted here by vector $F = [f_1, f_2, \ldots, f_M]^T$:

$$f_m : \mathrm{IR}^N \to \mathrm{IR}, \quad m = 1, 2, \ldots, M \tag{2}$$

The key issue of optimality in the Pareto sense is the *weak domination relation*. Alternative x^a is dominated by x^b (which is often denoted by $x^b \succeq x^a$) if and only if (assuming maximization of all objectives):

$$\forall m \;\; f_m(x^a) \leq f_m(x^b) \text{ and } \exists m \;\; f_m(x^a) < f_m(x^b) \tag{3}$$

A solution in the Pareto sense of the multi-objective optimization problem means determination of all non-dominated (in the sense of the defined above *weak domination relation*) alternatives from the set $\mathcal{D}$, which is sometimes called a *Pareto-optimal set*.

The Pareto-optimal set consists of globally optimal solutions, however there may also exist locally optimal solutions, which constitute locally non-dominated set (*local Pareto-optimal set*) [2]. The set $\mathcal{P}_{local} \subseteq D$ is local Pareto-optimal set if [13]:

$$\forall x^a \in \mathcal{P}_{local} : \nexists x^b \in D \text{ such that } x^b \succeq x^a \wedge \left\| x^b - x^a \right\| < \varepsilon \wedge \left\| F(x^b) - F(x^a) \right\| < \delta \quad (4)$$

where $\|\cdot\|$ is a distance metric and $\varepsilon > 0$, $\delta > 0$.

The set $\mathcal{P} \subseteq D$ is global Pareto-optimal set if [13]:

$$\forall x^a \in \mathcal{P} : \nexists x^b \in D \text{ such that } x^b \succeq x^a \quad (5)$$

These locally or globally non-dominated solutions create (in the criteria space) so-called local ($\mathcal{PF}_{local}$) or global ($\mathcal{PF}$) Pareto frontiers that can be defined as follows:

$$\mathcal{PF}_{local} = \left\{ y = F(x) \in \mathrm{I\!R}^M \;\mid\; x \in \mathcal{P}_{local} \right\} \quad (6a)$$

$$\mathcal{PF} = \left\{ y = F(x) \in \mathrm{I\!R}^M \;\mid\; x \in \mathcal{P} \right\} \quad (6b)$$

Multi-objective problems with one global and many local Pareto frontiers are called *multi-modal multi-objective problems* [2].

For the last 20 years a variety of evolutionary multi-criteria optimization techniques have been proposed. In the Deb's typology of evolutionary multi-objective algorithms (EMOAs) firstly the elitist and non-elitist ones are distinguished [3]. The main difference between these two groups of techniques consists in utilizing the so-called elite-preserving operators that give the best individuals (the elite of population) the opportunity to be directly carried over to the next generation regardless of the actual selection mechanism used. Deb's typology includes also so-called *constrained EMOAs*—i.e. algorithms and techniques that enable handling constraints connected with problem that is being solved.

Laumanns, Rudolph and Schwefel proposed co-evolutionary algorithm with predator-prey model and spatial graph-like structure for multi-objective optimization [6]. Deb introduced modified algorithm in which predators eliminated preys not only on the basis of one criteria but on the basis of the weighted sum of all criteria [3]. Li proposed other modifications to this algorithm [7]. The main difference was that not only predators were allowed to migrate within the graph but also preys could do it.

Co-evolution is the biological mechanism responsible for biodiversity and sympatric speciation. However it was not widely used as a mechanism of maintaining useful genetic diversity of population for evolutionary algorithms. It seems that co-evolution should introduce open-ended evolution, improve adaptive capabilities of EA (especially in dynamic environments) and allow speciation (the formation of species located within different areas of Pareto frontier or within local and global Pareto-frontiers in case of multi-modal multi-objective problems) but this is still an open issue and the subject of ongoing research.

3 Co-Evolutionary Multi-Agent System for Multi-Objective Optimization

The main idea of *co-evolutionary multi-agent system (CoEMAS)* is the realization of species and sexes co-evolution in *multi-agent system (MAS)* [4]. CoEMAS model, as opposed to the basic *evolutionary multi-agent system (EMAS)* model [1], allows for the existence of several species and sexes which can interact with each other and co-evolve. CoEMAS is especially suited for modeling different co-evolutionary interactions, such as resource competition, predator-prey and host-parasite co-evolution, sexual preferences, etc. Systems based on CoEMAS model can be applied, for example, to multi-modal function optimization and multi-objective optimization because such systems maintain population diversity and easily adapt to changing environment.

