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Agent-Based Multi-Objective Evolutionary Algorithms with Cultural and Immunological Mechanisms

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1. Introduction

Evolutionary algorithms are heuristic techniques for finding (sub)optimal solutions for hard global optimization problems. Evolutionary algorithms may be also applied to multimodal and multi-objective problems (for example compare (Deb, 2001)). In these cases however some special techniques must be used in order to obtain multiple high-quality solutions. Most important of these mechanisms are techniques that maintain population diversity because we are interested in finding the whole set of solutions—it would be a set of non-dominated solutions in the case of multi-objective optimization (all notions and ideas of multi-objective optimization may be found in (Deb, 2001)) and a set of individuals located within basins of attraction of different local optima in the case of multi-modal optimization problems.

Agent-based evolutionary algorithms result from mixing two paradigms: evolutionary algorithms and multi-agent systems. Two approaches are possible when we try to mix these two paradigms. In the first one we can use agent-based layer of the computing system as a "manager" of the computations. In this case each agent has sub-population of individuals inside of it. Agent tries to utilize computational resources in a best way—it observes the computational environment and tries to migrate to nodes which have free computational resources. In this approach evolving individuals are processed with the use of standard evolutionary algorithm.

In the second approach individuals are agents which live within the environment composed of computational nodes, compete for resources, reproduce, die, observe the environment and other agents, communicate with other agents, and can change the environment. The selection is realized in the decentralized way: there are some resources defined in the system and "worse" agents (which have "worse" solutions encoded within their genotypes) give some amount of their resources to "better" agents. These resources are needed for all activities, like reproduction, migration, etc. When an agent runs out of resources it dies and is removed from the system.

The example of the second approach is *evolutionary multi-agent system (EMAS)* model (Cetnarowicz et al., 1996), and *co-evolutionary multi-agent system (CoEMAS)* model (Dreżewski, 2003), which additionally allows for existence of many species and sexes of agents—it is also possible to define interactions between them and introduce co-evolutionary interactions.

The two mentioned approaches can be mixed in such a way that we use agent-based layer for managing the computations and each evolving individual is also an agent which can compete for resources, migrate within the environment, reproduce, and die.

Agent-based evolutionary algorithms have some distinguishing features, among which the most interesting seem to be:

1. The possibility of constructing hybrid systems. In such a case we can use many different bio-inspired techniques together, within one coherent agent-based computational model.

2. Relaxation of computational constraints—computations are decentralized and asynchronous because we use agent-based approach.

3. The possibility of introducing new biologically and socially inspired operators, which were hard or impossible to introduce in the case of "classical" evolutionary computations.

In this chapter we mainly focus on the first and third of the mentioned above issues. The main objective is to introduce two new mechanisms for EMAS model: cultural, and immunological. These mechanisms are applied in agent-based multi-objective evolutionary algorithm.

Following (Deb, 2001)—*multi-objective optimization problem*—*MOOP* in its general form is being defined as follows:

$$MOOP \equiv \begin{cases} Minimize/Maximize & f_m(\bar{x}), \quad m = 1,2\ldots,M \\ Subject\ to & g_j(\bar{x}) \geq 0, \quad j = 1,2\ldots,J \\ & h_k(\bar{x}) = 0, \quad k = 1,2\ldots,K \\ & x_i^{(L)} \leq x_i \leq x_i^{(U)}, \quad i = 1,2\ldots,N \end{cases}$$

Authors assume that readers are familiar with at least fundamental concepts and notions regarding multi-objective optimization in the Pareto sense (relation of domination, Pareto frontier and Pareto set etc) and because of space limitation their explanation is omitted in this chapter (interested readers can find definitions and deep analysis of all necessary concepts and notions of Pareto MOO for instance in (Coello et al., 2007; Deb, 2001)).

The chapter is organized as follows:

*   in section 2 shortcomings of naive application of EMAS model for solving multi-objective optimization problems are discussed and concluded with motivation for further research on advanced mechanisms that could be introduced into EMAS and overcome defined problems;

*   in section 3 short introduction into immune and cultural mechanisms is given and next our realization of immune-cultural Evolutionary Multi-Agent System for multi-objective optimization *ic*-EMAS is presented and discussed;

*   in section 4 we discuss shortly test suite, performance metric and noising algorithm used during experiments, and next we glance at obtained results;

*   in section 5 the most important remarks, conclusions and comments are given.

2. Shortcomings of naive application of EMAS model for solving MOOPs

Evolutionary Multi-Agent System (EMAS) discussed for instance in (Dobrowolski & Kisiel-Dorohinicki, 2002; Cetnarowicz et al., 1996; Socha & Kisiel-Dorohinicki, 2002; Dreżewski & Siwik, 2008*b*; Dreżewski et al., 2009) proved to be very promising computational model. Unfortunately, at the same time, results obtained during solving multi-objective

optimization problems (MOOPs) by distributed and decentralized agent-based evolutionary heuristic approach turned out to be not as high-quality as results obtained by *classical* equivalents and state-of-the-art algorithms.

During testing EMAS on various optimization problems, two core issues that could have great negative influence on obtained results have been identified i.e. algorithm stagnation and non-uniform distribution of agents over (approximation of) the Pareto frontier.

The crucial activities of agents in EMAS environment are interactions with another agents. In particular it means meetings with another agents and comparing with each other represented by them solutions. According to the *domination principle* when one of agents dominates the other one—*life energy* is transferred from dominated agent to the dominating one. Because almost any activity of EMAS agents depends on the amount of their resources (*life energy*)—it is now obvious why agents' interactions and flows of resources are so important.

Unfortunately, with time (during our experiments after ca. six hundreds of steps—see fig. 1b) the number of non-dominated agents is (almost) equal to the number of agents in environment. In the consequence, there are almost only mutually non-dominated individuals, so the probability that the solution represented by agent randomly selected from the whole population, will be dominating or dominated one is quite low.

From the point of view of Agent A in fig. 1a (Siwik et al., 2008) flow of energy takes place only when met agent is located in the Area A or in the Area C—so only if it meets Agents B and C or Agents F, G and H). In the consequence the process of evolution falls into stagnation. It implies that during meetings among agents the flow of energy disappears, so agents can neither reproduce nor die.

In the case of classical algorithms (like NSGA-II) such problem is not so significant, since individual is compared with all the others in each iteration. Similar solution (meetings and comparisons with the whole population in each step/iteration) is not possible in the case of EMAS-based approach since it is distributed and decentralized system and one of the main assumption in this case is lack of the global knowledge and lack of the global management of the whole population as well.
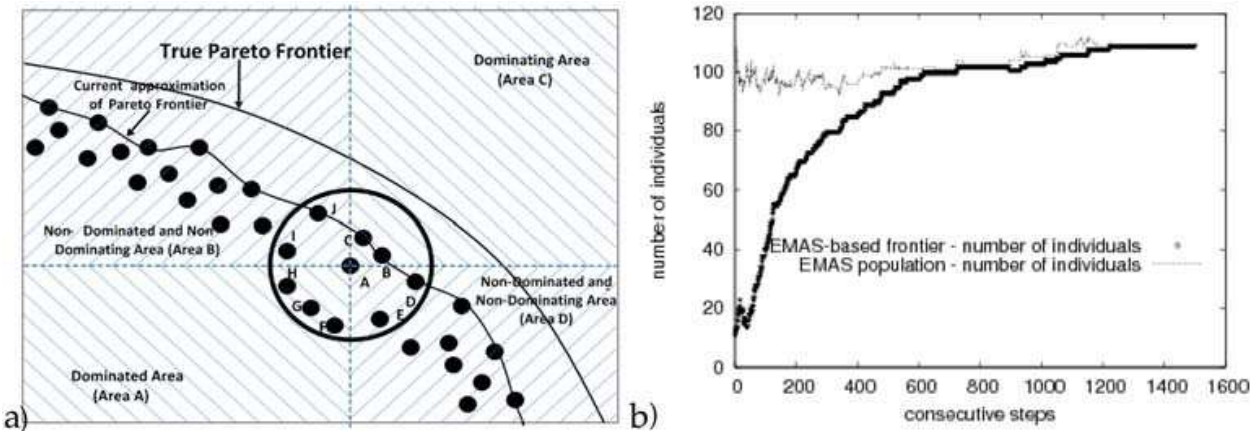

