

Co-Evolutionary Multi-Agent System with Predator-Prey Mechanism for Multi-Objective Optimization

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 allow for the application of such algorithms to problems for which it is difficult or even impossible to formulate explicit fitness function. These techniques also maintain population diversity, allows for speciation and help overcoming limited adaptive capabilities of evolutionary algorithms. In this paper the idea of *co-evolutionary multi-agent system with predator-prey 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 two species: predators and prey. Results from runs of presented system against test problem and comparison to classical multi-objective evolutionary algorithms conclude the paper.

1 Introduction

Co-evolution is the biological process responsible for speciation, maintaining population diversity, introducing arms races and open-ended evolution. In *co-evolutionary algorithms (CoEAs)* the fitness of each individual depends not only on the quality of solution to the given problem (like in *evolutionary algorithms (EAs)*) but also (or solely) on other individuals' fitness [7]. This makes such techniques applicable in the cases where the fitness function formulation is difficult (or even impossible). Co-evolutionary techniques for EAs are also aimed at improving adaptive capabilities in dynamic environments and introducing open-ended evolution and speciation into EAs by maintaining population diversity. As the result of ongoing research quite many co-evolutionary techniques have been proposed. Generally, each of these techniques belongs to one of two classes: competitive or cooperative.

Optimization problems in which multiple criteria have to be taken into account are called multi-objective (or multi-criteria) problems [2, 10]. Most real-life decision processes are such problems—decision maker must deal with multiple criteria (objectives). A solution in the Pareto sense of the multi-objective optimization problem means determination of all non-dominated (in the sense of *weak domination relation* [10]) alternatives from the set of all possible (feasible) decision alternatives. The set of all non-dominated alternatives is sometimes called a *Pareto-optimal set*. These locally or

globally non-dominated solutions create (in the criteria space) so-called local or global Pareto frontiers [2].

In the recent years evolutionary approach to multi-objective problems is the subject of intensive research. As a result of this research a variety of evolutionary multi-objective optimization techniques have been proposed. Evolutionary multi-objective algorithms (EMOAs) can be generally classified as elitist (in which best individuals can be directly carried over to the next generation) and non-elitist ones [2].

In the case of multi-objective optimization—high quality approximation of *Pareto frontier* should fulfill at least three distinguishing features: first of all it should be “located” as close to the ideal Pareto frontier as possible, secondly it should include as many alternatives as possible, and all proposed non-dominated alternatives should be evenly distributed over the whole ideal Pareto set.

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. Additionally, in the case of multi-objective problems with many local Pareto frontiers (so called multi-modal multi-objective problems defined by Deb in [2]) the loss of population diversity may result in locating only local Pareto frontier instead of a global one.

The basic idea of *evolutionary multi-agent systems (EMAS)* is the realization of evolutionary processes within the confines of multi-agent system. EMAS systems have already been applied successfully to discrete, continuous, combinatorial and non-combinatorial multi-objective optimization problems ([8]). It has been also shown that on the basis of the EMAS further research and more sophisticated approaches, models and mechanisms can be proposed [9].

The model of *co-evolutionary multi-agent system (CoEMAS)*, as opposed to the basic *evolutionary multi-agent system (EMAS)* model, allows for the co-existence of several species and sexes which can interact with each other and co-evolve. Co-evolutionary mechanisms can serve as the basis for niching and speciation techniques for EMAS systems [3]. CoEMAS systems can also be applied to multi-objective optimization, especially when there is need for maintaining population diversity and speciation [4, 5].

In the following sections the formal model of co-evolutionary multi-agent system with predator-prey mechanism is presented. Such system is applied to multi-objective optimization Kursawe problem and compared to other selected classical evolutionary techniques.

2 Co-Evolutionary Multi-Agent System with Predator-Prey Mechanism for Multi-Objective Optimization

The system presented in this paper is the CoEMAS with predator-prey mechanism (see fig. 1). There are two species: predators and prey in this system. Prey represent solutions of the multi-objective problem. The main goal of predators is to eliminate “weak” (i.e. dominated) prey.

