# Stochastic Star Communication Topology in Evolutionary Particle Swarms (EPSO)

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The distinctive characteristic of PSO models is the movement rule that defines how a new particle is created departing from its history and information from the swarm. This rule is so powerful that, by itself, under controlled circumstances, drives the swarm to the optimum of a problem defined in continuous variables (other formulations not discussed).

PSO models cannot be classified as Evolutionary models, because they lack a selection operator (or selection is trivial, stating that offspring always is better adapted that parents). However, the movement rule can be re-interpreted as a form of chromosome recombination, within the framework of Evolutionary Computing.

The basic movement rule, producing a new individual **X** for iteration (k+1) is based on

$$\mathbf{X}_i^{(k+1)} = \mathbf{X}_i^{(k)} + \mathbf{V}_i^{(k+1)}$$

where $\mathbf{V}_i$ is called the particle i velocity and is defined by

$$\mathbf{V}_i^{(k+1)} = \mathbf{A}\mathbf{V}_i^{(k)} + \mathbf{B}(\mathbf{b}_i - \mathbf{X}_i^{(k)}) + \mathbf{C}(\mathbf{b}_G - \mathbf{X}_i^{(k)})$$

where the first term of the summation represents inertia or habit, the second represents memory and the third represents cooperation or information exchange.

The parameters **A, B, C** are diagonal matrices with weights fixed in the beginning of the process (index m is for the memory weights and index c is for the cooperation weights). In a classical formulation, the parameter **A** is affected by a decreasing value with time (iterations), while the parameters **B** and **C** are multiplied by random numbers sampled from a uniform distribution in [0,1].

We can give a different aspect to the movement rule:

$$\mathbf{X}_i^{(k+1)} = \mathbf{X}_i^{(k)} + \mathbf{A}(\mathbf{X}_i^{(k)} - \mathbf{X}_i^{(k)}) + \mathbf{B}(\mathbf{b}_i - \mathbf{X}_i^{(k)}) + \mathbf{C}(\mathbf{b}_G - \mathbf{X}_i^{(k)})$$

$$\mathbf{X}_i^{(k+1)} = (1 + \mathbf{A} - \mathbf{B} - \mathbf{C})\mathbf{X}_i^{(k)} - \mathbf{A}\mathbf{X}_i^{(k-1)} + \mathbf{B}\mathbf{b}_i + \mathbf{C}\mathbf{b}_G$$

and we realize now that the sum of the parameters multiplying the four contributors to generate the offspring is equal to 1. It is therefore natural to identify this expression with an intermediary recombination with no. parents $\mu = 4$ and a special rule to determine who the parents are (they are not randomly selected) in an *enlarged population* including not only the active particles but also the direct ancestors and the set of the past best ancestors.

It is a recombination rule that has the remarkable property of pushing the population towards the optimum, as the PSO algorithms have demonstrated. Therefore, if joined together with a selection mechanism, which also pushes the population towards the optimum, one may expect that some cumulative effect may improve the performance of an optimizing algorithm.

Evolutionary Algorithms having as recombination rule the movement rule of PSO have been called EPSO or Evolutionary Particle Swarm Optimization algorithms, and have been favorably benchmarked against other evolutionary algorithms and PSO models, in laboratory and in real world problems, with applications in Power Systems. In particular, the basic version of EPSO is a self-adaptive algorithm or, more clearly said, an algorithm that has a self-adaptive recombination mechanism [1].

The paper will present the new results obtained with the application of EPSO and will discuss the improvement achieved by adopting a stochastic star communication topology, instead of the deterministic topologies usually adopted in PSO [2].

The generation of offspring in a self-adaptive EPSO with stochastic star communication is

$$\mathbf{X}_i^{(k+1)} = \mathbf{X}_i^{(k)} + \mathbf{V}_i^{(k+1)}$$

$$\mathbf{V}_i^{(k+1)} = w_{i1}^{*}\mathbf{V}_i^{(k)} + w_{i2}^{*}(\mathbf{b}_i - \mathbf{X}_i) + w_{i3}^{*}(\mathbf{b}_G^{*} - \mathbf{X}_i)\mathbf{P}$$

where the symbol * means that mutation acts on the marked parameters and **P** is a diagonal matrix affecting all dimensions of an individual, containing binary variables of value 1 with probability p and value 0 with probability (1-p); the p value controls the passage of information within the swarm and is 1 in classical formulations (this is the *star*).

Experimental results have suggested that a communication probability of p between 0.1 and 0.4 leads in many cases to better results than a classical deterministic star model with p = 1. One is lead to believe that restraining the free flow of information about the global best allows more local search by each particle, eliminates disturbing noise, allows the dynamics of particle movement to be more stable and avoids premature convergence. As it is easily observed, this is yet another way of acting on the recombination operator.

The paper will present evidence of the improvement achieved with the stochastic star scheme both in the case of test problems and in the case of application to Power System problems. Figure 1 shows how the efficiency of the algorithm depends on the value of probability p of the stochastic star – the results are from the application of EPSO in a clustering problem. One may see that in the region of p between 0.05 and 0.1 not only the best results are obtained but also their variance is smaller, i.e., the performance is more robust.

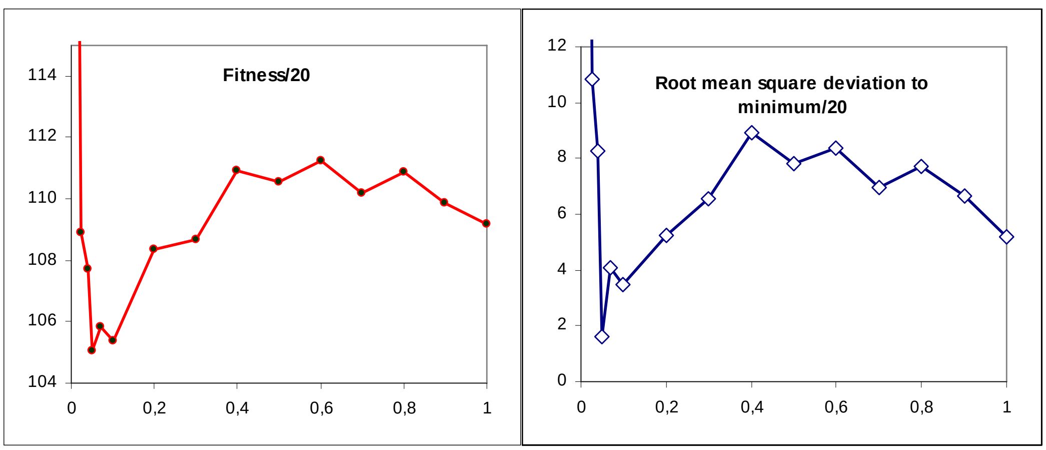


Figure 1 – Results from the application of EPSO in a clustering problem. Left: Fitness function value as a function of communication probability p (average of 20 runs). Right: Root mean square deviation from minimum solution in 20 runs, as a function of p..

## References

[1] V. Miranda and N. Fonseca, “EPSO – Best-of-Two-Worlds Meta-Heuristic Applied to Power System Problems”, *Proceedings of WCCI/CEC – World Conference on Computational Intelligence, Conference on Evolutionary Computation*, Honolulu (Hawaii), USA, June 2002

[2] V. Miranda and N. W. Oo, “New experiments with EPSO – Evolutionary Particle Swarm Optimization”, Proceedings of IEEE Symposium on Swarm Optimization, Indianapolis (Indiana), USA, May 2006