Fig. 1. Stagnation process in EMAS-based multi-objective optimization

Since in the basic implementation of EMAS there are no mechanisms responsible for even distribution of non-dominated solutions over the whole (approximation of the) Pareto frontier, there is also one more difficulty with effective applying "plain" EMAS for solving *MOOPs*— often non-dominated agents are grouped within some areas while other parts of

the Pareto frontier are not covered at all. Such situation is absolutely undesirable since main goals of multi-objective optimization is to find non-dominated solutions located as close to the true Pareto frontier as it is possible but simultaneously none of the objectives should be preferred. So, in other words, all found non-dominated solutions should be evenly dispersed over the whole Pareto frontier. The reason of mentioned problem is often associated with the fact that the probability of locating agents in some areas of the Pareto frontier is pretty low. Often large area in problem domain is mapped into relatively small function value range. EMAS should take such a situation into account and cover such problematic areas.

To recapitulate, it has to be said that introducing evolutionary mechanisms into the population of (autonomous) agents and proposed in this way distributed and decentralized model of evolution seemed to be very promising and attractive. On the other hand simultaneously however, direct and naive applying of such model for solving multi-objective optimization problems turned out to be fruitless to some extent—and that has been the reason and the motivation for researching on additional (advanced) mechanisms that could be introduced into EMAS to eliminate mentioned shortcomings.

Our research on such advanced mechanisms includes inter alia:

- elitist and semi-elitist mechanisms (Siwik & Natanek, 2008*b*; Siwik & Natanek, 2008*a*; Siwik & Kisiel-Dorohinicki, 2006; Siwik & Kisiel-Dorohinicki, 2005);
- flock-based mechanisms (Kisiel-Dorohinicki, 2004; Siwik et al., 2008);
- mechanisms dedicated for solving constrained MOOPs (Siwik & Sikorski, 2008);
- responsible mainly for diversity maintaining co-evolutionary mechanisms and techniques. In this group, the following approaches should be mentioned:
    - co-evolutionary multi-agent system with predator-prey interactions (Drezewski & Siwik, 2007*b*; Drezewski & Siwik, 2007*a*);
    - co-evolutionary multi-agent system with host-parasite interactions (Drezewski & Siwik, 2006*b*);
    - co-evolutionary multi-agent system with sexual selection (Drezewski & Cetnarowicz, 2007; Drezewski & Siwik, 2006*a*; Drezewski & Siwik, 2008*a*);

During further research it has turned out that also mechanisms borrowed from immunological as well as from cultural algorithms can be introduced into EMAS and improve significantly its effectiveness taking solving MOOPs into account. One of possible realization of immune-cultural Evolutionary Multi-Agent System *ic*-EMAS (which in particular allows for overcoming mentioned in this section shortcomings of simple EMAS) is presented in the next section.

3. Immune-cultural Evolutionary Multi-Agent System—*ic*-EMAS

The idea of artificial immune systems comes from the observation of natural, human-being immune system which is responsible—in general—for identification and destroying or neutralization of any kind of pathogens like viruses, bacteria, parasites, tumor-cells etc. Computer models of immune system are a subject of quite intensive research since 90s (Hunt & Cooke, 1995; Dasgupta, 1999; Forrest & Hofmeyr, 2000) and the most important and interesting features of (artificial) immune systems are self-organizing as well as adaptability and learning capabilities. In the consequence, artificial immune systems are very interesting computational approach providing fault tolerance, robustness, dynamism and adaptability (Frank, 1996; Hunt & Cooke, 1995; Castro & Timmis, 2002).

In immunology, there are two crucial concepts i.e. antigens and antibodies (Wierzchon, 2001). Antigens it is such kind of pathogen which can be recognized by immune system and can trigger off so-called immune response. Antigens activate immune cells—lymphocytes. Lymphocytes are producing antibodies which are able to destroy or to neutralize antigens. Lymphocytes posses so-called pattern recognition receptors so they are able to discover not-known so far antigens. Apart from that, immune system possesses also so-called immune memory and it is able to discover in more and more effective way antigens it has been in contact previously. It turns out, that computer model of natural immune systems can improve significantly multi-objective optimization algorithms (Coello & Nareli, 2005).

Immune system, like agent system, is autonomous so applying immune mechanisms within the agent system seems to be natural and smooth. Like in a real immune systems also here the most important issue and responsibility of "immune agents" is recognizing and neutralizing pathogens i.e. dominated specimen.

The most natural way to model immune system within agent system was introducing agents behaving like lymphocytes. Their antibodies can vary, with time, depending on met agents—it is a kind of equivalent of learning feature mentioned and observed in natural immune systems.

Lymphocyte-agent is a kind of EMAS agent so it possesses a genotype. It is also able to gather resources ("life energy") however, in this case, it does not need life energy to perform its activities—it can be said so that "lympho-agents" are immortal. During their life in EMAS environment lympho-agents are able to meet with ordinary agents only and during such meetings relation of domination is evaluated. If lympho-agent dominates met ordinary-agent it means that it meets antigen. According to the ideas and principles of immune systems it triggers an immune response i.e. antigen neutralization. In our realization the process of neutralization consists of two parts. First of all, lympho-agent takes 60% of ordinary-agent's life-energy (the value of 60% was taken on the basis of experiments performed). The second part of neutralization process consists in crossing over genotypes of ordinary- and lympho-agent and if better genotype is created it replaces the genotype of ordinary agent.

It is obviously possible that during the meeting between ordinary- and lympho-agent ordinary-agent dominates lympho-agent. In such a case the process of adaptation of lympho-agent takes place which is realized as taking over by lympho-agent mutated genotype of ordinary-agent. In the consequence lympho-agent is now able to recognize all of that antigens which so far it hasn't been able to dominate and to recognize as antigens (it is similar to some extent to so-called clonal selection known from natural immune systems (Castro & von Zuben, 2002)). During this process, lympho-agent transfers all of its life-energy to dominating ordinary-agent.

Very important parameter from the effectiveness of proposed agent-based artificial immune system point of view is the proper number of lympho-agents. In our realization the number of lympho-agents should be correlated (should be equal to) with the number of ordinary-agents located on the particular island.