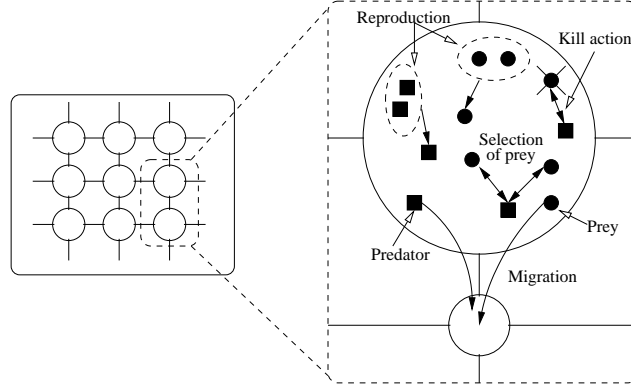


Fig. 1. CoEMAS with predator-prey mechanism

The *CoEMAS* is described as 4-tuple: $CoEMAS = \langle E, S, \Gamma, \Omega \rangle$ where E is the environment of the *CoEMAS*, S is the set of species ($s \in S$) that co-evolve in *CoEMAS*, Γ is the set of resource types that exist in the system, the amount of type γ resource will be denoted by r^γ , Ω is the set of information types that exist in the system, the information of type ω will be denoted by i^ω . There are two information types ($\Omega = \{\omega_1, \omega_2\}$) and one resource type ($\Gamma = \{\gamma\}$) in *CoEMAS*. Informations of type ω_1 contain nodes to which agent can migrate, when it is located in particular node of the graph. Informations of type ω_2 contain agents-prey which are located in the particular node in time t . There is one resource type ($\Gamma = \{\gamma\}$) in *CoEMAS*, and there is closed circulation of resource within the system.

The **environment** of *CoEMAS* is defined as 3-tuple: $E = \langle T^E, \Gamma^E = \Gamma, \Omega^E = \Omega \rangle$, where T^E is the topography of environment E , Γ^E is the set of resource types that exist in the environment, Ω^E is the set of information types that exist in the environment. The topography of the environment $T^E = \langle H, l \rangle$ where H is directed graph with the cost function c defined ($H = \langle V, B, c \rangle$, V is the set of vertices, B is the set of arches). The distance between two nodes is defined as the length of the shortest path between them in graph H . The $l: A \rightarrow V$ (A is the set of agents, that exist in *CoEMAS*) function makes it possible to locate particular agent in the environment space.

Vertice v is given by: $v = \langle A^v, \Gamma^v = \Gamma^E, \Omega^v = \Omega^E, \varphi \rangle$, where A^v is the set of agents that are located in the vertice v . Agents can collect two types of informations from the vertice. The first one includes all vertices that are connected with the vertice v and the second one includes all agents of species *prey* that are located in the vertice v .

The **set of species** is given by: $S = \{prey, pred\}$. The prey species is defined as follows: $prey = \langle A^{prey}, SX^{prey} = \{sx\}, Z^{prey}, C^{prey} \rangle$, where A^{prey} is the set of agents of prey species, SX^{prey} is the set of sexes which exist within the *prey* species, Z^{prey} is the set of actions that agents of species *prey* can perform, and C^{prey} is the set of relations of species *prey* with other species that exist in the *CoEMAS*. There is

only one sex sx ($sx \equiv sx^{prey}$) within the *prey* species, which is defined as follows: $sx = \langle A^{sx} = A^{prey}, Z^{sx} = Z^{prey}, C^{sx} = \emptyset \rangle$.

The set of actions $Z^{prey} = \{die, get, give, accept, seek, clone, rec, mut, migr\}$, where *die* is the action of death (prey dies when it is out of resources), *get* action gets some resource from another a^{prey} agent located in the same node (this agent is dominated by the agent that performs *get* action or is too close to him in the criteria space — such agent is found with the use of *seek* action), *give* actions gives some resource to another agent (which performs *get* action), *accept* action accepts partner for reproduction (partner is accepted when the amount of resource possessed by the prey agent is above the given level), *seek* action seeks for another prey agent that is dominated by the prey performing this action (or too close to it in criteria space) or seeks for partner for reproduction (prey starts seeking partner for reproduction when the amount of resource is above the given level), *clone* is the action of cloning prey (new agent with the same genotype as parent's one is created), *rec* is the recombination operator (intermediate recombination is used [1]), *mut* is the mutation operator (mutation with self-adaptation is used [1]), *migr* action allows prey to migrate between nodes of graph H (migrating agent loses some resource).

