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CO-EVOLUTIONARY MULTI-AGENT SYSTEM WITH SEXUAL SELECTION FOR MULTI-MODAL OPTIMIZATION

Evolutionary algorithms (EAs) often suffer from premature loss of population diversity what results in premature convergence and may lead to locating local optima instead of a global one. For multi-modal problem landscapes a simple EA will inevitably locate a single solution. If we are interested in finding multiple solutions of comparable fitness, some multi-modal function optimization techniques (so called *niching methods*) should be used. Niching techniques are aimed at forming and stably maintaining species (which live in different niches) throughout the search process. Sexual selection resulting from co-evolution of female mate choice and male display trait is considered to be one of the mechanisms responsible for speciation. This paper introduces the co-evolutionary multi-agent system with sexual selection mechanism. Such system is applied to multi-modal function optimization and the results from runs against commonly used test functions are presented. Also the comparison to other niching techniques is made.

1. INTRODUCTION

Evolutionary algorithms (EAs) have demonstrated in practice efficiency and robustness as global optimization techniques. However, they often suffer from premature loss of population diversity what results in premature convergence and may lead to locating local optima instead of a global one. What is more, both the experiments and analysis show that for multi-modal problem landscapes a simple EA will inevitably locate a single solution [10]. If we are interested in finding multiple solutions of comparable fitness, some multi-modal function optimization techniques (*niching methods*) should be used. Niching techniques [10] are aimed at forming and stably maintaining species living in different niches (optima) of multi-modal fitness

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landscape. Premature loss of population diversity also limits the adaptive capacities of EAs in dynamic environments.

The biological models of speciation include allopatric models (which require geographical separation of subpopulations) and sympatric models (where speciation takes place within one population without physical barriers). Sympatric speciation may be caused by different kinds of co-evolutionary interactions including sexual selection [6].

Although co-evolution and sexual selection are one of the biological mechanisms responsible for speciation and biological diversity they were not widely used as mechanisms of multi-modal optimization (niching techniques) for EAs.

This paper introduces the co-evolutionary multi-agent system based on the sexual selection mechanism. In such a system two sexes co-evolve: females and males. Females choose males for mating. Their mating choice is based on values of some important features of selected individuals. Females evolve to decrease the mating rate because of higher costs of reproduction and males evolve to increase it. Also the operator of grouping individuals into reproducing pairs is introduced.

Such system is applied to multi-modal function optimization. The results from runs against commonly used test functions are presented and the comparison to other niching techniques is made.

2. PREVIOUS RESEARCH ON SEXUAL SELECTION AS A SPECIATION MECHANISM

The understanding of speciation still remains a greatest challenge for evolutionary biology. Traditionally, there exist two basic approaches in evolutionary biology to understanding *speciation process* [4, 6]. The first one called *allopatric speciation* occurs when subpopulations of a given species become geographically isolated. After isolation they follow different evolutionary paths and — eventually — become different species. Resulting species are reproductively isolated even after secondary contact [4, 6].

The second kind of speciation is called *sympatric speciation*. In such model of speciation ecological conditions must induce disruptive selection and the mating system must evolve in such a way that reproductive isolation occurs between the phenotypes that are favored by disruptive selection. Such speciation results from different ecological interactions, including mutualism, predator-prey co-evolution, sexual selection, etc. [4]. Speciation process takes place within single population and geographical separation of subpopulations is not needed.

It has recently been suggested that sexual selection results from co-evolution of female mate choice and male display trait where females evolve to reduce direct costs associated with mating and keep them on optimal level and males evolve to attract females to mating [7, 8]. Gavrilets [6] presented a model where sympatric speciation is a consequence of sexual selection. His model exhibits three general dynamic regimes. In the first one there is endless co-evolutionary chase between the

sexes where females evolve to decrease the mating rate and males evolve to increase it. In the second regime, female alleles split into two clusters both at the optimum distance from the male allele and males get trapped between the two female clusters with relatively low mating success. In the third one males answer the diversification of females by splitting into two clusters that evolve toward the corresponding female clusters. As a result the initial population splits into two species that are reproductively isolated.

Todd and Miller [13] showed that natural selection and sexual selection play complementary roles and both processes together are capable of generating evolutionary innovations and biodiversity much more efficiently. Sexual selection allows species to create its own peaks in fitness landscapes. This aspect of sexual selection can result in rapidly shifting adaptive niches what allows the population exploring different regions of phenotype space and escaping from local optima. The authors also presented the model of sympatric speciation via sexual selection.

