A Study on Time-varying Partially Connected Topologies for the Particle Swarm

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Abstract - This paper presents a study on the effects of dynamic and partially connected 2-dimensional topologies on the performance of the particle swarm optimization (PSO). The swarm is positioned on 2-dimensional grids of nodes and the particles move through the nodes according to a simple rule. Meanwhile, the von Neumann neighborhood is used to decide which particles influence each individual. Structures with growing size are tested on a classical benchmark and compared to several configurations such as *lbest*, *gbest* and the standard von Neumann configuration. The results show that the partially connected grids with von Neumann neighborhood structure performs more consistently when compared to lbest, gbest and the standard von Neumann topology.

Keywords: Particle Swarm Optimization, Population Structure.

1. Introduction

The Particle Swarm Optimization (PSO) algorithm [2] is a meta-heuristic for binary and real-valued function optimization inspired by the social behavior of bird flocks and fish schools. PSO has been applied with success to a number of problems and motivated several lines of research that investigate its main working mechanisms. One of these research lines deals with the population topology, which is the structure that defines the connections between the particles. These connections, in turn, define the flow of information through the swarm and therefore may deeply affect the convergence of the algorithm.

The particles are interconnected so that they acquire information on the regions explored by other particles. In fact, it has been claimed that the uniqueness of PSO lies in the dynamic interactions of the particles [3]. These networks of individuals may be of any possible structure, from sparse to dense (or even fully connected) graphs, with different degrees of connectivity and clustering in between. The most commonly used PSO population structures are known as *lbest* (which connects the individuals to a local neighborhood) and *gbest* (in which each particle is connected to every other individual). These topologies are well-studied and the major conclusions are that *gbest* is fast but is frequently trapped in local optima, while *lbest* is slower but converges more often to the neighborhood of the global optima. Since the first experiments on these topologies, researchers have tried to design structures that hold both *lbest* and *gbest* qualities. Some studies also try to understand what makes a good structure. In [3], for instance, Kennedy and Mendes investigate several types of topologies and recommend the use of a lattice with von Neumann neighborhood (which results in a connectivity degree between that of *lbest* and *gbest*).

This paper extends the concept of von Neumann configuration and investigates the behavior of a partially connected topology with von Neumann neighborhood, where not all the neighbors' cells of a given one are occupied. The particles are distributed on a grid of nodes. The size of the grid is set so that the number of nodes is larger than the number of particles. The particles are placed randomly on the grid and a simple set of rules guides their movements through the nodes during the run. The population structure is defined by the von Neumann neighborhood between the nodes, which means that the degree of connectivity of each particle varies between 1 and 5 during the run. Preliminary tests are conducted with local neighborhood random structures, that is, the particles move randomly through the grid, choosing between free adjacent nodes.

The structures are tested on a classical benchmark test set and compared to the *lbest*, *gbest* and standard von Neumann configuration. The results show that the partially connected von Neumann structure with random movement is able to improve the standard configuration. Furthermore, the proposed structure performs more consistently than the other topologies. It is believed that these results, together with the simplicity of the approach and its potential as a basis for more complex movement rules (based on fitness or Euclidean distance between the particles, for instance) validate this study.

The present work is organized as follows. The next section briefly describes the PSO and its topologies, while giving a general overview on previous studies of population structures

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for PSO. Section 3 describes the random partially connected structures used in this investigation. Section 4 describes the experiments and discuses the results. Finally, Section 5 concludes the paper and outlines future lines of research.