The set of relations of *prey* species with other species that exist within the system is defined as follows: $C^{prey} = \left\{ \xrightarrow{prey.get-} = \{\langle prey, prey \rangle\}, \xrightarrow{pred.give+} = \{\langle prey, pred \rangle\} \right\}$.

The first relation models intra species competition for limited resources (as a result of performing *get* action the fitness of another prey is decreased — “-”). The second one models predator-prey interactions (prey gives all the resource it owns to predator and dies — predator fitness is increased: “+”).

The **predator species** (*pred*) is defined analogically as *prey* species with the following differences. The set of actions $Z^{pred} = \{seek, get, migr\}$, where *seek* action seeks for the “worst” (according to the criteria associated with the given predator) prey located in the same node as predator performing this action, *get* action gets all resource from chosen prey, *migr* action allows predator to migrate between nodes of graph H (migrating agent loses some resource — if it can not afford the migration it stays at the same node).

The set of relations of *pred* species with other species that exist within the system is defined as follows: $C^{pred} = \left\{ \xrightarrow{prey.get-} = \{\langle pred, prey \rangle\} \right\}$. The relation models predator-prey interactions (predator gets all resources from selected prey, decreases its fitness and prey dies).

Agent a of species *prey* is given by: $a = \langle gn^a, Z^a = Z^{prey}, \Gamma^a = \Gamma, \Omega^a = \Omega, PR^a \rangle$. Genotype of agent a is consisted of two vectors (chromosomes): x of real-coded decision parameters' values and σ of standard deviations' values, which are used during mutation. $Z^a = Z^{prey}$ is the set of actions which agent a can perform. Γ^a is the set of resource types, and Ω is the set of information types.

The set of profiles PR^a includes resource profile (pr_1), reproduction profile (pr_2), interaction profile (pr_3), and migration profile (pr_4). Each time step prey tries to realize goals of the profiles (taking into account the priorities of the profiles: $pr_1 \triangleq pr_2 \triangleq pr_3 \triangleq pr_4$ — here pr_1 has the highest priority). In order to realize goals of the given profile agent uses strategies which can be realized within this profile.

Table 1. Comparison of proposed CoEMAS approach with selected classical EMOA's according to the *HV* and *HVR* metrics obtained during solving Kursawe problem

Step	HV / HVR		
	CoEMAS	PPES	NPGA
1	541.21 / 0.874	530.76 / 0.857	489.34 / 0.790
10	588.38 / 0.950	530.76 / 0.867	563.55 / 0.910
20	594.09 / 0.959	531.41 / 0.858	401.79 / 0.648
30	601.66 / 0.971	531.41 / 0.858	378.78 / 0.611
40	602.55 / 0.973	531.41 / 0.858	378.73 / 0.611
50	594.09 / 0.959	531.41 / 0.858	378.77 / 0.611
100	603.04 / 0.974	531.42 / 0.858	378.80 / 0.6117
600	603.79 / 0.975	577.44 / 0.932	378.80 / 0.611
200	611.43 / 0.987	609.47 / 0.984	378.80 / 0.611
4000	611.44 / 0.987	555.53 / 0.897	378.80 / 0.611
6000	613.10 / 0.990	547.73 / 0.884	378.80 / 0.611

Within pr_1 profile all strategies connected with type γ resource are realized ($\langle die \rangle$, $\langle seek, get \rangle$). This profile uses informations of type ω_2 . Within pr_2 profile strategy of reproduction ($\langle seek, clone, rec, mut \rangle$) is realized (informations of type ω_2 are used and reproducing prey give some resource to child with the use of $give$ action). Within pr_3 profile the interactions with predators are realized (strategy $\langle give \rangle$). Within pr_4 profile the migration strategy ($\langle migr \rangle$), which uses information i^{ω_1} , is realized—as a result of performing this strategy prey loses some resource.

