Elitism in agent-based evolutionary multiobjective optimization

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Abstract

This work introduces a new evolutionary approach to solving the problems of multiobjective optimization. Novelty of the proposed method consists in the application of an evolutionary multi-agent system equipped with the mechanism(s) of elitism, instead of its 'classical' (non-elitist) version. In the paper the model of an elitist evolutionary multi-agent system is described together with its sample realization, and preliminary experimental results.

Keywords: multiobjective optimization, evolutionary multi-agent systems, elitist evolutionary algorithms

1 Introduction

Solving real-life optimization problems based on some analytic model and using *classic* solving methods often occurs (especially if the process of optimization has to take into consideration more than one criterion) to be fruitless due to a large number of dimensions, different types of variables (continuous, discrete, binary), possible non-linearity, or even discontinuities of formulas (also performance functions) of the model. In this context, a need for a computational method arises that deals with multiobjective problems in order to obtain some approximation of the Pareto frontier, and moreover does not depend on the analytic shape of the model. Evolutionary algorithms fit this characteristics, yet they must be equipped with selection mechanisms effective for multiple criteria.

Some publications connected with evolutionary algorithms for multiobjective optimization distinguish at least two groups of such algorithms, i.e. elitist and non-elitist ones. It occurs that "translating" non-elitist evolutionary algorithms to agent-based models is possible and may lead to obtaining interesting solutions of multiobjective problems [5, 7]. The thesis proposed in this article can be formulated as follows: including the—borrowed from traditional evolutionary algorithms—elitism mechanism into an evolutionary multi-agent system in general, and into an evolutionary multi-agent system for multiobjective optimization in particular, is possible, quite simple in realization, and leads to obtaining quite promising results.

The paper is organized as follows. In section 2 basic concepts related to evolutionary multiobjective optimization, as well as the idea of elitism, its advantages and disadvantages are presented. In section 3 descriptions of evolutionary multi-agent systems in general and evolutionary multi-agent systems for multiobjective optimization in particular are presented. There are also some mechanisms for preserving diversity of the population in case of EMAS discussed. In section 4 an elitist agent-based approach is introduced and selected details of the realization are presented. Finally, preliminary results obtained using the proposed approach are discussed in section 5.

ISSN: 1137-3601.

2 Evolutionary approach for multiobjective optimization

During most real-life decision processes a lot of different factors have to be considered, and the decision maker often 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 multiobjective (or multicriteria) problem can be formulated as follows.

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

$$\vec{x} = [x_1, x_2, \ldots, x_N]^T \in \mathbb{R}^N \quad (1)$$

where N gives number of the variables. Then a subset of $\mathbb{R}^N$ of all possible (feasible) decision alternatives (options) can be defined by a system of:

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

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

$$f_m : \mathbb{R}^N \to \mathbb{R}, \quad m = 1, 2, \ldots, M \quad (2)$$

The key issue of optimality in the Pareto sense is the *domination relation*. Alternative $\vec{x}^a$ is dominated by $\vec{x}^b$ if and only if:

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

A solution of the multiobjective optimization problem in the Pareto sense means determination of all non-dominated alternatives from the set D.

For the last 20 years a variety of evolutionary multi-criteria optimization techniques have been proposed [2, 6]. 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. Of course if the algorithm finds a better solution than the one in the elite, this very solution becomes a new elitist solution.

The elitism is already known from classical (singleobjective) evolutionary algorithms, however there are lots of problems connected with applying this mechanism. The fundamental question is whether the elitist solution should take part in the evolutionary process, or it rather should only be a kind of a reference allowing the algorithm to affirm if an individual represents solution better than the best found until now. When the elite does not take part in the evolution process it seems to be rather weakly useful, because the population does not take advantage of the information gathered and represented by the elitist solutions. On the other hand, if the best solution(s) takes part in the process of evolution, then there is a danger, that the diversity of the population will be lost, which obviously can lead to blocking the population in the area of (local) optimum. To prevent this phenomenon the algorithm should be supplemented with some additional mechanisms responsible for preserving diversity of the population, which in turn may to some extent eliminate the influence and potential benefits of the applied elitism.