Cultural algorithm proposed by R. G. Reynolds from Wayne State University (Reynolds, 1994) has been developed as a kind of supplement of classical genetic algorithm. Such kind of algorithms are making the use of sociological (and archaeological) theories to propose a model of cultural evolution. It is realized by introducing to the system a kind of common (available for all individuals) consciousness which allows for determining the set of expected features and for steering the process of evolution and the behavior of specimens in

such a way to maximize the number of specimens possessing such features. On the other hand, the state of consciousness (so called belief space) depends on the knowledge and experience of individuals, so any change in the population can influence on it causing changes of preferred features. Cultural algorithm works on two levels, i.e.:

- on genome level with the use of mutation, crossover and selection mechanisms as usual in genetic algorithms;
- on the level of belief space being the representation of common consciousness storing the knowledge gathered by all individuals and influencing their behavior.

Both of these levels are able to communicate each other. A given number (fulfilling given conditions) of (best) individuals influences the belief space. Specimens belonging to such a group are chosen with the use of *acceptation*() function. Function *direction*() works in a different way—it influences genetic operators in such a way to maximize the number of individuals with expected features—where "expected features" are defined on the basis of the knowledge stored in the belief space.

Approaches utilizing ideas of cultural algorithm have been successfully applied to solving many optimization problems (Jin & Reynolds, n.d.; Jin & Reynolds, 2000). And what is more important from our point of view, cultural-like approaches have been also successfully applied to solving MOOPs (Coello & Becerra, 2003; Becerra & Coello, 2006).

In our EMAS-based realization of cultural mechanisms, belief space has been introduced on the level of each island. Similarly, to some extent, to solutions proposed in (Coello & Becerra, 2003) as the knowledge stored in the belief space—localization of (non-dominated) individuals in particular areas of search space was chosen. During the initialization, extreme values of each objective function for initial population is determined. Next, each found interval is divided into N_d subintervals. Those subranges divide belief space into $c = N_d^k$ cells. Each cell stores the number of non-dominated individuals representing the given area of search space.

Cultural mechanisms are used during crossover process. In simple EMAS, during reproduction one single offspring is created which is automatically added to the population. Now, after introducing cultural-oriented mechanisms, the process of reproduction looks as follows. First of all, making the use of crossover and mutation operators the number of $N_\mathcal{P}$ pretenders are being created. For each of them, their localization in belief space is being determined but in this moment they are not added to the belief space. First the tournament is being performed and only its winner is being added to the belief space and to the population—the rest of pretenders are destroyed. During the tournament each pretender meets all the others. During each meeting (compare Alg. 1) firstly relation of domination is evaluated. If one of them dominates the other, the value of p_v counter is being increased. If pretenders are mutually non-dominated their localization in the belief space is being checked. If one of them is located outside the borders of the belief space—it wins, else the numbers of individuals located in represented by both agents cells are being checked and the winner is the one representing less crowded cell. After performing such a tournament pretender with the highest number of victories becomes the descendant (the rest—as it was mentioned—is being destroyed).

As one may notice, belief space and cultural-oriented mechanisms address the second problem mentioned in previous section i.e. even distribution of non-dominated solution over the whole approximation of the Pareto frontier.

Algorithm 1. duelCultural($\mathcal{P}$) - tournament in *ic*-EMAS

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for all $p_i \in \mathcal{P}$ **do**
    for all $p_j \in \mathcal{P} \wedge p_i \neq p_j$ **do**
        if $p_i > p_j$ **then**
            $p_i.v = p_i.v + 1$
        else if $p_j > p_i$ **then**
            $p_j.v = p_j.v + 1$
        else
            if $(p_i.C = \emptyset \wedge p_j.C \neq \emptyset) \vee (\overline{p_i.C} > \overline{p_j.C} \wedge \overline{p_i.C} > 0)$ **then**
                $p_i.v = p_i.v + 1$
            else if $(p_i.C \neq \emptyset \wedge p_j.C = \emptyset) \vee (\overline{p_i.C} < \overline{p_j.C} \wedge \overline{p_j.C} > 0)$ **then**
                $p_j.v = p_j.v + 1$
            end if
        end if
    end for
end for
return rand($\{p_x : (p_x \in \mathcal{P}) \wedge (\forall p_y \in \mathcal{P} : p_x.v \geq p_y.v)\}$)

Now, keeping in mind both: immune and cultural-oriented mechanisms, interactions between lympho-agents and ordinary-agents with the use of belief space look as follows (compare Alg. 2): In our realization of immune-cultural EMAS (*ic*-EMAS) also lympho-agents posses information about their localization in belief space. Now, modified lympho-agent is able to recognize not only dominated agent but also agents located in more crowded cell in belief space. If lympho- and ordinary-agent are mutually non-dominated the one located in less crowded cell is being considered as the better alternative. In such a case immune response is different than in the case of domination, because in such a situation it is more important to neutralize antigen by transferring it to less crowded cell. That is why its genotype is replaced by mutated genotype of lympho-agent. Simultaneously, ordinary-agent transfers 40% of its life energy to lympho-agent. In Alg. 2 the complete algorithm of interaction between lympho-agent (l) and ordinary-agent (s) is presented where:

- l,s means lympho- and ordinary-agent respectively;
- $l.\mathcal{E}$ and $s.E$ means energy possessed by lympho- and ordinary-agent respectively;
- $\mathcal{P}$ means the set of pretenders and $N_\mathcal{P}$ means the number of pretenders;
- $x.\mathcal{E}$ means genotype of particular agents;
- $l.\mathcal{C}$ and $s._\mathcal{C}$ means the content of the cell in the belief space where particular agents belongs to;

4. Experimental results

To compare *classical*, i.e. non agent-based algorithms, with proposed in this chapter immune-cultural Evolutionary Multi-Agent System, at least two aspects have to be taken into consideration, since the effectiveness of optimization algorithm can be analyzed as the function of (algorithm's) step and as the function of time. *Decision maker* (algorithm's user) is interested obviously in time aspects (it is important for him how fast it is possible to obtain valuable results) and how precisely given algorithm is able to approximate the model (ideal)

Algorithm 2. immunoCulturalAction(l, s) - interaction between lympho-agent and ordinary agent in ic-EMAS

> **if** $l > s$ **then**
>> $l.\mathcal{E} = l.\mathcal{E} + 0.6 \cdot s.\mathcal{E}$
>> $s.\mathcal{E} = 0.4 \cdot s.\mathcal{E}$
>> **while** $\overline{\mathcal{P}} < N_{\mathcal{P}}$ **do**
>>> $t.\mathcal{G} = \text{crossover}(l.\mathcal{G}, s.\mathcal{G})$
>>> $t.\mathcal{G} = \text{mutate}(t.\mathcal{G})$
>>> $\mathcal{P} = \mathcal{P} \cup t$
>> **end while**
>> $c = \text{duelCultural}(\mathcal{P})$
>> $s.\mathcal{G} = c.\mathcal{G}$
> **else if** $s > l$ **then**
>> **if** $s.nonDominated = true$ **then**
>>> $l.\mathcal{G} = \text{mutate}(s.\mathcal{G})$
>> **end if**
>> $s.\mathcal{E} = s.\mathcal{E} + l.\mathcal{E}$
>> $s.\mathcal{E} = 0$
> **else if** $(l.C = \emptyset \wedge s.C \neq \emptyset) \vee (\overline{l.C} < \overline{s.C} \wedge \overline{l.C} > 0)$ **then**
>> $s.\mathcal{G} = \text{mutate}(l.\mathcal{G})$
>> $l.\mathcal{E} = l.\mathcal{E} + 0.4 \cdot s.\mathcal{E}$
>> $s.\mathcal{E} = 0.6 \cdot s.\mathcal{E}$
> **else if** $(l.C \neq \emptyset \wedge s.C = \emptyset) \vee (\overline{l.C} > \overline{s.C} \wedge \overline{s.C} > 0)$ **then**
>> **if** $s.nonDominated = true$ **then**
>>> $l.\mathcal{G} = \text{mutate}(s.\mathcal{G})$
>> **end if**
>> $s.\mathcal{E} = s.\mathcal{E} + l.\mathcal{E}$
>> $s.\mathcal{E} = 0$
> **end if**