Sánchez-Velazco and Bullinaria proposed gendered selection strategies for genetic algorithms (GAs) [12]. They introduced sexual selection mechanism, where males are selected on the basis of their fitness value and females on the basis of the so called indirect fitness. Indirect fitness is the weighted average of the individual's fitness value, age, and potential to produce fit offspring compared to her partner's direct fitness. Mutation rates are different for each gender. The authors applied their algorithm to Traveling Salesman Problem (TSP) and function optimization.

Lis and Eiben proposed multi-sexual GA (MSGA) for multi-objective optimization [9]. In MSGA the individuals with different sex are evaluated using different fitness functions (the number of sexes is the same as the number of objective functions). The crossover operator uses parents from all sexes (multi-parent crossover). The sex of the offspring is determined by the number of genes supplied by each parent (it has the sex of parent that supplied the largest number of genes). If the crossover is not applied the sex is determined randomly. The authors applied their algorithm to several multi-objective test problems.

Sexual selection as a mechanism for multi-modal function optimization was studied by Ratford, Tuson and Thompson [11]. In their technique sexual selection is based on the seduction function value. This function give a low measure when two individuals are very similar or dissimilar and high measure for individuals fairly similar. The Hamming distance in genotype space was used as a distance metric for two individuals. The authors applied their mechanism alone and in combination with crowding and spatial population model. Although in most cases their technique was successful in locating multiple peaks in multi-modal domain the strong tendency to lose all the peaks except one after several hundreds simulation steps was observed.

As it was presented here, sexual selection is the biological mechanism responsible for biodiversity and sympatric speciation. However it was not widely used as maintaining genetic diversity, speciation and multi-modal function optimization mechanism for evolutionary algorithms. It seems that sexual selection should introduce open-ended evolution, improve adaptive capacities of EA (especially in dy-
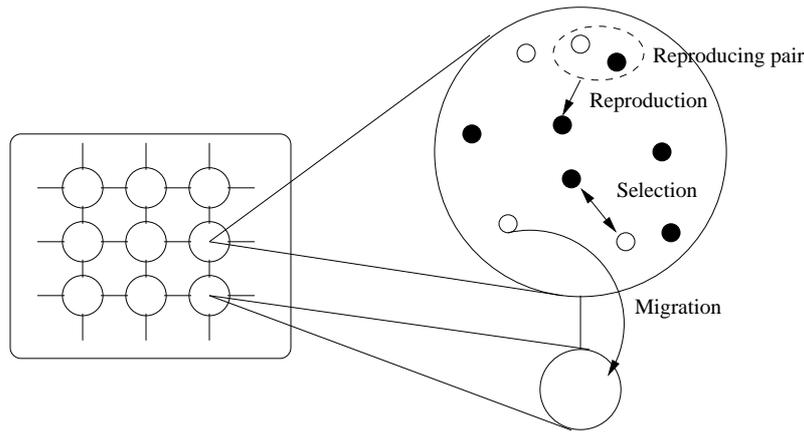
Figure 1. Co-evolutionary multi-agent system with sexual selection used in experiments

namic environments) and allow speciation (location of different optima in multi-modal domain) but this is still an open issue and the subject of ongoing research.

3. CO-EVOLUTIONARY MULTI-AGENT SYSTEM WITH SEXUAL SELECTION

The main idea of *evolutionary multi-agent system (EMAS)* is the modeling of evolution process in multi-agent system (MAS) [3]. Co-evolutionary multi-agent system (CoEMAS) allows modeling of biological speciation mechanisms based on co-evolutionary interactions (including sexual preferences), competition for limited resources, and geographical isolation [5].

In CoEMAS several (usually two) different species co-evolve. The goal of the second species is to cooperate (or compete) with the first one in order to force the population to locate Pareto frontier or proportionally populate and stably maintain niches in multi-modal domain. The application areas for CoEMAS include multi-modal function optimization (in stationary and dynamic environments) and multi-objective optimization.

The CoEmas with sexual selection mechanism (SCoEMAS) can be seen in figure 1. The topography of environment, in which individuals live, is graph with every node (place) connected with its four neighbors. There exist resource in the environment which is given to the individuals proportionally to their fitness function value. Every action (such as migration or reproduction) of individual costs some resource.