The situation is slightly different in the case of multiobjective optimization because it consists in searching for the whole set of solutions (the Pareto frontier) instead of a single one, and thus the elite should consist of more than one nondominated solution. Yet, the quality of this Pareto set approximation depends first of all on its "distance" from the actual (target) frontier, but also on its "density"—the number and possibly even distribution of individuals on the whole frontier, not only on its fragment(s). Applying elitism in this case causes faster "drifting" of solutions towards the actual Pareto frontier. This allows for better approximation of the frontier, but unfortunately can also cause concentration of individuals around some parts of the frontier, which is obviously extremely undesirable.

Thus, summarizing, in both cases (i.e. in single- and multi-objective evolutionary optimization) the elitism is potentially very useful, however it has to be supported by some additional mechanisms preserving diversity of the population. According to the already mentioned Deb's typology elitist EMOAs include many practically used algorithms, among others: Rudolph's algorithm, distance-based Pareto GA, strength Pareto GA, thermodynamical GA, Pareto-archived evolution strategy, multi-objective messy GA, multi-objective micro GA, elitist multi-objective EA with coevolutionary sharing, etc. At the same time non-elitist EMOAs include: vector evaluated GA, vector-optimized evolution strategy, weight-based GA, random weighted GA, niched-pareto GA, predator-prey evolution strategy, distributed sharing GA, modified NESSY algorithm, nash algorithm, etc.

3 Agent-based approach to multiobjective optimization

An *evolutionary* multi-agent system is a kind of MAS, in which basic agent interaction mechanisms are designed so that evolutionary processes emerge at a population level [4, 1]. This means that agents are able to *reproduce* (generate new agents) and may *die* (be eliminated from the system) realizing the phenomena of *inheritance* and *selection*. Inheritance is to be accomplished by the appropriate definition of reproduction, which is similar to classical evolutionary algorithms: a set of parameters describing basic behaviours of an agent is encoded in its genotype, and is inherited from its parent(s)—with the use of mutation and recombination.

The proposed principle of selection corresponds to its natural prototype and is based on the existence of non-renewable resource called *life energy*, which is gained and lost when agents execute actions. The increase in energy may be considered as a reward for 'good' behaviour of an agent, the decrease—as a penalty for 'bad' behaviour (of course which behaviour is considered 'good' or 'bad' depends on the particular problem to be solved). At the same time the level of energy determines which actions an agent is able to execute. In particular, low energy level should increase the possibility of death and high energy level should increase the possibility of reproduction.

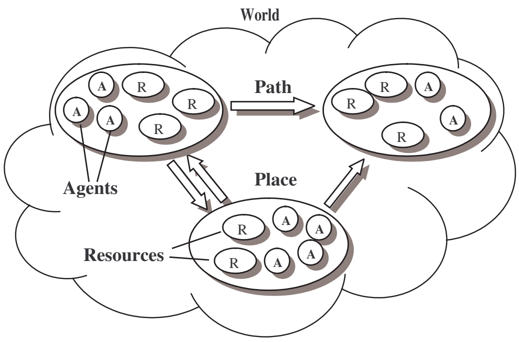


Figure 1: The structure of the environment in EMAS

The environment of EMAS is organized in places, like in the classical migration model of a parallel evolutionary algorithm (fig. 1). The place is an abstraction of rich in resources local environment, where agents can perform their tasks. In fact the number of agents acting within specific place depends—first of all—on amount of available resources. Paths represent direct connections between places and thus show possibilities of migration. Migration is limited by means of path weights: every agent which wants to migrate from one place to another has to pay specific amount of resources. If an agent does not have sufficient quantity of resources, it cannot go through the specific path.

In order to find the approximation of the Pareto frontier for a given multicriteria optimization problem, agents of EMAS act according to the energetic reward/punishment mechanism, which prefers non-dominated agents [5, 7]. This is done via so-called *domination principle*, forcing dominated agents to give a fixed amount of their energy to the encountered dominants. This may happen, when two agents communicate with each other and obtain information about their quality with respect to each objective function. The flow of energy connected with the domination principle causes that dominating agents are more likely to reproduce, whereas dominated ones are more likely to die. This is because in the system there are two energy thresholds defined: the so-called death and reproduction threshold (see fig. 2).