solution (in the case of multi-objective optimization it is of course true Pareto frontier). On the other hand, researchers, during the process of algorithm development should keep in mind also its effectiveness per computational step. Because of its significance for the *Decision Maker* in this chapter time aspects and comparisons will be presented. It is important to notice in this place that all experiments have been performed with the use of one single hardware and software environment and if it was only possible with the same value of particular parameters. There is also one more important disclaimer that has to be underlined here. The goal of this chapter is to present, for the first time, the general idea of introducing both: immune and cultural mechanisms into EMAS with explanation of shortcomings of applying simple EMAS for solving MOOPs and it is not the goal of this chapter to present detailed and deep experimental analysis and comparisons. Therefore, in this section only general—it can be said: from bird's eye view—results are presented. Detailed discussion of obtained results not only for ZDT but also for CTP and DTLZ test suites, values of particular parameters and their influence on the behavior of proposed *ic*-EMAS are presented and discussed in (Goik et al., 2007).

4.1 Test suite, performance metric, state-of-the-art algorithms and noise

As it was mentioned, in the course of this chapter there are presented only selected, general results obtained during solving the Zitzler-Deb-Thiele test suite which in the literature is known and identified as the set of test problems ZDT1-ZDT6 ((Zitzler, 1999, p. 57–63), (Zitzler et al., 2000), (Deb, 2001, p. 356–362), (Coello et al., 2007, p. 194–199)).

Two main distinguishing features of high-quality solution of MOOPs are: closeness to the true Pareto frontier as well as dispersion of found non-dominated solution over the whole (approximation) of the Pareto frontier (see fig. 2).
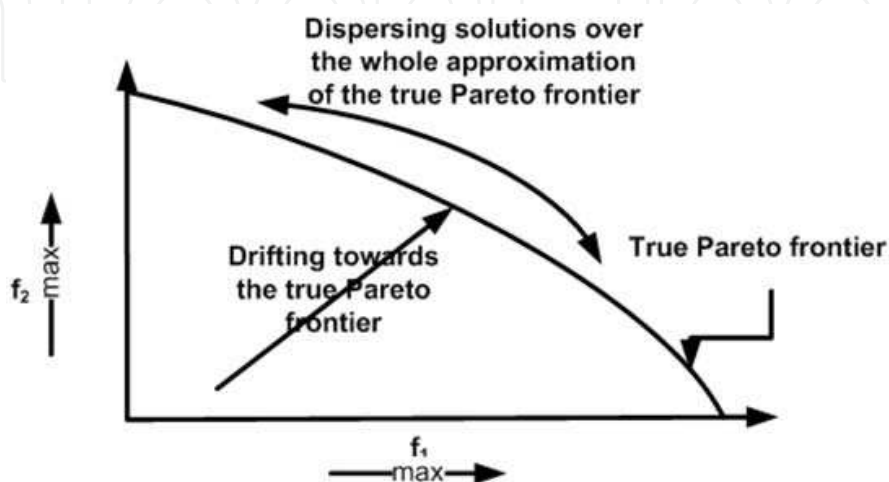
Fig. 2. Two goals of multi-objective optimization

In the consequence, despite that using only one single measure during assessing the effectiveness of (evolutionary) algorithms for multi-objective optimization is not enough (Zitzler et al., 2003), since Hypervolume Ratio measure (HVR) (Zitzler & Thiele, 1998) allows for estimating both of these aspects — in this chapter discussion and presentation of obtained results is based on this very measure.

Hypervolume or Hypervolume ratio (HVR), describes the area covered by solutions of obtained result set. For each solution, hypercube is evaluated with respect to the fixed reference point. In order to evaluate hypervolume ratio, value of hypervolume for obtained set is normalized with hypervolume value computed for true Pareto frontier. HV and HVR are defined as follows:

$$ \mathrm{HV} = v(\bigcup_{i=1}^{N} v_i) \quad \mathrm{HVR} = \frac{\mathrm{HV}(PF^*)}{\mathrm{HV}(PF)} \tag{1a} $$

where v_i is hypercube computed for $i-th$ solution, PF^* represents obtained Pareto frontier and PF is the true Pareto frontier.

To assess (in a quantitative way) proposed *ic*-EMAS, the comparison with results obtained with the use of state-of-the-art algorithms has to be made. That is why we are comparing results obtained by *ic*-EMAS with results obtained by NSGA-II (Deb et al., 2002) and SPEA2 (Zitzler & Thiele, 1999) algorithms since these very algorithms are the most efficient and most commonly used evolutionary multi-objective optimization algorithms.

When one considers applying proposed optimization method for solving real-life problems its effectiveness in noisy environment has to be considered and assessed since in real-life problems noise can not be avoided.

To assess the behavior of algorithm solving multi-objective optimization problem(s)—several forms of noise can be considered and introduced (in order to simulate real situations). So, the noise can be considered at the level of objective function evaluation, as well as at the level of decision variables and finally the noise can be introduced as the—so called— environmental noise (Bui et al., 2004; Miller, 1997; Siwik et al., 2008).

Since several forms of noise can be considered—to omit such considerations as: how strong and how often repeating noise at the level of decision variables results in noise at the level of objective function evaluation (especially that it depends on the particular problem that is being solved)—in this chapter authors focus on objective function evaluation noise (see Algorithm 3).

Such kind of noise simulation directly affects fitness value, and directly influences the quality of obtained result set, and allows in the consequence for direct observation of algorithm's ability for coping with noise occurrences.

Algorithm 3. Noising algorithm

1: **if** Agent A dominates Agent B **then**
2:     Assume that Agent B dominates Agent A with the probability of NoiseRisk parameter
3: **end if**
4: **if** Agent B dominates Agent A **then**
5:     Assume that Agent A dominates Agent B with the probability of NoiseRisk parameter
6: **end if**
7: **if** Agents A and B are mutually non-dominated **then**
8:     the result of assessing the relation of domination is not affected
9: **end if**

4.2 A glance at obtained results

In figures fig. 3 and fig. 4 there are presented results obtained by NSGA-II, SPEA2, *ic*- EMAS and EMAS approaches solving ZDT1 to ZDT6 problems in environment with no occurrence of noise.