3.1 Co-evolutionary Multi-Agent System with Host-Parasite Model

The essence of host-parasite approach consists in common evolutionary process (co-evolution) of two populations: population of *hosts* — representing problem solutions and population of *parasites* — representing tests that should be passed by *hosts*. *Hosts'* fitness value is proportional to the number of tests that each of them passed whereas *parasites'* fitness function value depends on number of *hosts* that do not pass test represented by given *parasite*. Of course each population can be characterized by its own: size, selection type, type of representation, genetic operators, probabilities of crossover and mutation etc. So, in another words, these are co-evolving but simultaneously independent populations.

Presented *co-evolutionary multi-agent system for multi-objective optimization with host-parasite mechanism* has been developed using *JagWorld* platform — a kind of Java-based infrastructure supplying basic mechanisms such as communication, parallelization etc. required during implementation systems according to both *EMAS* and *CoEMAS* model.

Realization of presented system required implementation of two kinds of agents: *host-agents* (representing solutions of problem that is being solved) and *parasite-agents* (representing "tests" for *host-agents* or rather for solutions represented by *host-agents*). The behavior of *host-agent* is similar to the behavior of "standard" agents characteristic for *EMAS-based* systems. So, *host-agent* "lives" in a place, it can move between places, and in every step it consumes resources needed for its life-activity. The fitness value is not directly assigned to the *host-agent* but it depends indirectly on interactions with population of *parasites* (*host-agents* representing worse solutions are more likely to be *infected* by *parasite-agents*). Each *parasite-agent*, similarly to the *host-agent*, consumes resources needed for living in the system in every step of simulation, but these agents do not receive resources from the environment, as it takes place in the case of *host-agents* but it takes resources from infected *host*.

The most distinguishing feature of *parasite-agent* is its possibility to infecting *host-agents*. In every step each *parasite-agent* that does not infect any *host-agent* tries to infect non-infected *host*. To infect a *host-agent* the *parasite-agent* performs specific test consisting in comparing objectives values represented by its genotype with objectives

Table 1. Comparison of proposed CoEMAS approach with selected classical EMOA's according to the *Coverage of two sets* metrics

Coverage of two sets $\delta(A,B)$				
	SPEA	**VEGA**	**NPGA**	**CoEMAS**
SPEA	✓	0.08	0.00	0.04
VEGA	0.92	✓	0.30	0.32
NPGA	1.00	0.62	✓	0.40
CoEMAS	0.96	0.70	0.58	✓

values of *host-agent* that is being infected. The probability of infection is higher or lower depending on performed test.

Both *host-agents* and *parasite-agents* can reproduce if they posses enough amount of resources. *Host's* reproduction consists in creating one descendant from two ready-for-reproduction individuals using crossover operator and then mutation operator is applied to created descendant. Parental individuals survive reproduction process but they loss some of their resources in aid of their offsprings. *Parasite's* reproduction consists in creating two descendants from one parental individual using mutation operator. Parental *parasite-agent* transfers half of its life-energy to each of its descendants and then dies.

At last, mentioned above test that is being performed by *parasite-agent* on *host-agent* before infection consists in comparing — in the sense of domination relation (see eq. (3)) — solutions represented by assaulting *parasite-agent* and *host-agents* that is being assaulted. The more solution represented by *host-agent* is dominated by *parasite-agent* the higher is the probability of infection.

3.2 Simulation Experiments — Preliminary Qualitative Results

After implementation some experiments have been performed, but because of space limitations only some qualitative conclusions (not quantitative results) will be here presented. Namely, proposed *co-evolutionary multi-agent system for multi-objective optimization with host-parasite mechanism* has been tested using, inter alia, *Binh* and slightly modified *Schaffer* test functions that are defined as follows:

$$F_1(Binh) = \begin{cases} f_1(x,y) = x^2 + y^2 \\ f_2(x,y) = (x-5)^2 + (y-5)^2 \\ where \quad -5 \le x,y \le 10 \end{cases}$$

$$F_2(Modified\,Schaffer) = \begin{cases} f_1(x) = x^2 \\ f_2(x) = (x-2)^2 \\ where \quad -32 \le x \le 32 \end{cases}$$

Additionally, on the same *JagWorld* platform there have been implemented also some "classical" evolutionary algorithms for multi-objective optimization i.e. *Vector Evaluated Genetic Algorithm (VEGA)* [9, 10], *Niched-Pareto Genetic Algorithm (NPGA)* [5] and *Strength Pareto Evolutionary Algorithm (SPEA)* [13].