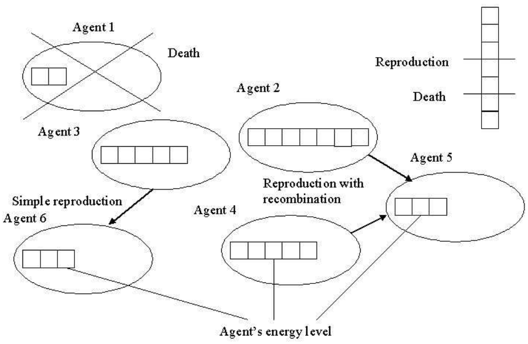


Figure 2: Energy thresholds in non-elitist MAS

From the biological point of view, two main goals of every agent is to survive and create offspring. Both these goals are connected with possessing by agents high enough level of energy. As it is shown in fig. 2 an agent exists in the system as long as its live energy does not fall below death threshold. If it happens (i.e. if in the consequence of meetings and comparisons with other agents, agent's energy level falls below this threshold) the agent dies and is removed from the system (see Agent 1 in fig. 2).

The second "biological" goal of agents is to create offspring. However, even if the agent affirms that it is time for reproduction (see presented below procedure `Make_a_decision()`), an agent has to posses high enough level of energy to perform this action: its level of energy has to be higher than the so-called reproduction level. In fig. 2 only Agent 2, Agent 3 and Agent 4 are able to reproduce (their level of energy is higher than reproduction threshold), whereas the level of energy of Agent 5 and Agent 6 is, as a matter of fact, higher than the death threshold (so, they are able to survive), but it is lower than the reproduction threshold, and so these two agents are not able to reproduce at the moment. Because, as it was mentioned, the flow of energy between agents is connected with relation of domination only agents that at least n times (where n depends on current parameters of EMAS) dominated other agents (so, in the sense of Pareto optimization agents that represent better solutions than, at least, n other agents)—are able to gather enough energy to reproduce, whereas agents that were dominated at least m times (i.e. agents that at least m times had to give a dose of their energy to the dominating agents) die and are removed from the system. In this way, in successive generations, non-dominated agents should make up better approximations of the Pareto frontier.

In the above-described system there is no elitism—all agents have the same status no matter how good solutions they represent (e.g. how much life energy they own). The same status means that exactly the same actions are available for every agent acting within the system. Moreover the same status means that all agents act according to the same algorithm of decision making:

```
Procedure Make_a_decision {
 Random choice of an agent
 if (I dominate this agent)
  Get energy from dominated agent
 else
  Give energy to dominating agent
 if (The other agent is similar to me)
  Get energy from similar agent
 if (It is time for reproduction)
  Reproduction
 if (I want to move)
  Move to another place }
```

The loss of diversity of the population is one of the most important problem connected with evolutionary computations in general, and with agent-based evolutionary computations in particular. That is why there have to be implemented mechanisms that are responsible for preserving the appropriate diversity of the population, such as the energetic mechanism of crowd [7]. The following step in the procedure `Make_a_decision()`:

```
if(The other agent is similar to me)
    Get energy from similar agent
```

causes that the energetic distance of the "similar agent" from the reproduction threshold increases, and simultaneously decreases the distance from the death threshold. So, in this way it is possible that this similar agent will die, which in consequence increases the probability that in the system completely new individuals will appear. In the mentioned procedure there is also one more step that helps preserve the diversity of the population:

```
If (I want to move)
    Move to another place
```

It is obvious that appearing in the place individual that was created in another place allows to insert to this target place potentially completely new genetic material. This individual can of course represent solution that is better as well as worst than solutions represented by agents living in this place. But, what is most important, with very high probability this new agent is a carrier of entirely new solution, so it can resume the evolution process in this place that could come to a standstill.