As one may see, on all five diagrams from fig. 3 and fig. 4 presenting values of HVR metric for ZDT problems—introducing into EMAS, discussed in this chapter cultural and immunological mechanisms significantly positively influence evolutionary agent-based systems, however in the comparison to state-of-the-art algorithms (SPEA2 and NSGA-II) it can not be said that *ic*-EMAS is better alternative—since in the case of ZDT4 problem (see fig.4a) it is better than classical algorithms but in the case of ZDT6 (see fig.4b) it is worse and in the case of ZDT1, ZDT2 and ZDT3 problems (see fig.3abc) it allows for obtaining only as valuable results as mentioned well-known referencing algorithms.

The situation is completely different when experiments are conducted in noisy environment. In fig. 5 and fig. 6 there are presented results obtained by *ic*-EMAS as well as by NSGA-II and SPEA2 algorithms during solving ZDT1–ZDT6 problems with the simulation of noisy environment with the probability of the occurrence of noise equal to 20%. As one may see, only in the case of ZDT1 problem all three approaches allow for obtaining similar results
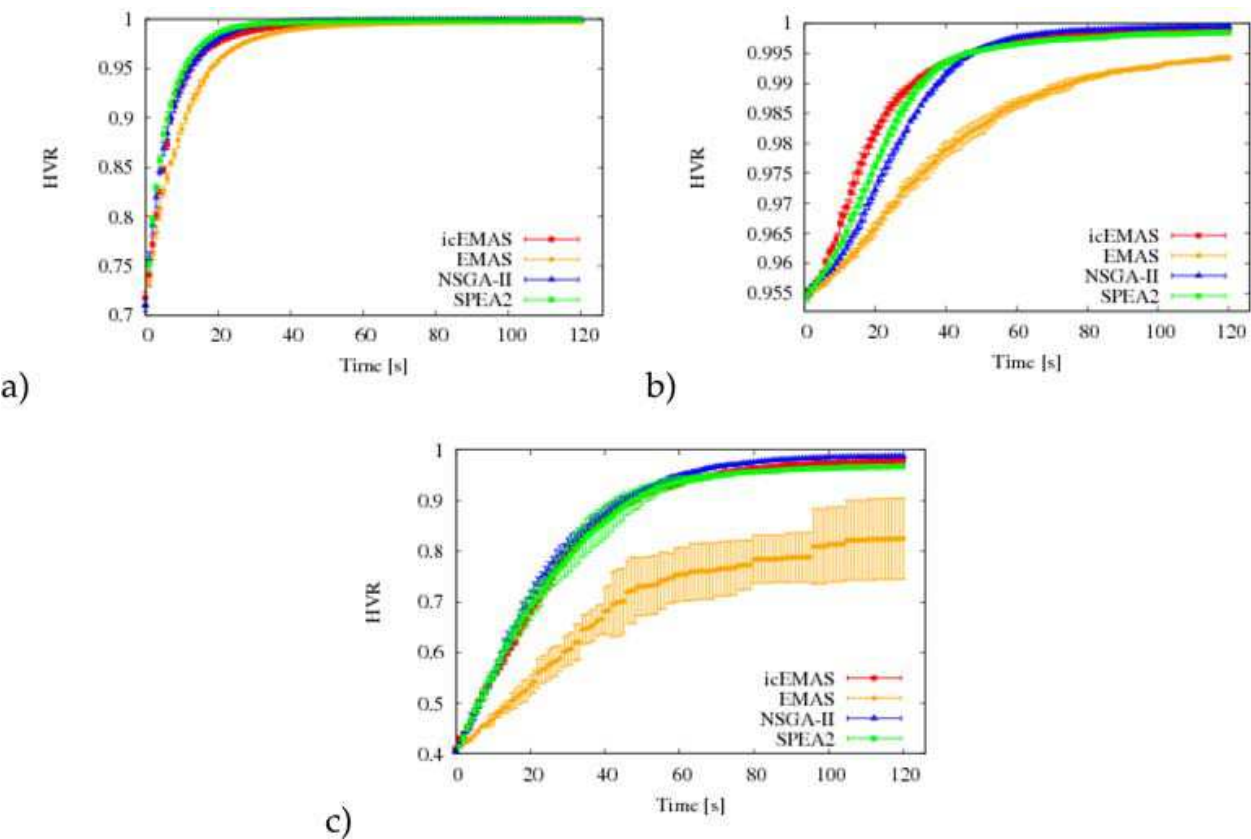
Fig. 3. HVR values obtained solving ZDT1 (a), ZDT2 (b) and ZDT3 (c) in environment without noise
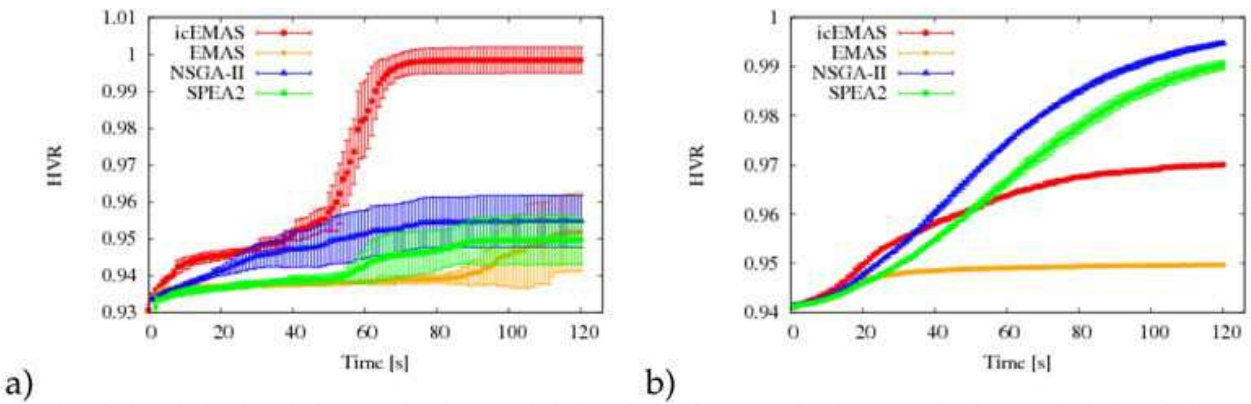

Fig. 4. HVR values obtained solving ZDT4 (a) and ZDT6 (b) problems in environment without noise