2. PSO AND POPULATION STRUCTURE

PSO is a population-based algorithm in which a group of solutions travels through the search space according to a set of rules that favor their movement towards optimal regions of the space. The algorithm is described by a simple set of equations that define the velocity and position of each particle. The position vector of the *i-th* particle is given by $\vec{X}_i = (x_{i,1}, x_{i,2}, \ldots x_{1,D})$, where D is the dimension of the search space. The velocity is given by $\vec{V}_i = (v_{i,1}, v_{i,2}, \ldots v_{1,D})$. The particles are evaluated with a fitness function $f(\vec{X}_i)$ in each time step and then their positions and velocities are updated by:

$$v_{i,d}(t) = v_{i,d}(t-1) + c_1 r_1 (p_{i,d} - x_{i,d}(t-1)) + c_2 r_2 (p_{g,d} - x_{i,d}(t-1)) \quad (1)$$

$$x_{i,d}(t) = x_{i,d}(t-1) + v_{i,d}(t) \quad (2)$$

were p_i is the best solution found so far by particle i and p_g is the best solution found so far by the neighborhood. Parameters $r_1$and r_2 are random numbers uniformly distributed in the range $[0, 1]$ and $c_1$and c_2 are acceleration coefficients that tune the relative influence of each term of the formula. The first term, influenced by the particle's best solution found so far, is known as the *cognitive part*, since it relies on the particle's own experience. The last term is the social part, since it describes the influence of the community in the velocity of the particle.

In order to prevent particles from stepping out of the limits of the search space, the positions $x_{i,d}(t)$ of the particles are limited by constants that, in general, correspond to the domain of the problem: $x_{i,d}(t) \in [-Xmax, Xmax]$. Velocity may also be limited within a range in order to prevent the *explosion* of the velocity vector: $v_{i,d}(t) \in [-Vmax, Vmax]$. Usually, $Xmax = Vmax$.

Although the classical PSO may be very efficient on numerical optimization, it requires a proper balance between local and global search, as it often gets trapped in local optima. In order to achieve a better balancing mechanism, Shi and Eberhart [8] added the inertia weight ω, that allows a fine-tuning of the local and global search abilities of the algorithm. The modified velocity equation is:

$$v_{i,d}(t) = \omega . v_{i,d}(t-1) + c_1 r_1 (p_{i,d} - x_{i,d}(t-1)) + c_2 r_2 (p_{g,d} - x_{i,d}(t-1)) \quad (3)$$

By adjusting ω (usually within the range [0, 1.0]) together with the constants c_1 and c_2, it is possible to balance exploration and exploitation abilities of the PSO.

The neighborhood of the particle (which defines in each time-step the value of p_g) is a key factor in the performance of PSO. Most of the PSOs use one of two simple sociometric principles for defining the neighborhood network. One connects all the members of the swarm to one another, and it is called *gbest*, were g stands for *global*. The degree of connectivity of *gbest* is $k = n$, where n is the number of particles. The other typical configuration, called *lbest* (where *l* stands for local), creates a neighborhood that comprises the particle itself and its k nearest neighbors. The most common *lbest* topology is the ring structure, in which the particles are arranged in a ring structure (resulting in a degree of connectivity $k = 3$, including the particle).

As stated above, the topology of the population affects the performance of the PSO and one must chose the configuration according to the target-problem. Furthermore, each topology has its own typical behavior and its choice may also depend on the objectives or tolerance of the optimization process. Since all the particles are connected to every other and information spreads easily through the network, the *gbest* topology is known to converge fast but unreliably (it often converges to local optima). The *lbest* converges slower than the *gbest* structure because information spreads slower through the network. However, and for the same reason, it is also less prone to converge prematurely to local optima.

In summary, the choice of the structure affects the performance and in-between the ring structure with $k = 3$ and the *gbest* with $k = n$ there are several types of structures, each one with its advantages on a certain type of scenarios. Sometimes it is not possible to choose the best configuration: the structure of the problem may be unknown, or the time requirements do not permit preliminary tests. Therefore, the research community has dedicated substantial efforts on studying the properties of PSO's population structures.