Table 2. Comparison of proposed CoEMAS approach with selected classical EMOA's according to the *Coverage difference of two sets* metrics

Coverage difference of two sets $\xi(A,B)$				
	SPEA	**VEGA**	**NPGA**	**CoEMAS**
SPEA	✓	8	0	6
VEGA	116	✓	3	13
NPGA	154	42	✓	25
CoEMAS	197	27	7	✓

Table 3. Comparison of proposed CoEMAS approach with selected classical EMOA's according to another four metrics

	Size of dominated space ($\wp$)	**Average distance to the model Pareto set (M_1)**	**Distribution (M_2)**	**Spread (M_3)**
SPEA	39521	0.8	0.21	10.2
VEGA	39405	2.3	0.11	10.3
NPGA	39368	3.2	0.18	10.1
CoEMAS	39324	3.7	0.15	9.9

To compare proposed approach with implemented classical algorithms also some metrics have been used. Obtained values of these metrics are presented in Table 1, Table 2 and Table 3.

Assuming the following meaning of used below symbols: $\mathcal{P}$—Pareto set defined in eq. (5), $A, B \subseteq D$—two sets of decision vectors, $\sigma \geq 0$—appropriately chosen neighborhood parameter and $\|\cdot\|$—the given distance metric, then the measures presented in these tables are defined as follows [13]:

- $\delta(A,B)$—the coverage of two sets maps the ordered pair (A,B) to the interval $[0,1]$ in the following way:

$$\delta(A,B) = \frac{|\{b \in B \mid \exists a \in A : a \geq b\}|}{|B|} \tag{7}$$

- $\xi(A,B)$—the coverage difference of two sets ($\wp$ denotes value of the *size of dominated space* measure):

$$\xi(A,B) = \wp(A+B) - \wp(B) \tag{8}$$

- M_1—the average distance to the Pareto-optimal set $\mathcal{P}$:

$$M_1(\mathcal{P}) = \frac{1}{|\mathcal{P}|} \sum_{p \in \mathcal{P}} min\{\|p - x\| \mid x \in \mathcal{P}\} \tag{9}$$

- M_2—the distribution in combination with the number of non-dominated solutions found:

$$M_2(\mathcal{P}) = \frac{1}{|\mathcal{P} - 1|} \sum_{p \in \mathcal{P}} |\{r \in \mathcal{P} \mid \|p - r\| > \sigma\}| \tag{10}$$

– M_3—the spread of non-dominated solutions over the set A:

$$M_3(\mathcal{P}) = \sqrt{\sum_{i=1}^{N} max\{\|p_i - r_i\| \mid p, r \in \mathcal{P}\}} \tag{11}$$

Basing on defined above test functions and measures, some comparative studies of proposed co-evolutionary agent-based system and mentioned above very well known, and commonly used algorithms (i.e. *VEGA*, *NPGA* and *SPEA*) could be performed and conclusions from such experiments can be formulated as follows:

– Within the group of implemented algorithms *SPEA* has turned out to be definitely the best one;
– *NPGA* has turned out to be slightly worse than *SPEA* if the distance to the model Pareto frontier has been considered, and they have been very similar if distribution non-dominated individuals over the whole Pareto frontier has been considered;
– *VEGA*-based solutions have been almost as close to the model Pareto frontier as they have been in case of *SPEA* — however these solutions have been focused around some parts of Pareto set — what confirms the tendency of *VEGA* for preferring chosen objective(s);
– proposed *CoEMAS* system with *host-parasite* mechanism has turned out to be comparable to the *classical algorithms* according almost all considered metrics except for *Average distance to the model Pareto set* (see. Table 3);

It has to be mentioned here that preliminary experiments have been performed using very simple test functions and some potential advantages of proposed co-evolutionary system could not be here observed — but of course further experiments especially with very difficult multi-dimensional and dynamic testing problems will be conducted and proposed approach should turn out especially useful in case of multi-modal multi-objective problems such as Zitzler's t_4 test function [13].

4 Concluding Remarks

Evolutionary algorithms often suffer from premature loss of population diversity what limits their adaptive capabilities and possible application to hard problems like multi-modal and multi-objective optimization. To avoid such problems niching and co-evolutionary techniques for evolutionary algorithms are proposed and applied. However, co-evolutionary techniques are rather rarely used as mechanisms of maintaining useful population diversity.

The model of *co-evolutionary multi-agent system* allows co-evolution of several species and sexes. This results in maintaining population diversity and improves adaptive capabilities of systems based on *CoEMAS* model. In this paper the *co-evolutionary multi-agent system with host-parasite mechanism for multi-objective optimization* has been presented. The system was run against commonly used test problems and compared to classical VEGA, SPEA, and NPGA algorithms. Presented results show that SPEA is the best of all compared algorithms. Proposed CoEMAS with host-parasite mechanism was comparable to the other classical algorithms, except for *average distance to the model Pareto set* metric. This fact results from the tendency to maintain high population diversity what could be very useful in the case of hard dynamic and multi-modal multi-objective problems.

Future work will include more detailed comparison to other classical algorithms with the use of hard multi-dimensional, dynamic, and multi-modal multi-objective test problems. Also the application of other co-evolutionary mechanisms like sexual selection and predator-prey are included in future plans.

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