There are two sexes within the species living in the system: females and males. Reproduction takes place only when individuals have enough amount of resource. The genotypes of all individuals are real-valued vectors. Intermediate recombination [2] and mutation with self-adaptation [1] are used for females and males.

The female's cost of reproduction is higher than male so their mating rate is lower. Each time step males search for the reproduction partners (females) in their neighborhood. Female chooses reproduction partner only if they are both on the
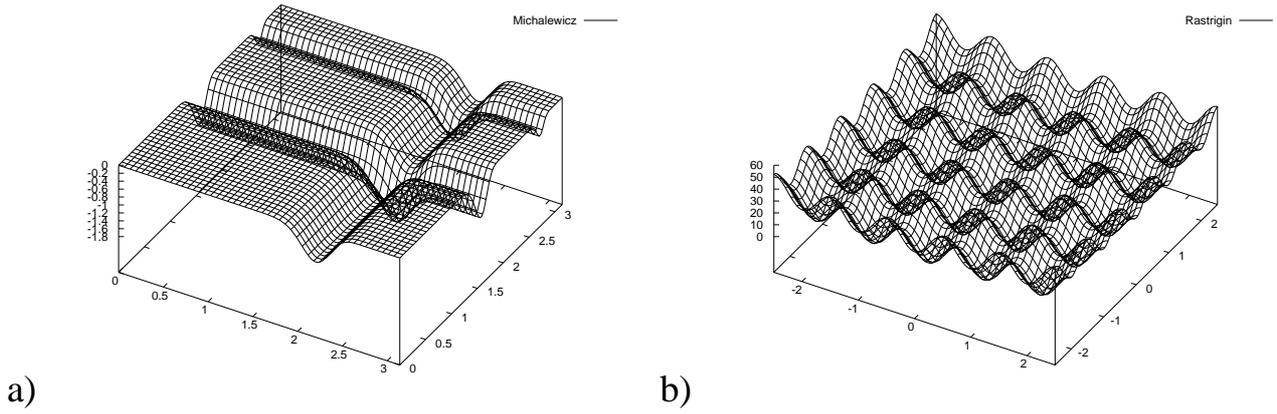
Figure 2. Michalewicz (a) and Rastrigin (b) test functions

same optima of multi-modal fitness landscape. Modified version of hill-valley function [14] is used in order to check if two individuals are located on the same optima. Instead of three deterministically selected points, ten randomly generated points are used in order to evaluate hill-valley function value. The decision of acceptance is made on the basis of distance between female and male in phenotype space (Euclidean metric is used). The probability of acceptance is greater for more similar individuals.

Also, the operator of grouping individuals into reproducing pairs is introduced. If female chooses male for reproduction they move together within the environment and reproduce during some simulation steps.

The system was applied to multi-modal function optimization and run against four commonly used test functions.

4. SIMULATION EXPERIMENTS

First simulation experiments were aimed at testing if SCoEMAS described in previous section is able to detect and stably maintain most of peaks in multi-modal domain throughout the search process. Also, the comparison to deterministic crowding (DC) niching technique [10] and EMAS without any niching mechanisms was made.

4.1. TEST FUNCTIONS

Four functions: Michalewicz, Rastrigin, Schwefel and Waves were used as the test fitness landscapes in the experiments (see fig. 2 and 3).