(see fig. 5a) whereas in the case of ZDT2, ZDT3, ZDT4 and ZDT6 problems (see fig. 5bc and fig. 6ab) — proposed in this chapter immune-cultural Evolutionary Multi-Agent Systems is definitely the best alternative. In fig. 7 there are presented visualizations of Pareto frontiers' approximations obtained by *ic*-EMAS, NSGA-II and SPEA2 algorithms in noisy environment after 15 (a), 30 (b), 60 (c) and 120 (d) seconds solving ZDT3 problem. It is obviously coherent with the values of HVR measure presented in figures 5 and 6 and confirms that in noisy environment *ic*-EMAS is better alternative than state-of-the-art NSGA-II and SPEA2 algorithms.
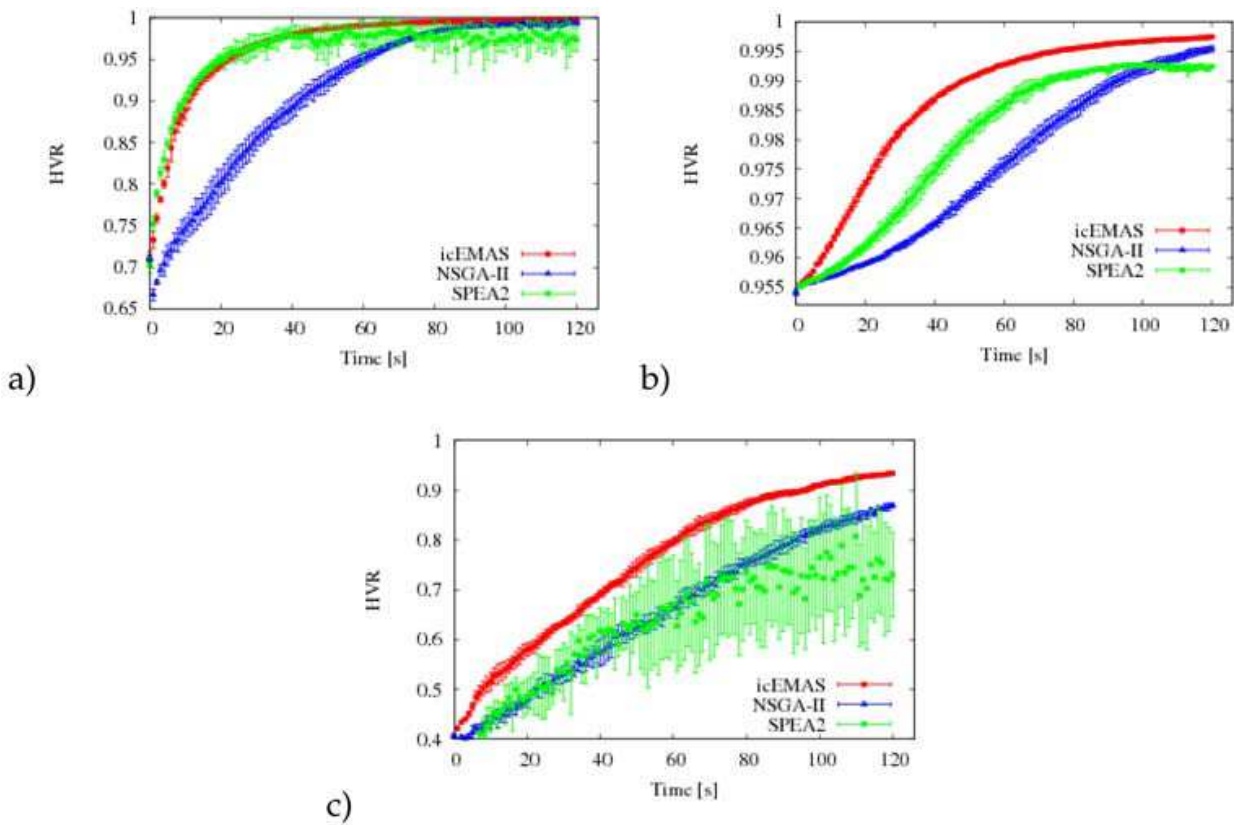
Fig. 5. HVR values obtained solving ZDT1 (a), ZDT2 (b) and ZDT3 (c) problems in noisy environment with the probability of noise occurrence equal to 20%
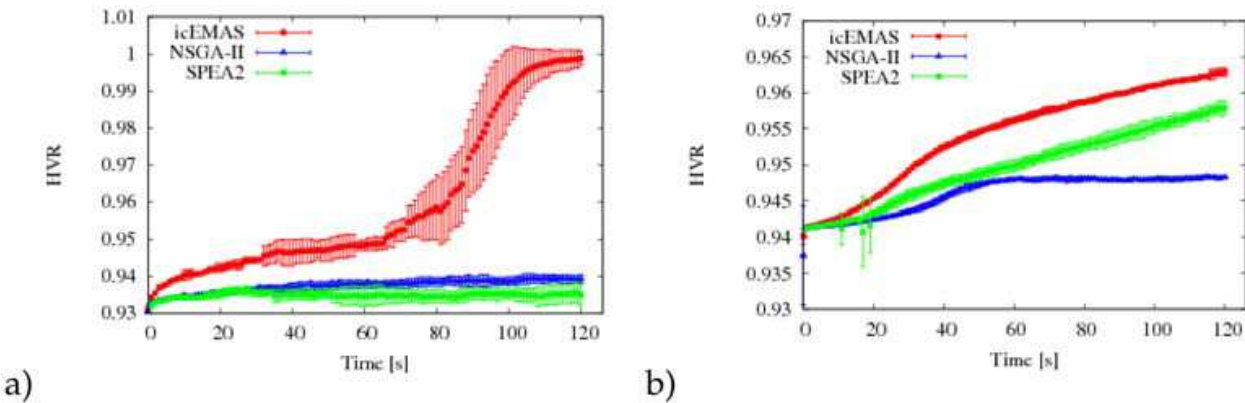

Fig. 6. HVR values obtained solving ZDT4 (a) and ZDT6 (b) problems in noisy environment with the probability of noise occurrence equal to 20%

5. Conclusions

To recapitulate considerations presented in the course of this chapter, it is worth to say, that:

- in this chapter, for the first time, the general idea of realization of cultural and immune mechanisms in decentralized way within the confines of EMAS model is presented;
- EMAS model turns out to be so flexible that introducing considered mechanisms was possible, moreover, as it was discussed, it can be done in elegant, smooth and fully consistent with distributed, autonomous and decentralized agent-oriented way;
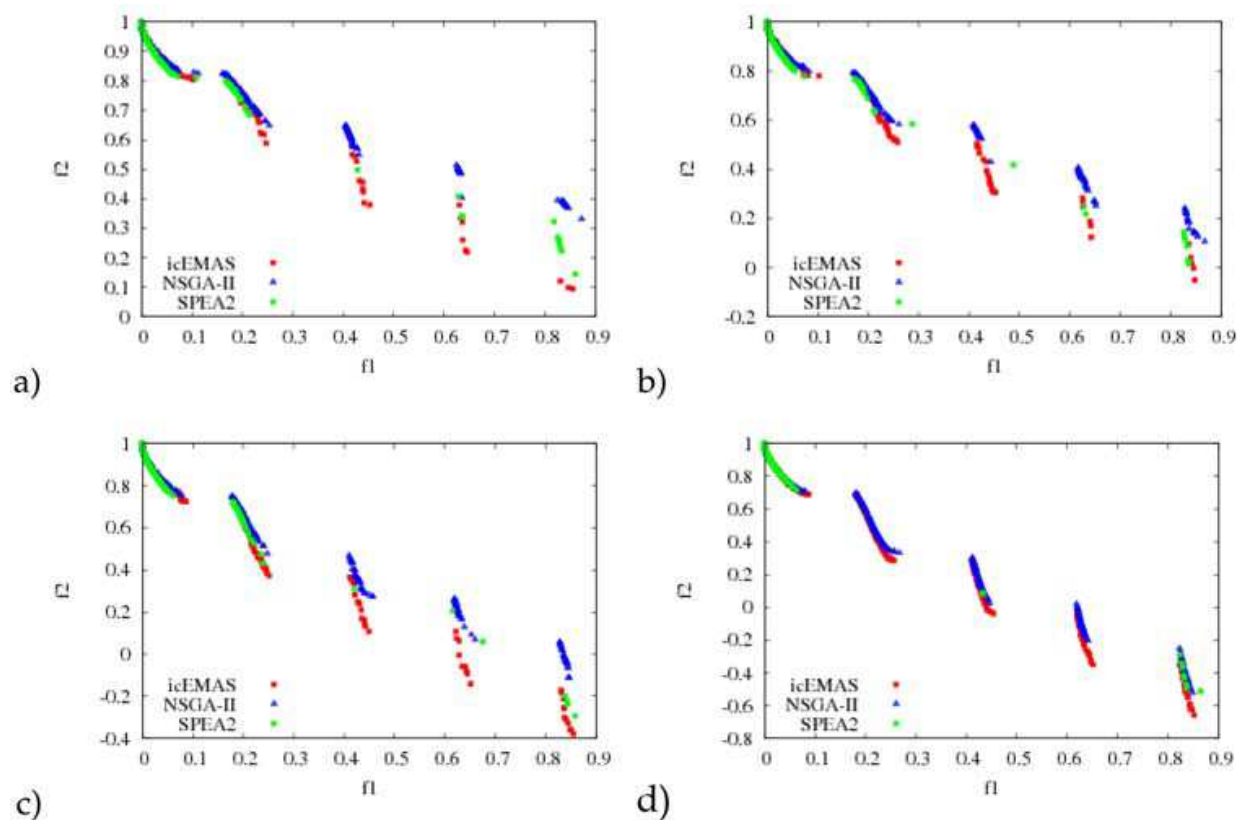
Fig. 7. Approximation of Pareto frontiers obtained by *ic*-EMAS, NSGA-II and SPEA2 in noisy environment after 15 (a), 30 (b), 60 (c) and 120 (d) seconds solving ZDT3 problem