4 Elitist EMAS for multiobjective optimization

Including elitism mechanism into EMAS consists in modification of agent's decision-making algorithm. In general such modified procedure can be formulated as follows:

```
Procedure Make_an_elitist_decision {
 Make_a_decision()
 if (I belong to the elite)
  if (I want to perform elitist action)
   Perform elitist action(s)}
```

As one may notice, the only difference between `Make_an_elitist_decision()` procedure and `Make_a_decision()` procedure (i.e. between elitist and non-elitist agent's decision making) consists in adding two additional decision points and one additional block of operations. The first additional decision point is connected with checking if an agent belongs to the elite of agent's society. If so, the agent has to make another decision—if it wants to take advantage of belonging to the elite (and perform elitist actions).

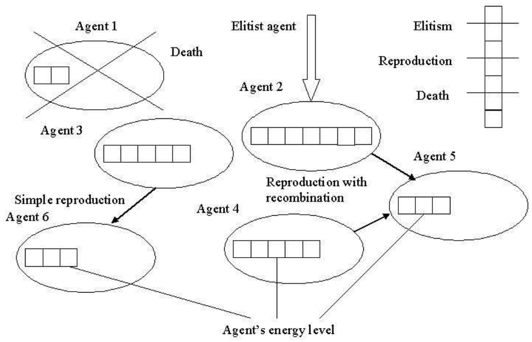


Figure 3: Energy thresholds in elitist multi-agent system

Unfortunately, in case of multicriteria optimization there is the problem with definition of the elite because *Since there are many objective functions, it is not as straightforward as in the single-objective case to identify the elites. In such situations, the non-dominating ranking comes to our rescue* [3, p.240]. In the described realization the mechanism allowing for identification of the elite is based on the level of life energy gathered (or lost) by agents during their life. Thus, beside two energy thresholds for reproduction and death, an additional energy level was introduced to the system (fig. 3).

This additional, so-called *elitist* energy level, is higher than the reproduction one and, the more so, than the death level of course. Because the flow of energy is connected with the relation of domination it is obvious that agents with high level of energy belong to the elite of the society (in the sense of domination). It allows for unambiguous identification of the elite of the population, and moreover, it also seems to be quite elegant, easy to understand and to implement solution that does not require any complicated operations and computations, and which de facto is a kind of the above-mentioned *non-dominating ranking*.

In the considered case, apart from the additional energy level, the elitism is based also on a slightly modified structure of the environment (see fig. 4). In comparison to the structure of environment presented in fig. 1 this modification consists in introducing an additional, elitist type of place. Exceptionality of this place lies in the fact that the price that agent has to pay for using path connected with this special place is much more higher than prices for using other paths. In consequence, only agents possessing high enough level of energy (i.e. higher than the elitist threshold) are able to use these paths. These places are special also because there are only coming in paths to this place(s). Thanks to this elitist agents (with energy level higher than elitist threshold, and which decided to migrate to this place) are not able to go back from elitist place to "ordinary" places, and in consequence they can not take a part in the process of evolution.

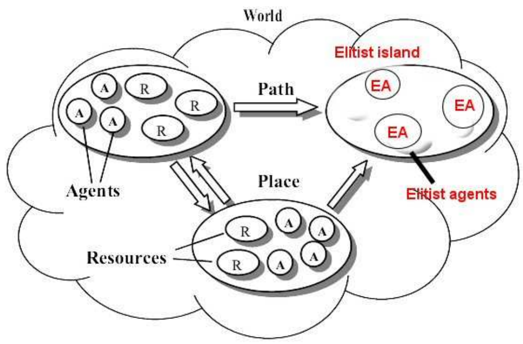


Figure 4: The structure of the environment of elitist EMAS

After asserting that it belongs to the elite, an agent makes a decision if it wants to perform elitist operations. If so, the agent migrates to the elitist place, and if this place is not empty it tries to introduce itself to all other members of the elite of its society. If the agent meets during this process agents that it dominates, it eliminates them from the system. Similarly, if it occurs during this process that agent is dominated by another member of the elite, it is eliminated from the environment. Thanks to this the consecutive approximations of the Pareto frontier (the non-dominated solutions) are represented by agents located in the elitist place. Moreover, during the process of initial meetings agent checks also its similarity to the met agents, and eliminates the ones too similar to itself. This allows for the desirable dispersion of the individuals over the whole Pareto frontier to be achieved, as it was mentioned in section 3. Similarity between agents can be measured both in the space of arguments (for example agents are considered as similar if the sum of differences between appropriate decision variables represented by two individuals is no grater than given value) and in the space of objectives (individuals are "similar" - if the sum of differences between appropriate objecives represented by comparing agents is no grater than given value).