Michalewicz function is given by

$$f_1(x) = -\sum_{i=1}^{n} \left(sin(x_i) * (sin(i * x_i^2/\pi))^{20} \right) \quad x_i \in [0, \pi] \text{ for } i = 1, \ldots, n \quad (1)$$
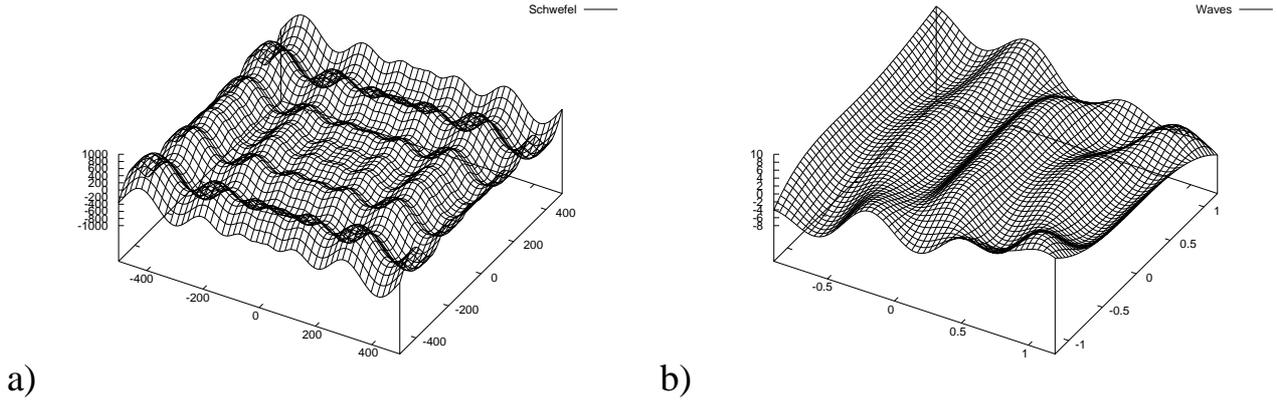
Figure 3. Schwefel (a) and Waves (b) test functions

Rastrigin function is given by

$$f_2(x) = 10*n + \sum_{i=1}^{n}\left(x_i^2 - 10*\cos(2*\pi*x_i)\right) \quad x_i \in [-2.5, 2.5] \text{ for } i = 1, \ldots, n \quad (2)$$

Schwefel function is given by

$$f_3(x) = \sum_{i=1}^{n}\left(-x_i * \sin\left(\sqrt{|x_i|}\right)\right) \quad x_i \in [-500.0, 500.0] \text{ for } i = 1, \ldots, n \quad (3)$$

For this three functions n is the number of dimensions ($n = 2$ in all experiments).

Waves function is given by [14]

$$\begin{aligned}
f_4(x, y) = &-\left((0.3*x)^3 - (y^2 - 4.5*(y^2))*x*y- \right.\\
&\left. 4.7*\cos(3*x - (y^2)*(2+x))*\sin(2.5*\pi*x)\right) \quad (4)\\
&where \quad x \in [-0.9, 1.2], \ y \in [-1.2, 1.2]
\end{aligned}$$

4.2. RESULTS

In this section the results from runs of SCoEMAS against four test functions are presented. The system is compared to EMAS and DC niching technique.

Figures 4 and 5 show the location of SCoEMAS individuals in fitness landscape (Rastrigin function) during the typical simulation. At the beginning there are 50 females (represented with squares) and 50 males (represented with crosses). It can be seen that as the simulation goes on the individuals reproduce and locate themselves near the minima in multi-modal domain. What is more the subpopulations are stable, and do not disappear throughout the simulation.
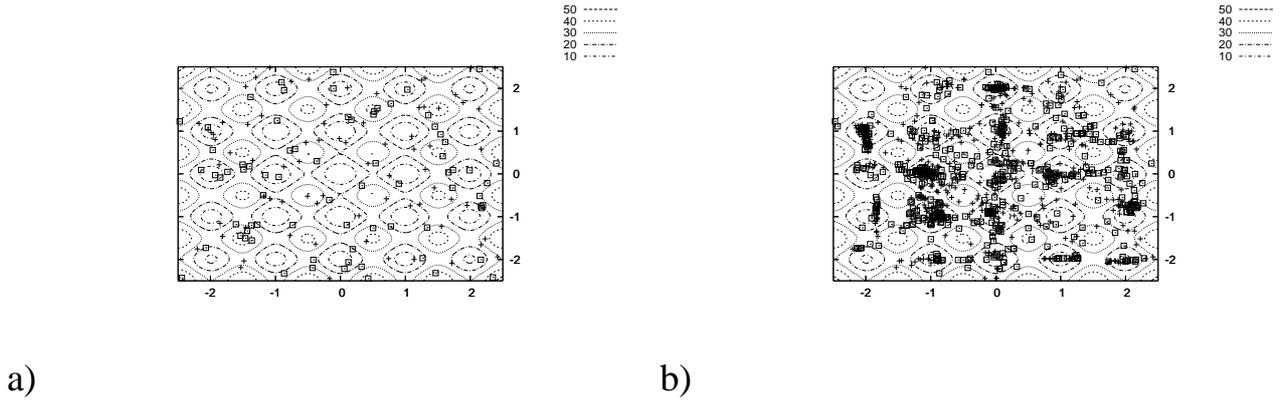
a)   b)