Agent a of species $pred$ is defined analogically to $prey$ agent. The main differences are genotype and the set of profiles. Genotype of agent a is consisted of the information about the criterion associated with this agent. The set of profiles PR^a includes resource profile (pr_1), and migration profile (pr_2). Within pr_1 profile all strategies connected with type γ resource are realized ($\langle seek, get \rangle$). This profile uses informations of type ω_2 . Within pr_2 profile the migration strategy ($\langle migr \rangle$), which uses information i^{ω_1} , is realized. As a result of performing this strategy predator loses some resource.

3 Test Problem and Experimental Results

Presented in the course of this paper agent-based co-evolutionary approach for multi-objective optimization has been tested using a lot of benchmark problems such as Kursawe problem, Laumanns problem, set of Zitzler's problems etc. Because of space limitations it is possible to present in this paper only selected results. Authors decided to discuss obtained results on the basis of Kursawe problem. Its definition is as follows:

$$Kursawe = \begin{cases} f_1(x) = \sum_{i=0}^{n-1} \left(-10 \exp \left(-0.2 \sqrt{x_i^2 + x_{i+1}^2} \right) \right) \\ f_2(x) = \sum_{i=1}^n |x_i|^{0.8} + 5 \sin x_i^3 \\ n = 3 \quad -5 \leq x_1, x_2, x_3 \leq 5 \end{cases}$$

In the case of Kursawe problem optimization algorithm has to deal with disconnected two-dimensional Pareto frontier and disconnected three dimensional Pareto set. Additionally, a specific definition of f_1 and f_2 functions causes that even very small changes in the space of decision variables can cause big differences in the space of objectives. These very features cause that *Kursawe* problem is quite difficult for solving in general—and for solving using evolutionary techniques in particular.

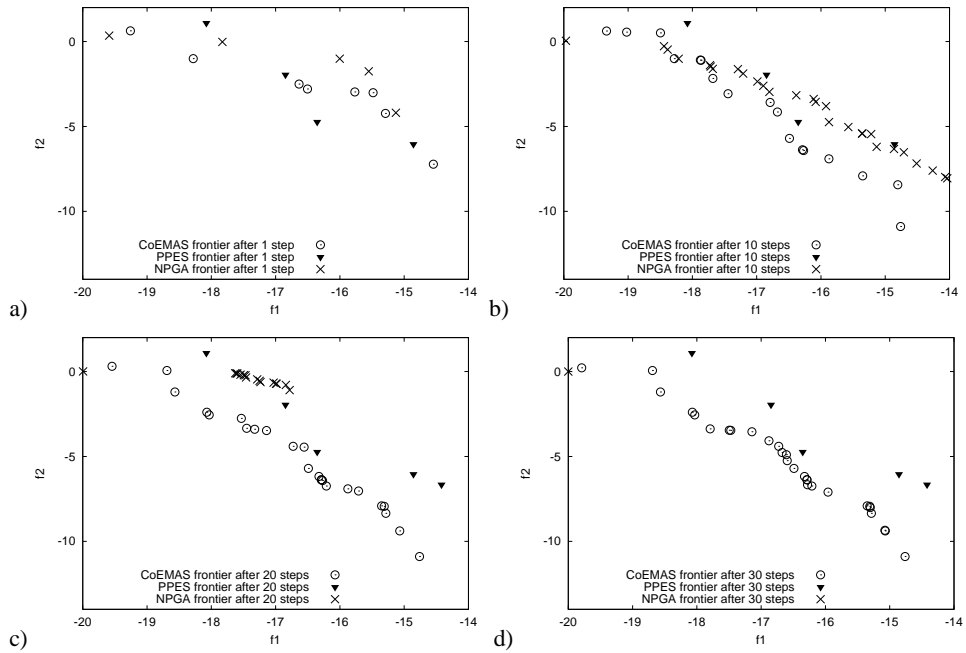


Fig. 2. Pareto frontier approximations obtained by CoEMAS, PPES and NPGA after 1, 10, 20, and 30 steps

For the sake of clarity, “model” Pareto set and frontier will be omitted in further figures presenting their approximations obtained by algorithms that are being analyzed.