After all these meetings an agent begins (according to the assumption that the elite does not take a part in the process of evolution) the only activity consisting in meetings with agents entering the elitist place.

5 Experimental studies

The described above elitist multi-agent system for multi-objective optimization was tentatively evaluated using—inter alia—Max-Ex problem which is defined as maximization of:

$$f_1(x) = 1.1 - x_1 \quad f_2(x) = 60 - \frac{1+x_2}{x_1} \qquad (4)$$

where

$$0.1 \le x_1 \le 1 \quad 0 \le x_2 \le 5 \qquad (5)$$

The implementation was realized with the use of jAgWorld platform: a Java-based clone of AgWorld [1] software framework based on PVM, facilitating agent-based implementations of distributed evolutionary computation systems (for further reference see *http://agworld.sf.net/*).

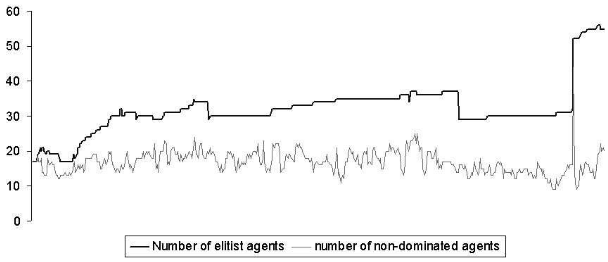
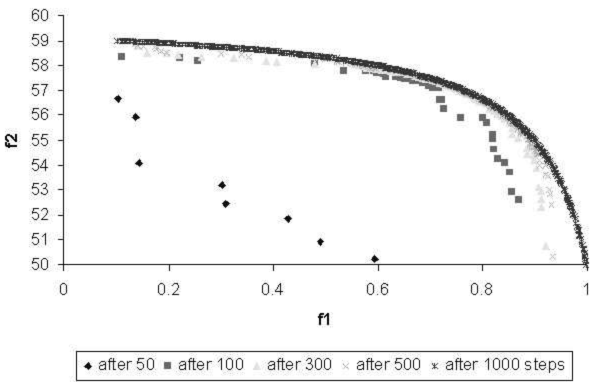
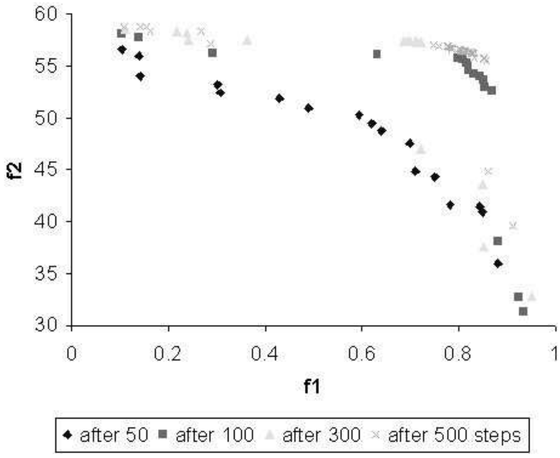


Figure 5: Number of elitist and non-dominated individuals



a)



b)

Figure 6: Approximations of the Pareto frontier represented by elitist (a) and non-dominated (b) individuals