Figure 4. The location of individuals in SCoEMAS during the 0th (a) and 100th (b) simulation step (Rastrigin function)

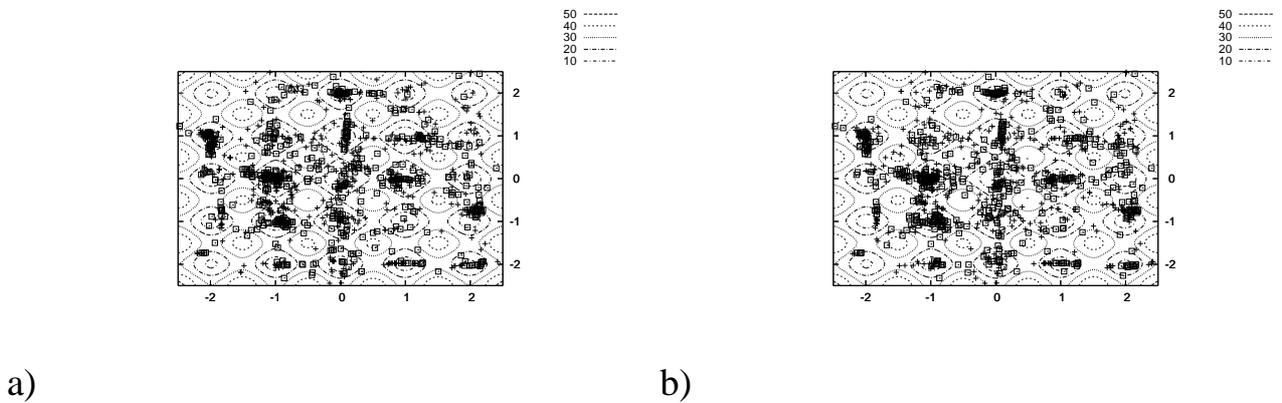a)   b)

Figure 5: The location of individuals in SCoEMAS during the 500th (a) and 5000th (b) simulation step (Rastrigin function)

Figures 6 and 7 show the average number of located minima from 20 simulations. The minima was classified as located when there was at least one individual closer than 0.03 for Michalewicz function, 0.05 for Rastrigin function, 10.0 for Schwefel function and 0.025 for Waves function. The experiments was made for three techniques: SCoEMAS, EMAS, and DC.

The SCoEMAS stood relatively well when compared to other techniques. It stably maintained minima during almost the whole simulation. Although DC quickly located greater number of minima but there was quite strong tendency to lose almost all of them during the rest part of simulation. Simple EMAS, without any niching mechanisms was not able to stably populate more than one minima. It turned out that in case of multi-modal landscape it works just like simple EA.

To sum up, simple EMAS can not be applied to multi-modal function optimization without introducing special mechanisms such as co-evolution. DC have some limitations as niching techniques — it has the strong tendency to lose minima during the simulation. The fact of relatively poor performance of DC was also observed in other works [15]. CoEMAS with sexual selection is valid and promising niching technique but still more research is needed.
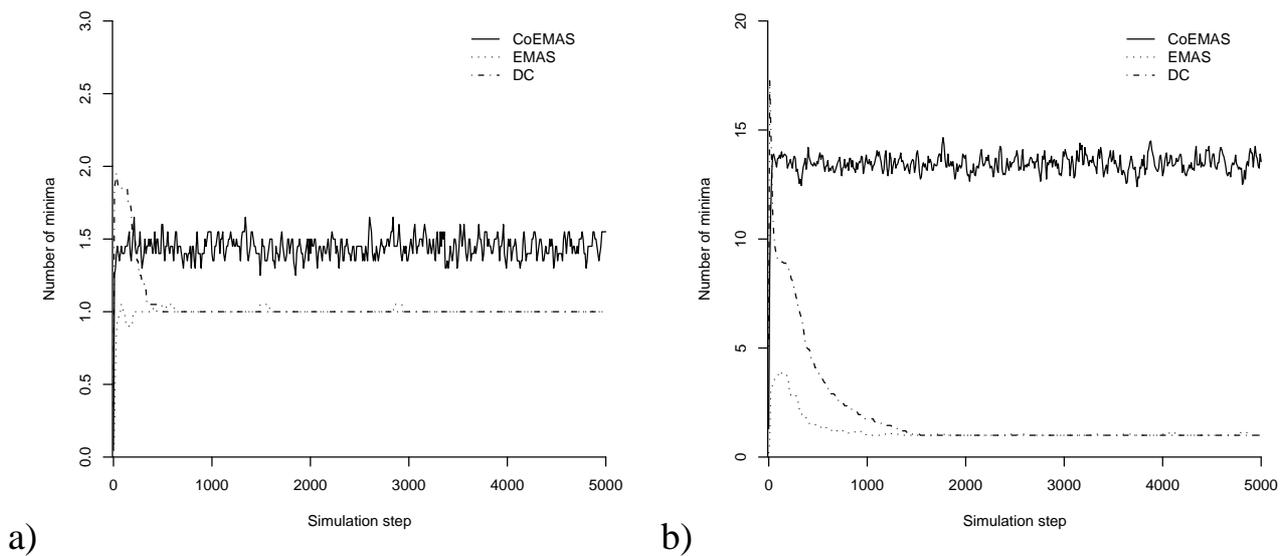
Figure 6. The number of located minima of Michalewicz (a) and Rastrigin (b) function