In 2002, Kennedy and Mendes [3] published an exhaustive study on population structures for PSO. They tested several types of structures, including the *lbest*, *gbest* and von Neumann configuration. They also tested populations arranged in graphs that were randomly generated and optimized to meet some criteria. They concluded that when the configurations were ranked by the performance at 1000 iterations the structures with $k = 5$ perform better, but when ranked according to the number of iterations needed to meet the criteria, configurations with higher degree of connectivity perform better. These results are consistent with the premise that low connectivity favors robustness, while higher connectivity favors convergence speed (at the expense of reliability). Amongst the large set of graphs tested in [3], the von Neumann configuration performed more consistently, and in the conclusions the authors recommend its use.

In [5], Parsopoulos and Vrahatis proposed a unified PSO (UPSO) which combines both the *gbest* and *lbest* configurations. Equation 1 is modified in order to include a term with p_g and a term with p_i. A parameter balances the weight of each term. The authors argue that the proposed scheme exploits the good properties of *gbest* and *lbest*. The same algorithm was later applied to dynamic optimization problems [6].

Peram *et al.* [7] proposed the fitness–distance-ratio-based PSO (FDR-PSO). The algorithm defines the "neighborhood" of a particle as its k closest particles in the population (measured in Euclidean distance). A selective scheme is also included: the particle selects near particles that have also visited a position of higher fitness. The algorithm is compared to a standard PSO and the authors claim that FDR-PSO performs better on several test functions. However, the FDR-PSO is compared only to a *gbest* configuration, which is known to converge frequently to local optima in the majority of the functions of the test set.

More recently, a comprehensive-learning PSO (CLPSO) [4] was proposed. Its learning strategy abandons the global best information and introduces a complex and dynamic scheme that uses all other particles' past best information. CLPSO can significantly improve the performance of the original PSO on multimodal problems.

More complex strategies deal with the population in a centralized manner. For instance, in [1], the PSO varies the size of the swarm during the run, while running a solution-sharing scheme that, like in [4], uses the past best information from every particle.

This work uses a 2-dimensional framework to force a dynamic behavior in the population structure and variability in the connectivity degree. The main objective is to search for a good compromise between high and low connectivity schemes, using dynamic connections and local interactions provided by the supporting framework. Since the von Neumann configuration was recommended in [3], we use it as a base-structure.

With the proposed scheme, we wish to avoid complex regulation or decision strategies, as well as extra parameters that could complicate the tuning of the PSO (the CLPSO, for instance, is highly dependent on a set of probability values that decides which strategy to follow). The connectivity of the resulting network of particles is simply regulated by the size of the grid and the structure itself limits the connectivity. Although it is possible that the behavior of these structures on partially connected grid could be modeled by dynamic graphs, we believe that the proposed framework is simple to test, analyze and visualize. Furthermore, the general scheme can be easily extended in order to incorporate information retrieved by the search process. However, in this paper, the investigation is limited to swarms with a random movement scheme. Non-random versions of these structures will be studied in the future.

3. PARTIALLY CONNECTED STRUCTURES

This paper proposes a framework for partially connected 2-dimensional PSO population structures. In the beginning of the run, the particles are randomly distributed on a 2-dimensional toroidal grid of nodes with size $s = X \times Y > n$, where n is the swarm size. In each time-step, each particle moves randomly to an adjacent free node. The candidate nodes are defined by the Moore neighborhood. If a particle is surrounded by other particles (i.e., all the nodes in the particle's Moore neighborhood are occupied by other particles), it remains in the same site until a node in the neighborhood is freed.

The configuration of the swarm on the grid in each time-step defines the p_g positions in Equation 1. If the best position found so far by any individual in the von Neumann neighborhood of the particle is better than the current p_g, then the new p_g is set to that position.

The particles are supplied with a kind of memory: while a new p_g is not transmitted to the particle by one of its current neighbors, the particle continues to update its velocity and position with the previous p_g, which may correspond to a particle that is no longer in its neighborhood. On the other hand, the particle is no longer connected to the particle that transmitted the p_g value, and if that particle visits a better position, it will not be transmitted to the individual.