As it was mentioned above—Kursawe problem is a quite demanding multi-objective problem with disconnected both Pareto set and Pareto frontier as well. In this section both some qualitative and quantitative characteristics obtained during solving this problem are discussed. To give a kind of reference point, results obtained by CoEMAS are compared with results obtained by “classical” (i.e. non agent-based) predator-prey evolutionary strategy (PPES) [6] and another classical evolutionary algorithm for multi-objective optimization: niched pareto genetic algorithm (NPGA) [10].

In fig. 2 and fig. 3 there are presented approximations of Pareto frontier obtained by all three algorithms that are being analyzed after 1, 10, 20, 30, 50, 100, 600 and 2000 time steps. As one may notice initially, i.e. after 1, 10 and partially after 20 (see fig. 2a,

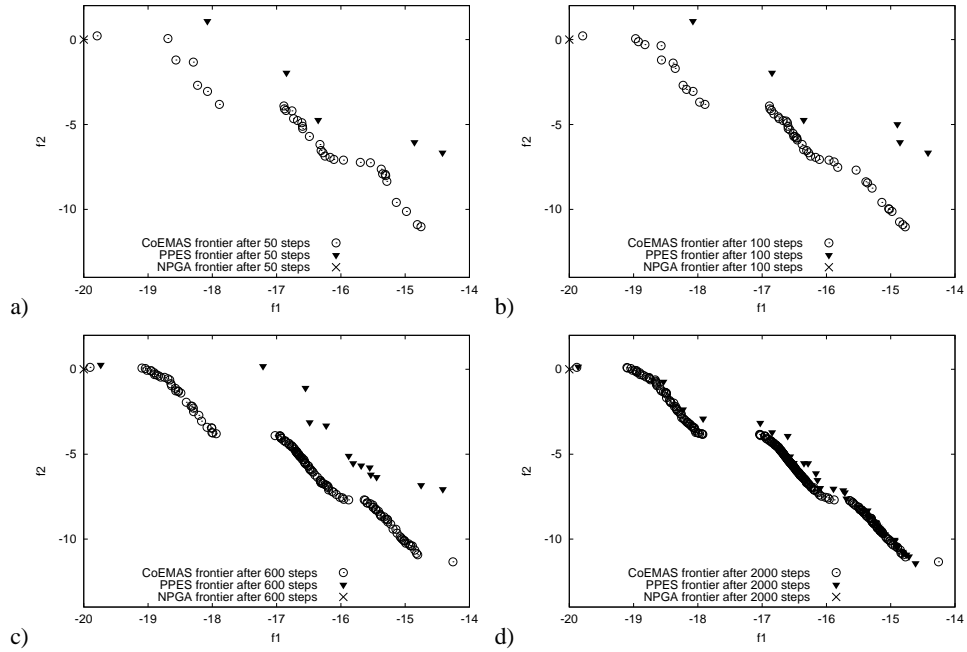


Fig. 3. Pareto frontier approximations obtained by CoEMAS, PPES and NPGA after 50, 100, 600, and 2000 steps

2b and 2c) steps, Pareto frontiers obtained by all three algorithms are—in fact—quite similar if the number of found non-dominated individuals, their distance to the model Pareto frontier and their dispersing over the whole Pareto frontier are considered. Afterwards yet, definitely higher quality of CoEMAS-based Pareto frontier approximation is more and more distinct. It is enough to mention that NPGA-based Pareto frontier almost completely disappears after about 30 steps, and PPES-based Pareto frontier is—as the matter of fact—better and better but this improving process is quite slow and not so clear as in the case of CoEMAS-based solution.

Because solutions presented in fig. 2 and in fig. 3 (especially in fig. 3d) partially overlap, in fig. 4, fig. 5 and fig. 6 there are presented Pareto frontiers obtained by analyzed algorithms after 2000, 4000 and 6000 time steps separately. There is no doubt that—what can be especially seen in fig. 4a, fig. 5a, and in fig. 6a—CoEMAS is definitely the best alternative since it is able to obtain Pareto frontier that is located very close to the model solution, that is very well dispersed and what is also very important—it is more numerous than PPES and NPGA-based solutions.

