



# A new approach to particle swarm optimization algorithm



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## ABSTRACT

Particularly interesting group consists of algorithms that implement co-evolution or co-operation in natural environments, giving much more powerful implementations. The main aim is to obtain the algorithm which operation is not influenced by the environment. An unusual look at optimization algorithms made it possible to develop a new algorithm and its metaphors define for two groups of algorithms. These studies concern the particle swarm optimization algorithm as a model of predator and prey. New properties of the algorithm resulting from the co-operation mechanism that determines the operation of algorithm and significantly reduces environmental influence have been shown. Definitions of functions of behavior scenarios give new feature of the algorithm. This feature allows self controlling the optimization process. This approach can be successfully used in computer games. Properties of the new algorithm make it worth of interest, practical application and further research on its development. This study can be also an inspiration to search other solutions that implementing co-operation or co-evolution.

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## 1. Introduction

Observations of systems of living organisms are inspiration for the creation of modern computational techniques. Evolution algorithms are like metaphors of biological organisms, adopting from them terminology and mechanisms of operation as well. Adaption mechanisms borrowed from biology decide on the distribution of individuals in the environment. These operators perform the functions responsible for the exploration of environment and the exploitation of areas of local extrema. Adaptation mechanisms make these algorithms more efficient than a completely random search of solution space. Creating an artificial system as a metaphor or set of metaphors connected with the functioning of living organisms removes associated with it restrictions. Unfortunately, for such a system greater limits associated with its implementation are imposed. From the No Free Lunch Theorem (Wolpert & Macready, 1997) one can result that there is no universal optimization algorithm for all classes of tasks. This is a consequence of relation between the behavior of algorithm and the problem being solved. However, it gives the inspiration to create new solutions and conducts investigations on the behavior of the algorithm and its suitability for solving the problems of particular class. In most cases it leads to the attempts to increase the calculation efficiency by modifying the existing algorithms. Particularly interesting group consists of algorithms that implement co-evolution in

natural environments because the NFL theorem cannot be applied to them. Evolutionary algorithms differ from stochastic algorithms in very efficient adaptive mechanism for searching the solution space. That is why stochastic algorithms require greater number of iterations in the optimization process but are less likely to stop the optimization process in the local optimum. The usefulness of the algorithm is determined by the rules that are well-developed for stochastic algorithms. However, defining metaphors of natural environments for the algorithms – that is, *de facto*, the creation of completely new algorithms is not trivial.

New algorithm must therefore be searched in the group of algorithms that implement co-evolution (cooperation) in natural environments basing on rules developed for stochastic algorithms. The main aim is to obtain an algorithm on which operation the environment would have a very small impact. This feature allows controlling the optimization process and not only tuning the algorithm to the problem being solved as it is nowadays. Many problems are treated as unchangeable – they are represented by the stationary environment. However, the change in resources, tasks or other elements of the system results in the changes of problem from stationary into non-stationary – these problems are represented by the non-stationary environment. The majority of the algorithms used in non-stationary environments are adapted from algorithms applied in the stationary environments. The presented algorithm has been designed to use it in the non-stationary environments. Thus, the article presents the situation which is opposite to the mostly discussed. An unusual look at the

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optimization algorithms made it possible to develop the new algorithm and define its metaphors in two groups of algorithms. These algorithms can be used to describe artificial life. The resulting algorithms are effective optimization algorithms and the proposed approach introduces new features in their operation. The new algorithm and its metaphors in the group of immune algorithms and particle swarm optimization algorithms are presented in the article. Functions of behavior scenarios are defined in the particle swarm optimization algorithm. New properties of the algorithm resulting from the co-operation mechanism have been shown. It determines the algorithm behavior and reduces the environmental impact. This is the original and unpublished achievement of work. Immune algorithm is not widely discussed because research results were partially presented in Gosciniaik (2008) and the results of research carried out on its development require a new study. Modern PSO algorithms of high-efficiency should be classified as the hybrid algorithms. This proposed algorithm is presented rather as a base one – the base for future modifications. It was compared with different algorithms, also older (there are the references to the older literature) because presented there solutions can be considered as a base form, which is subject to further improvements. On the basis of the description it is being easy to notice the necessity to make modifications that will create a hybrid algorithm of high efficiency.