One of the most interesting issues regarding the behaviour of the considered EMAS can be the information whether—and if so—how fast and how precisely the system is able to approximate the desired set of nondominated solutions. In our case the current approximation of the Pareto frontier is represented by elitist agents (i.e. agents located in the elitist place(s)). It is obvious that at the beginning this special place(s) is empty because there are no any elitist agents in the system. Gradually, there appear in the system agents that in consecutive meetings are able to dominate other agents and in consequence to gather enough energy to migrate to the special elitist place. Thus, analyzing the quality of the approximation of the Pareto frontier is limited to observing and analyzing amount and quality of elitist agents. In fig. 6a there is shown the set of elitist agents after 50, 100, 300, 500 and 1000 steps of system operation. The approximation of the Pareto frontier obtained after 50 steps is of course extremely non-satisfying. Starting from this point the population of agents acting according to the description presented in section 4 gradually improves the solution (the approximation of the Pareto frontier) - in sense both - the distance to the model Pareto frontier and the number of individuals belonging to this frontier as well. As one may see the Pareto frontier (i.e. the set of elitist agents) obtained by the system after 500 steps already seems to be acceptable comparing with the model Pareto frontier. Of course the further operations of the system allows for better and better approximation of the Pareto frontier. And finally after about 1000 steps (see fig. 6a) - the set of elitist agents represents excellent solution that is very close, dense and distributed over the whole model Pareto frontier.

The quality of the obtained solution (fig. 6a) confirms that proposed idea of elitist evolutionary multi-agent system seems to work - however the question is what is the influence of the included elitism on the behavior of the system - it is since obvious and it was presented in previous works that agents acting within the EMAS devoided of the elitism mechanism are able to find very good approximations of the Pareto frontier. In fig. 6b there are presented the consecutive approximations of the Pareto frontier represented by currently nondominated individuals in one of the place of the evolutionary multi agent system in which the elitism mechanism was not implemented. Moreover, to present some unfavorable effects - there also all mechanisms responsible for preserving the diversity of the population (and in consequence diversity of the Pareto frontier) were switched off. Comparing "frontiers" presented in these figures (i.e. in fig. 6a and fig. 6b) it can be said that:

- In almost every step Pareto frontiers represented by the set of elitist individuals are much closer to the model Pareto frontier than frontiers represented by non-dominated (but non-elitist) individuals - thus elitism allows for faster drifting to the model Pareto frontier.

- In consecutive steps the set of elitist agents includes more and more individuals - whereas there are no any mechanisms assuring the growth of number of non-dominated agents. As a result - while frontiers presented in fig. 6a are more and more dense - the number of non-dominated individuals presented in fig. 6b is almost constant. (This phenomenon is confirmed by fig. 5 presenting the number of non-dominated and elitist individuals in consecutive steps).

- Because of the lack of mechanisms preserving diversity of the population - consecutive approximations of the Pareto frontiers presented in fig. 6b are more and more focused around the (small) part of the Pareto frontier - whereas elitist agents in every step are distributed almost over the whole Pareto frontier. The example presented in fig. 6b has been choosed with premeditation as one of the worst case - it shows however how important are mechanisms responsible for preserving of the diversity of the population (transfer of resources between similar individuals) and approximation of the Pareto frontier (similar agents entering the elitist place are simply eliminated from the system).

The described above example shows that including elitism into EMAS allows for better (in the sense of the distance to the model Pareto frontier and distribution individuals over the whole Pareto frontier as well) approximation of the Pareto frontier - one may ask however what in case of more difficult problems and if results also are so promising in such case(s)? To answer this question - results obtained during solving so-called Kursawe problem are presented below. This problem is defined as minimization of:

$$f_1(x) = \sum_{i=0}^{n-1} \left(-10 \exp\left(-0.2\sqrt{x_i^2 + x_{i+1}^2}\right)\right) \quad (6)$$