It is of course quite difficult to compare algorithms only on the basis of qualitative results, so in Table 1 there are presented values of HV and HVR metrics (which are described in [2]) measured after 1, 10, 20, 30, 40, 50, 100, 600, 2000, 4000 and 6000

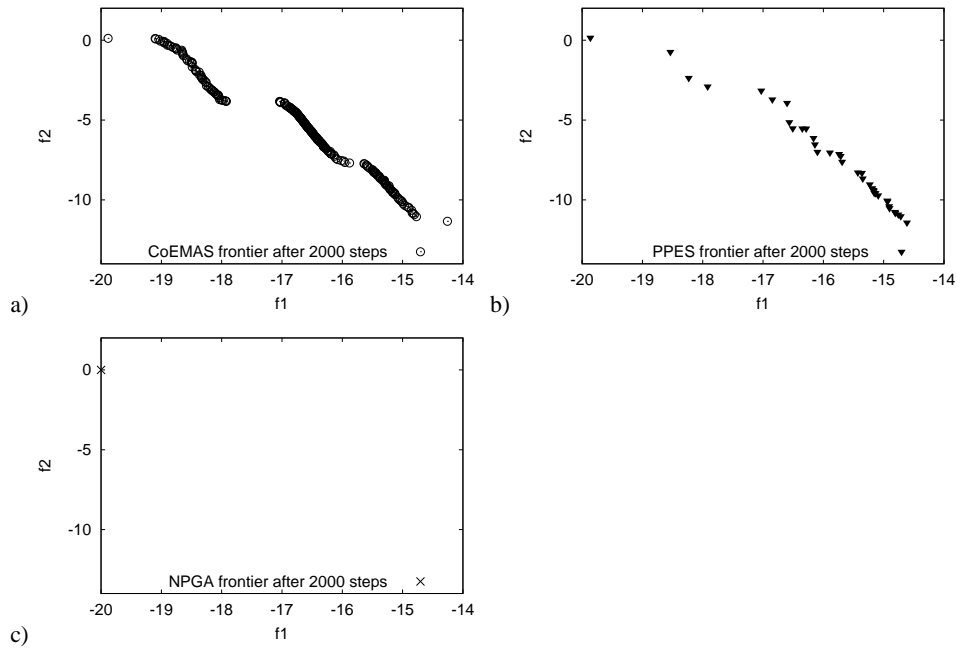


Fig. 4. Pareto frontier approximations obtained by CoEMAS, PPES and NPGA after 2000 steps

steps. The results presented in this table confirm that in the case of Kursawe problem CoEMAS is much better alternative than “classical” PPES or NPGA.

4 Concluding Remarks

Co-evolutionary techniques for evolutionary algorithms makes it possible to apply such algorithms to solving problems for which it is difficult or even impossible to formulate explicit fitness function. Co-evolutionary techniques are rather rarely used as mechanisms of maintaining useful population diversity or as speciation and niching techniques. However, there has been recently growing interest in co-evolutionary algorithms and in the application of such algorithms to multi-objective optimization problems.

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 predator-prey mechanism for multi-objective optimization* has been presented. The system was run against commonly used test problem and compared to classical PPES and NPGA algorithms.

Presented results of experiments with Kursawe problem (as another not presented here results obtained with another mentioned above benchmark problems) clearly show that CoEMAS not only properly located Pareto frontier of this test problem but also the results of this system was better than in the case of two other “classical” algorithms.