- introduced cultural and immune mechanisms significantly improved the effectiveness of simple EMAS taking the quality of obtained approximations of the Pareto frontier into account as well as time needed for obtaining such high-quality results;
- as it was stated in section 2, there are two shortcomings when applying simple EMAS for solving MOOPs i.e. stagnation and lack of mechanisms responsible for dispersing individuals over the whole approximation of the Pareto frontiers. Proposed in this chapter immune mechanisms address the first problem whereas cultural mechanisms address the second one;
- in the consequence, in the function of time, *ic*-EMAS i.e. presented in this chapter realization of immune-cultural Evolutionary Multi-Agent System allows for obtaining as high quality results as it is possible with the use of state-of-the-art algorithms like NSGA-II and SPEA2;
- what is more, in noisy environment *ic*-EMAS turns out to be even significantly more effective than mentioned state-of-the-art EMOAs;
- significant superiority of *ic*-EMAS over NSGA-II and SPEA2 comes from the phenomenon that can be called *soft* selection. Even, if in a given step strong agent (individual) because of the noise turns out to be dominated—the only consequence is the lost (the part) of its energy. But still—on the contrary to classical algorithms where in such a situation individual is usually removed from the population — it can operate in the environment and during the next meeting(s) with another agents, when only the noise disappears it dominates another agents, so it gains energy and it can reproduce etc. etc. So, to recapitulate in a *soft* model of selection represented by evolutionary

multi-agent systems (and by *ic*-EMAS in particular)—temporary noise does not cause losing strong/promising (often non dominated in fact) individuals;

- because proposed immune-cultural agent-based approach seems to be very promising one, further research on hybridization of EMAS and cultural and immune systems will be conducted with special attention to real-life optimization and decision-supporting applications.

6. References

Becerra, R. & Coello, C. (2006). Solving hard multiobjective optimization problems using econstraint with cultured differential evolution, In: *Parallel Problem Solving from Nature - PPSN IX, 9th International Conference*, Vol. 4193 of *LNCS*, Reykjavik, Iceland, pp. 543–552

Bui, L. T., Essam, D., Abbas, H. A. & Green, D. (2004). Performance analysis of evolutionary multi-objective optimization methods in noisy environments, In: *8th Asia Pacific Symposium on Intelligent and Evolutionary Systems*, Monash University, Melbourne, Australia

Castro, L. & Timmis, J. (2002). Artificial immune systems: a new computational intelligence approach, Spronger-Verlag

Castro, L. & von Zuben, F. (2002). Learning and optimization using the clonal selection principle, *IEEE Transactions on Evolutionary Computation, Special Issue on Artificial Immune Systems* 6(3), 239–251

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

Coello, C. & Becerra, R. (2003). Evolutionary multiobjective optimization using a cultural algorithm, In: *IEEE Swarm Intelligence Symposium Proceedings*, IEEE Service Center, Indianapolis, Indiana, USA, pp. 6–13

Coello, C., Lamont, G. & Van Veldhuizen, D. (2007). *Evolutionary Algorithms for Solving Multi-Objective Problems*, second edn, Springer, New York. ISBN 978-0-387-33254-3

Coello, C. & Nareli, C. (2005). Solving multiobjective optimization problems using an artificial immune system, *Genetic Programming and Evolvable Machines* 6(2), 163–190

Dasgupta, D. (1999). Artificial Immune Systems and Their Applications, Springer-Verlag

Deb, K. (2001). Multi-Objective Optimization using Evolutionary Algorithms, John Wiley & Sons

Deb, K., Pratap, A., Agarwal, S. & Meyarivan, T. (2002). A Fast and Elitist Multiobjective Genetic Algorithm: NSGA–II, *IEEE Transactions on Evolutionary Computation* 6(2), 182–197

Dobrowolski, G. & Kisiel-Dorohinicki, M. (2002). Management of evolutionary mas for multiobjective optimisation, In: T. Burczynski & A. Osyczka, (Ed.), *Proceedings of symposium on Evolutionary methods in mechanics*, Kluwer Academic Publishers, Cracow, pp. 81–90

Dreżewski, R. (2003). A model of co-evolution in multi-agent system, In: V. Mařík, J. Müller & M. Pěchouček, (Ed.), *Multi-Agent Systems and Applications III*, Vol. 2691 of *LNCS*, Springer-Verlag, Berlin, Heidelberg, pp. 314–323

Dreżewski, R. & Cetnarowicz, K. (2007). Sexual selection mechanism for agent-based evolutionary computation, In: Y. Shi, G. D. van Albada, J. Dongarra & P. M. A. Sloot, (Ed.), *Computational Science – ICCS 2007*, Vol. 4488 of *LNCS*, Springer-Verlag, Berlin, Heidelberg, pp. 920–927

Dreżewski, R., Sepielak, J. & Siwik, L. (2009). Classical and agent-based evolutionary algorithms for investment strategies generation, In: A. Brabazon & M. O Neill, (Ed.), *Computational Intelligence in Finance*, Vol. 2, Springer-Verlag, Berlin, Heidelberg

Dreżewski, R. & Siwik, L. (2006*a*). Co-evolutionary multi-agent system with sexual selection mechanism for multi-objective optimization, In: *Proceedings of the IEEE World Congress on Computational Intelligence (WCCI 2006)*, IEEE

Dreżewski, R. & Siwik, L. (2006*b*). Multi-objective optimization using co-evolutionary multiagent system with host-parasite mechanism, In: V. N. Alexandrov, G. D. van Albada, P. M. A. Sloot & J. Dongarra, (Ed.), *Computational Science − ICCS 2006*, Vol. 3993 of *LNCS*, Springer-Verlag, Berlin, Heidelberg, pp. 871–878

