VAREPSO and SUBEPSO - New developments and testing of EPSO and DEEPSO

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***Abstract*—This paper reports new developments made at the general model of EPSO (Evolutionary Particle Swarm Optimization). Besides the original process behind EPSO, the main goal is actually presenting variants to EPSO and, if possible, improve its performance and efficiency, at same time that results are compared and analysed with same values from original version of EPSO. The constant search for improving the existing models, therefore creating algorithms that are not only more efficient but also computationally lighter, stand as the main purpose of this paper. It will be presented two (2) new variants, its ideologies and theories behind, the results and its performances.**

***Index Terms*—Computation, Efficiency, EPSO, Evolutionary ALgortithms, Variant.**

I. INTRODUCTION

THIS paper pretends to introduce to the community two new variants of the meta-heuristic process EPSO - Evolutionary Particle Swarm Optimization. Born in 2002 at INESC Porto [1], this algorithm came out from the PSO - Particle Swarm Optimization, that comprises a computational technique inspired in the collective behaviour of a group of individuals who act in a coordinated and organized fashion, fostering the information exchange between each of them.

EPSO stands out as the fusion of the best aspects of all worlds, since it is able to combine two mechanisms and to allow the algorithm to "learn" which values it must define to mutation weights. Hence it pushes the progress forward toward the problem's optimum. In other words, it combines two fundamental aspects: on the one hand the *movement equation* - which is a distinctive aspect from PSO -, and on the other the selection operation with auto-adaptation capacity.

This fusion is what defines EPSO as a hybrid optimization model. Several tests showed a more robust, more efficient and more reliable algorithm, whose results may be considered better than any seen in the past. In electric energy systems, this is also used in a broad set of applications.

The search not only for a more robust but also for a quicker and a computationally lighter method is definitely a barrier which is difficult to break. Nonetheless, there are several theories arising from brain stimulation exercises, from which a set of ideas can be put into practice, tested and compared to the original model.

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Considering the constant increase in complexity of the aforementioned problems, the search for equally more complex algorithms implies higher computational efforts. With this arises the challenge of optimizing the already existing models. In order to achieve this goal, several variants of the original EPSO algorithm will be implemented in the C++ language [2], registering the program's reaction to the implemented changes. As it was said before, this paper will present some results from these proposed variants of EPSO.

II. STATE OF THE ART

Inspired in biology and the observation of nature, many algorithms have been proposed, the most important family being the Evolutionary Computation algorithms. The *Particle Swarm Optimization, PSO* is another example, as it was inspired by the collective movement of bird flocks or bee swarms and will be approached in greater detail in the following sections. [3][4].

Born of the original PSO model, ESPO borrows the *particle movement process*. In this model each particle groups a set of vectors that define its **position**, more specifically the position vector X_i, the **speed** vector V_i, and the vector for the **best position occupied by the particle up until that exact moment,** b_i. A fourth term is then added to EPSO, symbolizing the **cooperation**, in other words, the best position occupied by the total set of particles of the swarm, which is memorized in the vector b_G. The **movement rule** that determines the new position of each particle of the solution swarm:

$$\mathbf{X}_i^{new} = \mathbf{X}_i + \mathbf{V}_i^{new} \tag{1}$$

Where V_i can be defined as the speed of the particle X_i and is calculated as follows:

$$\mathbf{V}_i^{new}{=}W_{in_i}.\mathbf{V}_i{+}Rnd().W_{m_i}(\mathbf{b}_i{-}\mathbf{X}_i){+}Rnd().W_{e_i}(\mathbf{b}_G{-}\mathbf{X}_i)\mathbf{P} \tag{2}$$

As previously stated, the equation 2 compasses the several aforementioned factors, featuring the inertia as its first term, which represents the fact that the particle keeps its movement on the same direction as presented before. Memory stands out as the second term, defined by the presence of the vector with the best *fitness* position that was reached up until that moment, and which attracts the particle to that best. Last but not least, the cooperation factor stimulates the swarm's information exchange, so that the particle is also attracted to the best point reached by the whole cluster.