With the 2-dimensional framework, the connectivity is limited by the neighborhood. Please note that the most commonly used population topologies may be configured by this model: *lbest* is configured by a one-dimensional lattice with size $1 \times N$, with $N = n$; the standard von Neumann configuration is described by a grid with size $X \times Y = n$ and von Neumann neighborhood with Manhattan distance $r = 1$; and a *gbest* configuration may modeled by setting $X \times X = n$ with Moore neighborhood with range $r = X/2 - 1$.

PSO on a partially connected random structure
1. For each particle $1 \rightarrow n$:
1.1. Initialize particle i
1.2. Evaluate particle's position $\overrightarrow{x_i}$: $f(\overrightarrow{x_i})$
1.3. Set $p_g(i) = p_i(i) = f(\overrightarrow{x_i})$
2. Set grid size: $X \times Y$
3. Place the particles randomly on the grid
4. For each particle $1 \rightarrow n$
4.1. If the fitness of the best position found so far p_j by any of the particles j in the von Neumann neighborhood of particle i is better than $p_g(i)$, then $p_g(i) = p_j$
4.2. Choose randomly a free node in the Moore neighborhood and move the particle to that node.
5. For each particle $1 \rightarrow n$
5.1. Update velocity and position using equations 2 and 3.
5.2. Evaluate particle's position $\overrightarrow{x_i}$: $f(\overrightarrow{x_i})$
5.2. If $f(\overrightarrow{x_i}) < f(p_i(i))$, then $p_i(i) = \overrightarrow{x_i}$
5. If the stop criterion is not met, go to 4

Table 1. Dynamic PSO on a partially connected grid.

function	*mathematical representation*	*Range of search/ Range of initialization*	*stop*
Sphere f_1	$f_1(\vec{X}) = \sum_{i=}^{D} x_i^2$	$(-100, 100)^{30}$ $(50, 100)^{30}$	0.01
Rosenbrock f_2	$f_2(\vec{x}) = \sum_{i=1}^{D-1} (100(x_{i+1} - x_i^2)^2 + (x_i - 1)^2$	$(-100, 100)^{30}$ $(15, 30)^{30}$	100
Rastrigin f_3	$f_3(\vec{x}) = \sum_{i=1}^{D} (x_i^2 - 10\cos(2\pi x_i) + 10)$	$(-10, 10)^{30}$ $(2.56, 5.12)^{30}$	100
Griewank f_4	$f_4(\vec{x}) = 1 + \frac{1}{4000}\sum_{i=1}^{D} x_i^2 - \prod_{i=1}^{D} \cos\left(\frac{x_i}{\sqrt{i}}\right)$	$(-600, 600)^{30}$ $(300, 600)^{30}$	0.05
Schaffer F5	$f_6(\vec{x}) = 0.5 + \frac{\left(\sin\sqrt{x^2+y^2}\right)^2 - 0.5}{\left(1.0 + 0.001(x^2+y^2)\right)^2}$	$(-100, 100)^2$ $(15, 30)^2$	0.00001

Table 2. Benchmarks for the experiments. Dynamic range, initialization range and stop criteria.

This paper studies the performance of structures with growing size. The particles are allowed to move within a Moore neighborhood with range 1. The interaction is defined by the von Neumann neighborhood with Manhattan distance 1. The dynamic particle swarm on partially connected grid is summarized in Table 1.

4. EXPERIMENTS AND RESULTS

For testing the various topologies, an experimental setup was constructed with five benchmark unimodal and multimodal functions that are commonly used for investigating the performance of PSO (see [3], [5] and [9], for instance). The functions are described in Table 2. The optimum (minimum) of all functions is located in the origin with fitness 0. The dimension of the search space is set to $D = 30$ (except Schaffer, with 2 dimensions).

The population size n is set to 40. The acceleration coefficients are set to 1.494 and the inertia weight is 0.729, a typical configuration for PSO's parameters (see [9]). $Xmax$ is defined as usual by the domain's upper limit and $Vmax = Xmax$. A total of 50 runs for each experiment are conducted. *Asymmetrical initialization* was used (the initialization range for each function is given in Table 2).