## 2. The comparison of selected algorithms

The analysis of algorithms operation becomes more complicated. Modifications affect many aspects of algorithm's operation. There are lots of terms that are closely dependent on each other. Exploration and exploitation of the solution space are contradictory goals. It becomes extremely difficult to maintain an appropriate balance between exploration and exploitation of the solution space during the work of an algorithm. Convergence realizes the exploitation and reduces the diversity of the population. Reducing of the population diversity causes the loss of information on the solution space – the memory loss. Concentrated individuals form a cluster. The excessive closeness of particles does not increase the information on the solution space. So in this place it should be reminded that the aim of this algorithm operation is to search for solution space to designate the global extreme or set of local extremes. There is also the effect of modifications on the algorithm operation. Frequently used modification is a mutation – but it may have the character improving the exploration or exploitation. Co-evolutionary systems are the most interesting. The co-evolution can be different in each group of algorithms and the functions creating co-evolution can be different in each cooperating system. There is also the group of modifications basing on applying of other methods known from mathematics – implementing as a local method. Presentation of the structure of base algorithm will be preceded by the discussion on the selected algorithms. This discussion is very general, and it has only been used to introduce existing solutions. However, this would help to understand the concept of the new algorithm.

During dislocation, population forms a compact group of individuals that exploits one part of the solution area; however, exploration is carried out by the movement of population. Phases of movement can be distinguished – in each phase the dislocation effectiveness of a population is not the same. Swarm adapts to the environment during subsequent iterations. The swarm leader represents the position of the best adaptation (the best solution). The assignment of swarm particle neighbors is performed usually once at the beginning of calculations – it makes the designation of the best adapted neighbor easier. The change in behavior of particles swarm is a function of changes in the leader behavior. There are many modifications of the above-mentioned PSO

algorithm – the majority of them can be found in Sedighzadeh and Masehian (2009), Chen and Chi (2010), Gao and Xu (2011) and Tsoulos and Stavrakoudis (2010). The behavior of the PSO algorithm depends on the internal weights. The exploration or exploitation nature of the algorithm work depends on the inertia weight. Appropriate change in this coefficient during the algorithm work will have a significant impact on the efficiency of its work. Linear decrease in the weight factors was proposed in the work (Shi & Eberhart, 1998). In the paper (Fan & Shi, 2001) the inertia weight is reducing in the course of the algorithm work. In Shi and Eberhart (2001) the decrease in inertia weight using fuzzy methods was proposed. In paper Peram, Veeramachaneni, and Mohan (2003) is proposed an improved self-adaptive particle swarm optimization algorithm (ISAPSO). In the process of algorithm evolution parameters are changed dynamically: cognitive and social learning rates parameters. It allows to maintain the diversity of the population. Control strategy has a random character which permits to take into account the various constraints of solved the problem. In Hu, Eberhart, and Shi (2003) a local neighborhood version is used – only the behavior of neighboring particles is taken into account. Keeping diversity of populations during the algorithm work is also important for PSO algorithms. The diversity of the population increases the chances of local extreme leaving. For keeping diversity of population PSO algorithm with self-organized criticality was introduced in Lovbjerg and Krink (2002). In order to achieve a greater variety of particles the “critical value” is created when two particles are too close to each other. Negative entropy was used in Xie, Zhang, and Yang (2002) to discourage premature convergence.

The neighborhood of other particles has the impact on the behavior of particles in the swarm. The neighborhood's analysis is the basis for separation of species or the use of multi-swarm. In Hu and Eberhart (2002) a dynamically changing neighborhood was used. The influence of neighbors, which depends on the fitness function and the position in relation to particles, is presented in the study (Mendes, Kennedy, & Neves, 2004). To achieve it, in Blackwell and Bentley (2002) some collision-avoiding mechanisms were applied, the individuals moving was used in the study (Lovbjerg & Krink, 2002), whereas mutation was applied in the paper (Miranda & Fonseca, 2002). It should be here mentioned that operators typical of genetic algorithms, such as mutation, crossover or selection were used in PSO (Angeline, 1998). In Leontitsis, Kontogiorgos, and Pange (2006) the introduction of an additional repeller was suggested. It influences the swarm behavior by directing it into the areas of the environment which have better adaptation.

The use of multi-swarm allows to maintain the diversity of the particles. Algorithms creating clusters are particularly noteworthy. There are very interesting groups of algorithms.

In multi-swarm and clusters creating systems there are key issues such as: how to define a promising area in the solution space and how to implement motion of the particles in the direction of various sub-areas, how to determine the required number of sub-swarms or clusters, and how to generate the sub-swarms or clusters.

In Brits, Engelbrecht, and van den Bergh (2002) NbestPSO algorithm was proposed, which is designed to locate many solutions. Particle's neighborhood in NbestPSO algorithm is defined as the closest particles in the population. The best neighborhood is determined on the base of the average distance of the nearest particles.

In Brits, Engelbrecht, and van den Bergh (2002) NichePSO algorithm was proposed – the main swarm can create sub-swarm when the niche is identified. The criterion for a sub-swarm creation is the lack of significant changes in subsequent iterations, while the sub-swarm can absorb particles or other sub-swarms in dependance on the distance. In Bird and Li (2006) the adaptive

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