$$f_2(x) = \sum_{i=1}^{n} |x_i|^{0.8} + 5 \sin x_i^3 \quad (7)$$

where

$$n = 3 \quad -5 \le x_1, x_2, x_3 \le 5 \quad (8)$$

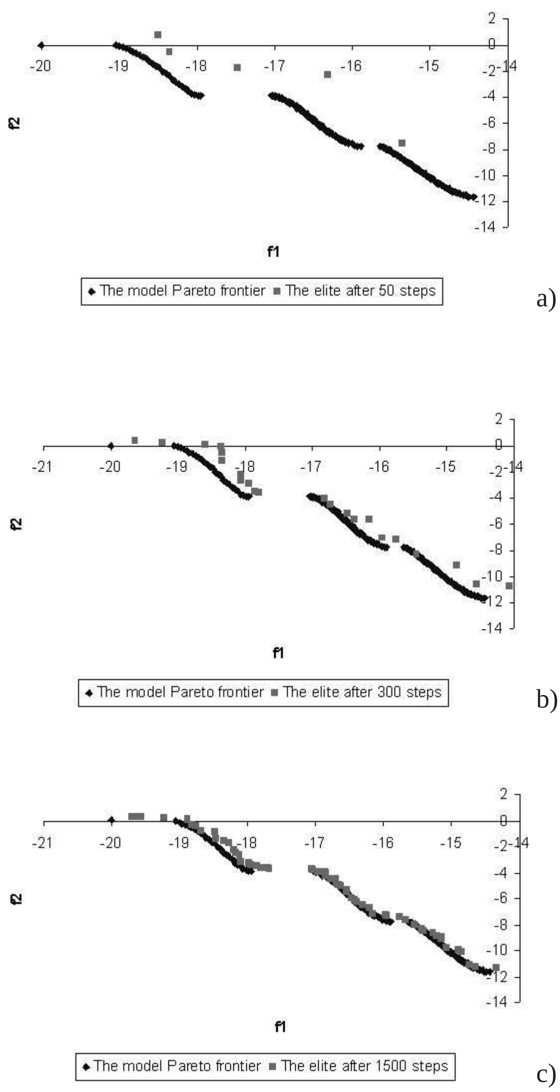


Figure 7: The elitist individuals after (a) 50 (b) 300 and (c) 1500 steps of system operation

Consecutive frontiers (i.e. set of elitist agents) obtained by the system after 50, 300 and 1500 steps are presented in fig. 7. As one may see—also in case of more difficult problems (i.e. problem with three decision variables and disconnected Pareto frontier) the elitist evolutionary multi-agent system for multiobjective optimization seems to work in a very promising way. Approximations of the Pareto frontier presented in fig. 7 show that system obtains frontiers that are both—closer and closer to the model Pareto frontier, and more and more dense. In fig. 7c there is presented the model Pareto frontier and its approximation obtained by the system after 1500 steps. And although in this case the approximation is not so close, so dense and so distributed over the whole Pareto frontier as in the case of the previous problem—it is still very good and at least acceptable solution.

6 Concluding remarks

The proposed idea of an elitist evolutionary multi-agent system for multiobjective optimization proved working in a number of tests and the preliminary results are quite promising. What is maybe even more important, the described approach shows that including elitism to the evolutionary multi-agent system is possible and simple in realization. One may ask why too similar elitist agents are removed from the system and they do not go back to one of the ordinary places. First of all because this is a proposition consistent with a general assumption—that the elite does not take a part in the process of evolution. Secondly because such mechanism could have unfavourable influence on the diversity of populations in ordinary places, however this will surely be the subject of further research.

As it was stated one of the distinguishing feature of the approximation of the Pareto frontier (apart from its distance from the model frontier obviously and dispersing individuals over the whole Pareto set as well) is its ”density”. This means that the more points belonging to the Parteo frontier are found the better it is. The general principle of agent’s activity and additional mechanisms responsible for eliminating from the elitist place dominated agents, cause that at any moment the elitist place includes currently the best approximation of the model Pareto frontier. Moreover, described in the previous sections mechanism responsible for eliminating too similar solutions from the elitist place, ensures suitable dispersing individuals over the whole Pareto frontier. If so, there is the possibility to base the stop condition on the amount of agents located in the elitist places. If this number (that is of course the parameter of the system) is high enough, it ensures the appropriate density of the Pareto frontier which—thanks to above described mechanisms—is adequately dispersed and as close to the model Pareto frontier as possible. However, because increasing the number of agents located in the elitist place (understood as the stop condition) has the influence not only on the density of the approximation frontier but also on the distance from the model Pareto frontier, the optimal value of this parameter will be also the subject of further research.

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