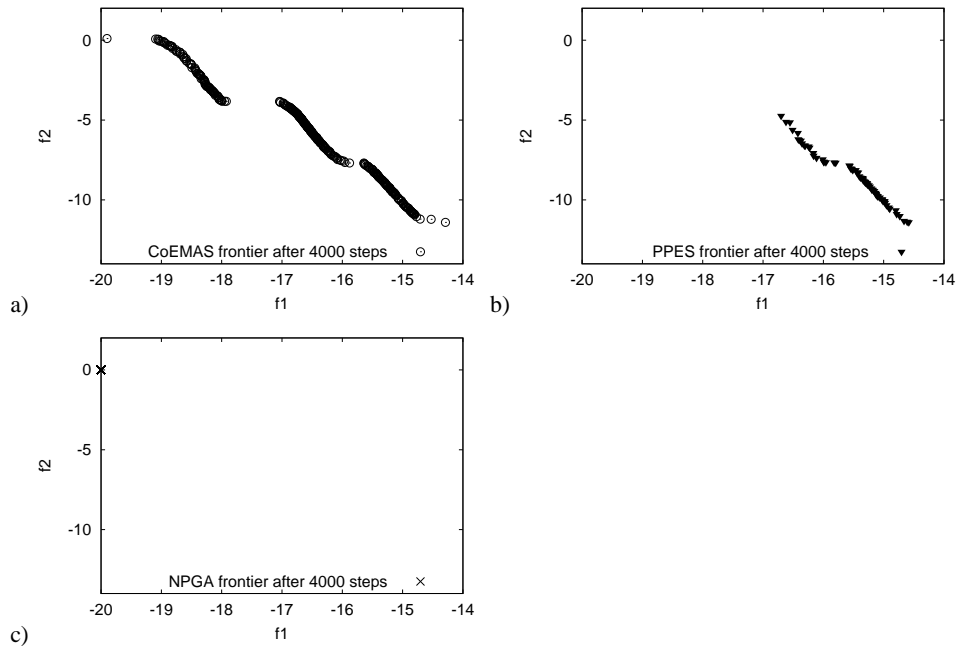


Fig. 5. Pareto frontier approximations obtained by CoEMAS, PPES and NPGA after 4000 steps

CoEMAS was able to obtain solutions that were located very close to the “ideal” Pareto frontier, that were very well dispersed and more numerous than PPES and NPGA-based solutions. This was the result of the tendency to maintain high population diversity what could be especially very useful in the case of hard dynamic and multi-modal multi-objective problems (as defined by Deb [2]).

Future work will include more detailed comparison to other classical algorithms with the use of hard multi-modal multi-objective test problems. Also the application of other co-evolutionary mechanisms like symbiosis (co-operative co-evolution) are included in future plans.

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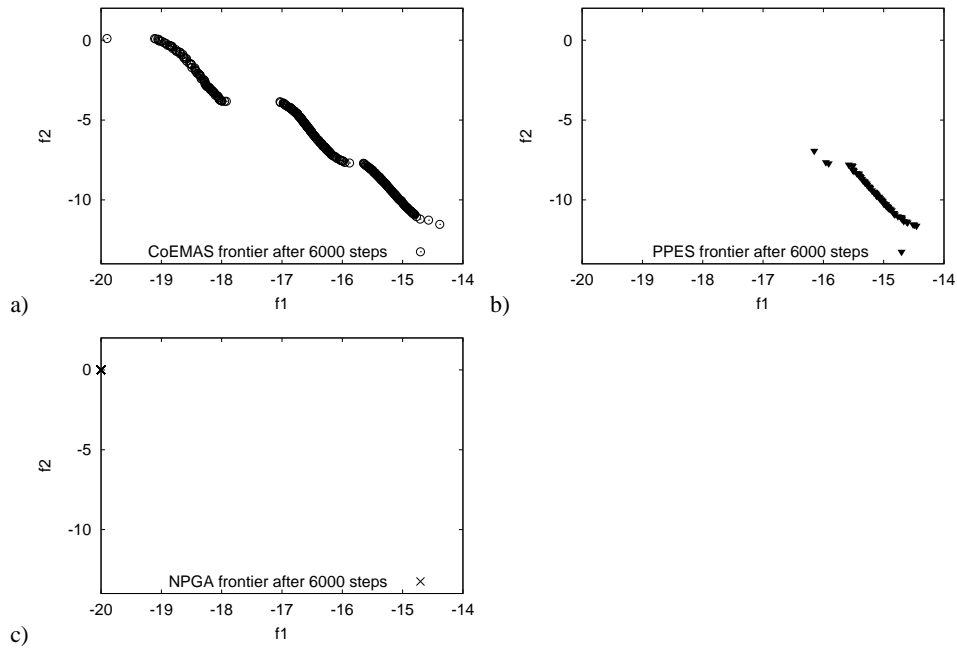


Fig. 6. Pareto frontier approximations obtained by CoEMAS, PPES and NPGA after 6000 steps

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