III. VARIANTS TO EPSO - VAREPSO AND SUBEPSO

The first proposal of a variant to original version of EPSO, called "VAREPSO", is inspired on thoughts from change of variables. From iteration to iteration, the swarm is analysed and the dimensions are target of evaluations about their relation between each other. According with some criterion, each particle suffers a re-scaling on dimension that shows a large amplitude between extremes particles.

This idea emerges from the fact that, at some moments, the swarm spreads through dimensional space and big disparities among dimensions appear. With this, we do a reduction of the differences of distance between extreme particles of dimension. This increases the equality among dimensions and could conduct to a faster and computational lighter convergence.

Secondly, the "SUBEPSO" is a variant that come from a simple rhetoric question: "Why not the creation of an EPSO inside another?". At first sight, this could be seems strange, however, it makes a little sense. The main idea was creating a smaller swarm inside the big one, which we call mum-swarm. The smaller one, named son-swarm, would be centralized around one of two options: 1) based on the global best position that until that iteration, has registered the best *fitness* yet or 2) based on a position from a random selected particle.

The objective of these satellite swarms were to further research in area in which it showed more favorable at that time or then look in other areas of dimensional space to prevent possible "jams" in local optima, respectively. Therefore, in each generation of particles at main swarm, it would be created a smaller cluster that, developed with few iterations could analyse and evaluate if that specific dimensional space is favorable or not to mum-swarm progression.

IV. RESULTS OF VARIANTS TO EPSO

Both variants were target of several tests. Using optimization functions and having the reference of original EPSO results, we could evaluate the performances of each other. For optimization with these variants to EPSO, were used functions like Rosenbrock, Sphere, Alpine, Griewank and Ackley. The following table shows the performances of each variant:

Table I
AVERAGE OF COMPUTATIONAL EFFORTS WITH OPTIMIZATION OF SEVERAL FUNCTIONS.

	Function	No. of Iterations	No. of Evaluations
Original EPSO	Rosenbrock	10545.4	421816
	Sphere	518.1	20724
	Alpine	1467.5	58700
	Griewank	549.2	21968
	Ackley	269.8	10792
VAREPSO	Rosenbrock	9777.7	391108
	Sphere	477.5	19100
	Alpine	47.4	1896
	Griewank	17.5	700
	Ackley	22.1	884
SUBEPSO	Rosenbrock	9652.6	386436
	Sphere	523	21252
	Alpine	10.5	660
	Griewank	7.7	548
	Ackley	12.6	744

With some of these results, it has shown the potential that these variants have. To prove that, SUBEPSO was applied to a energy system problem, based on states estimation, where least squares criterion was used on minimization of error deviation. The following figure illustrates the performance:

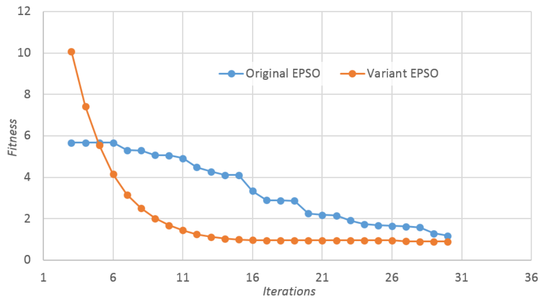

Figure 1. *Fitness* progression for states estimation, with original EPSO and SUBEPSO.

The previous illustration shows the effect that this variant has the acceleration in beginning of the optimization process, contributing to increase of the computational efficiency of the original algorithm EPSO.

V. CONCLUSIONS

Through the presented results, we can withdraw several important conclusions. First, an interpretation of how the swarm spreads into the dimensional space, doing successive analyses about the difference between dimensions could be beneficial to the convergence of EPSO. Actually, VAREPSO showed some potential solving problem like, Alpine, Griewank and Ackley with computation efforts improvements in order of 90%.

In other hand, a specific swarm created inside swarm-mum proved that is a good variant EPSO strategy, showing results of improvements in order of 96% at same functions, and otherwise that in a real environment like a energy system problem, SUBEPSO improved the original version of EPSO, by accelerating the progression of *fitness*.

Finally, two variants arise in the attempt to launch a new paradigm in the scope of evolutionary computation, and especially in the scope of EPSO. The constant strive for increasing the models' efficiency, whilst keeping their robustness, was the main scope of this thesis.

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