5. CONCLUDING REMARKS

The idea of *co-evolutionary multi-agent system (CoEMAS)* allows us to model many ecological interactions between species and individuals such as predator-prey and host-parasite co-evolution, mutualism, sexual selection, etc.

In this paper sample CoEMAS with sexual selection mechanism was presented. This system was applied to multi-modal function optimization. It properly detected and maintained minima in multi-modal fitness landscapes and, as presented preliminary results show, has proved to be the valid and promising niching technique. It turned out that presented system was able to detect and stably maintain more minima of test functions than other classical niching technique (DC) and EMAS.

Future research will include more detailed comparison to other niching techniques, and the influence of different parameters' values on the minima location. Also the parallel implementation of CoEMAS using MPI is included in future research plans.

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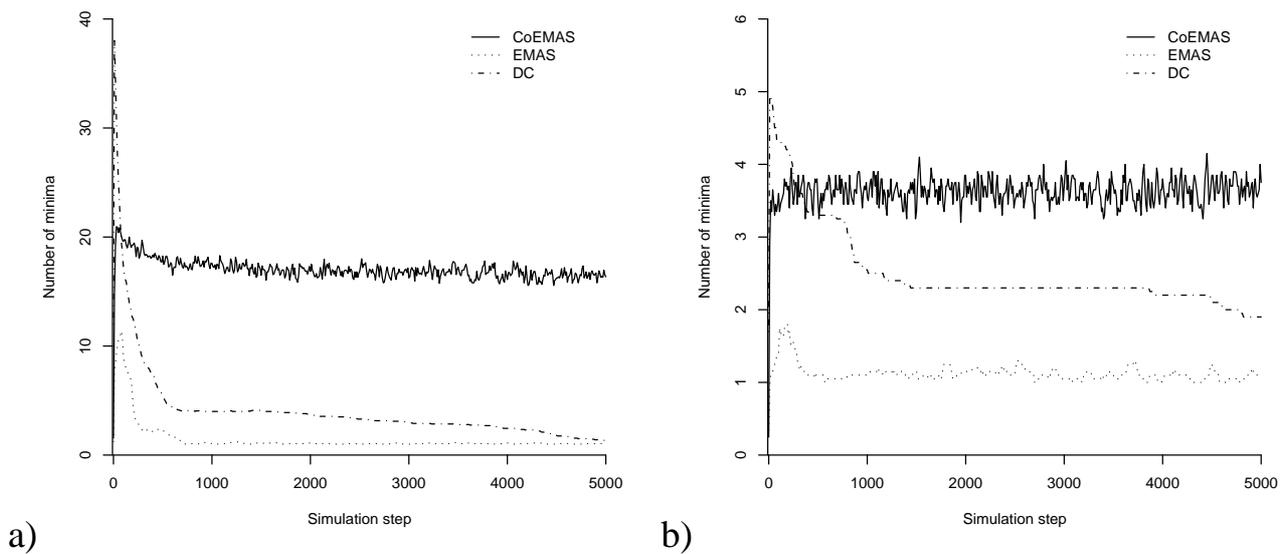
Figure 7. The number of located minima of Schwefel (a) and Waves (b) function

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