Dreżewski, R. & Siwik, L. (2007*a*). The application of agent-based co-evolutionary system with predator-prey interactions to solving multi-objective optimization problems, In: *Proceedings of the 2007 IEEE Symposium Series on Computational Intelligence*, IEEE

Dreżewski, R. & Siwik, L. (2007*b*). Co-evolutionary multi-agent system with predator-prey mechanism for multi-objective optimization, In: B. Beliczynski, A. Dzielinski, M. Iwanowski & B. Ribeiro, (Ed.), *Adaptive and Natural Computing Algorithms*, Vol. 4431 of *LNCS*, Springer-Verlag, Berlin, Heidelberg, pp. 67–76

Dreżewski, R. & Siwik, L. (2008a). Agent-based multi-objective evolutionary algorithm with sexual selection, In: Proceedings of 2008 IEEEWorld Congress on Computational Intelligence (WCCI 2008), 2008 IEEE Congress on Evolutionary Computation (CEC 2008), number IEEE Catalog Number: CFP08ICE-CDR, ISBN: 978-1-4244-1823-7, IEEE, Research Publishing Services, Hong Kong, pp. 3680–3685

Dreżewski, R. & Siwik, L. (2008*b*). Co-evolutionary multi-agent system for portfolio optimization, In: A. Brabazon & M. O Neill, (Ed.), *Natural Computation in Computational Finance*, Vol. 1, Springer-Verlag, Berlin, Heidelberg, pp. 271–299

Forrest, S. & Hofmeyr, S. (2000). *Design principles for the immune system and other distributed autonomous systems*, Oxford University Press, chapter Immunology as information processing, pp. 361–387

Frank, S. (1996). The Design of Natural and Artificial Adaptive Systems, Academic Press: New York

Goik, P., Siwik, L. & Kisiel-Dorohinicki, M. (2007). Applying of immune and cultural algorithms for solving multiobjective optimization problems, Internal report 9/07, Department of computer Science, University of Science and Technology, Krakow, Poland

Hunt, J. & Cooke, D. (1995). An adaptive, distributed learning systems based on the immune system, In: *Proceedings of the IEEE International Conference on Systems, Man and Cybernatics*, pp. 2494–2499

Jin, X. & Reynolds, R. (2000). Mining knowledge in large-scale databases using cultural algorithms with constraint handling mechanisms, In: *Congress on Evolutionary Computation*, IEEE Service Center., New Jersey

Jin, X. & Reynolds, R. (n.d.). Using knowledge-based evolutionary computation to solve nonlinear constraint optimization problems: a cultural algorithm approach, In: *Congress on Evolutionary Computation*, IEEE Service Center, pp. 1672–1678

Kisiel-Dorohinicki, M. (2004). Flock-based architecture for distributed evolutionary algorithms, In: L. Rutkowski, J. Siekmann, R. Tedeusiewicz & L. Zadeh, (Ed.), *Artificial Intelligence and Soft Computing – ICAISC 2004*, Vol. 3070 of *Lecture Notes in Artificial Intelligence*, Springer-Verlag

Miller, B. L. (1997). Noise, Sampling, and efficient genetic Algorithms, PhD thesis, University of Illinois at Urbana-Champaign, Urbana, IL. IllIGAL Report No. 97001

Reynolds, R. (1994). An introduction to cultural algorithms, In: *Proceedings of the Annual Conference on Evolutionary Programming*, World Scienfific Publishing

Siwik, L. & Kisiel-Dorohinicki, M. (2005). Elitism in agent-based evolutionary multiobjective optimization, *Inteligencia Artificial 9*(28). Special issue: New trends on Multiagent systems and soft computing

Siwik, L. & Kisiel-Dorohinicki, M. (2006). Semi-elitist evolutionary multi-agent system for multiobjective optimization, In: V. N. Alexandrov, G. D. van Albada, P. M. A.

Sloot & J. Dongarra, (Ed.), *Computational Science − ICCS 2006*, Vol. 3993 of *LNCS*, Springer-Verlag, Reading,UK, pp. 831–838

Siwik, L. & Natanek, S. (2008*a*). Elitist evolutionary multi-agent system in solving noisy multiobjective optimization problems, In: *Proceedings of 2008 IEEE World Congress on Computational Intelligence (WCCI 2008), 2008 IEEE Congress on Evolutionary Computation (CEC 2008)*, number IEEE Catalog Number: CFP08ICE-CDR, ISBN: 978-1- 4244-1823-7, IEEE, Research Publishing Services, Hong Kong, pp. 3318–3325

Siwik, L. & Natanek, S. (2008*b*). Solving constrained multi-criteria optimization tasks using elitist evolutionary multi-agent system, In: *Proceedings of 2008 IEEEWorld Congress on Computational Intelligence (WCCI 2008), 2008 IEEE Congress on Evolutionary Computation (CEC 2008)*, number IEEE Catalog Number: CFP08ICE-CDR, ISBN: 978- 1-4244-1823-7, IEEE, Research Publishing Services, Hong Kong, pp. 3357–3364

Siwik, L., Psiuk, M. & Sroka, P. (2008). Flock-based evolutionary multi-agent system in solving noisy multi-objective optimization problems, In: *Proceedings of 2008 IEEE World Congress on Computational Intelligence (WCCI 2008), 2008 IEEE Congress on Evolutionary Computation (CEC 2008)*, number IEEE Catalog Number: CFP08ICECDR, ISBN: 978-1-4244-1823-7, IEEE, Research Publishing Services, Hong Kong, pp. 3403–3411

Siwik, L. & Sikorski, P. (2008). Efficient constrained evolutionary multi-agent system for multi-objective optimization, In: Proceedings of 2008 IEEE World Congress on Computational Intelligence (WCCI 2008), 2008 IEEE Congress on Evolutionary Computation (CEC 2008), number IEEE Catalog Number: CFP08ICE-CDR, ISBN: 978-1-4244- 1823-7, IEEE, Research Publishing Services, Hong Kong, pp. 3211–3218

Socha, K. & Kisiel-Dorohinicki, M. (2002). Agent-based evolutionary multiobjective optimisation, In: *Proc. of the 2002 Congress on Evolutionary Computation*, IEEE

Wierzchon, S. T. (2001). Artificial immune systems theory and applications, EXIT

Zitzler, E. (1999). Evolutionary Algorithms for Multiobjective Optimization: Methods and Applications, PhD thesis, ETH Zurich, Switzerland

Zitzler, E., Deb, K. & Thiele, L. (2000). Comparison of Multiobjective Evolutionary Algorithms: Empirical Results, *Evolutionary Computation 8*(2), 173–195

Zitzler, E. & Thiele, L. (1998). An evolutionary algorithm for multiobjective optimization: The strength pareto approach, Technical Report 43, Swiss Federal Institute of Technology, Zurich, Gloriastrasse 35, CH-8092 Zurich, Switzerland

Zitzler, E. & Thiele, L. (1999). Multiobjective Evolutionary Algorithms: A Comparative Case Study and the Strength Pareto Approach, *IEEE Transactions on Evolutionary Computation 3*(4), 257–271

Zitzler, E., Thiele, L., Laumanns, M., Fonseca, C. & da Fonseca, V. (2003). Performance assessment of multiobjective optimizers: An analysis and review, *IEEE Transactions on Evolutionary Computation 7*(2), 117–132

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