Two sets of experiments were conducted. In the first one, the algorithms were run for a limited amount of iterations (3000 for f_1 and f_5, 10000 for f_2, f_3 and f_4) and the fitness of the best solution found was averaged over the 50 runs. In the second set of experiments the algorithms were all run for 20000 iterations or until meeting a stop criterion. The criteria were taken from [3] and are given in Table 2. The number of iterations required to meet the criterion was recorded and averaged over the 50 runs. A success measure was defined as

	f_1	f_2	f_3	f_4	f_5
VN	1.05e-35 ±1.06e-35	1.31e+01 ±2.16e+01	6.99e+01 ±1.83e+01	6.25e-03 ±8.23e-03	1.94e-04 ±1.37e-03
VN (7×7)	2.69e-39 ±6.81e-39	1.00e+01 ±1.14e+01	7.19e+01 ±1.59e+01	7.73e-03 ±8.57e-03	9.72e-04 ±2.94e-03
VN (8×8)	**9.37e-38 ±2.29e-37**	**1.41e+01 ±2.52e+01**	**6.87e+01 ±1.93e+01**	**7.14e-03 ±1.00e-02**	**1.94e-04 ±1.37e-03**
VN (9×9)	9.13e-37 ±2.10e-36	9.72e+00 ±1.88e+01	6.89e+01 ±1.71e+01	7.68e-03 ±9.56e-03	1.94e-04 ±1.37e-03
VN (10×10)	7.66e-36 ±2.10e-36	1.12e+01 ±2.16e+01	6.66e+01 ±1.94e+01	6.40e-03 ±7.69e-03	1.94e-04 ±1.37e-03

Table 3. von Neumann topologies. Best fitness values averaged over 50 runs.

	f_1	f_2	f_3	f_4	f_5
VN	489.86 ±18.55 (50)	1443.24 ±1547.11 (50)	748.98 ±1706.20 (49)	458.36 ±29.10 (50)	454.56 ±659.27 (50)
VN (7×7)	444.50 ±23.19 (50)	1432.20 ±1845.74 (50)	267.00 ±78.12 (47)	408.80 ±25.45 (50)	309.42 ±425.56 (45)
VN (8×8)	**458.16 ±19.44 (50)**	**2135.12 ±2417.81 (50)**	**278.39 ±87.21 (46)**	**421.24 ±26.88 (50)**	**299.92 ±461.57 (49)**
VN (9×9)	474.96 ±22.60 (50)	1589.56 ±2137.00 (50)	314.43 ±81.37 (49)	450.56 ±54.45 (50)	264.80 ±395.90 (49)
VN (10×10)	492.32 ±23.47 (50)	2416.00 ±2069.21 (50)	320.63 ±69.97 (48)	452.60 ±24.96 (50)	206.94 ±196.17 (49)

Table 4. von Neumann topologies. Iterations to a solution averaged over 50 runs and number of successful runs.

the number of runs in which an algorithm attains the fitness value established as the stop criterion. These experiments are similar to those described in [3].

PSOs with *lbest*, *gbest* and von Neumann configurations were tested on the five benchmark problems. Then, partially connected structures with size 7×7, 8×8, 9×9 and 10×10 were also tested. The experiments return three independent performance metrics: best fitness, iterations to a solution, and success rate. It is difficult to compare all the versions of the algorithms in all the functions considering the complete set of metrics. Success rate and iterations to a solution, for instance, are particularly difficult to compare, because an algorithm may be very fast in meeting the criteria, while meeting it in a few number of runs. Therefore, we start by comparing each topology in each function.

4.1 Random Partially Connected Topology

Table 3 and Table 4 compare the standard von Neumann configuration with partially connected von Neumann structures. Table 3 gives the averages best fitness found by the swarms. Table 4 gives, for each algorithm and each function, the averaged number of iterations required to meet the criterion, and the number of runs in which the criterion was met.

An inspection of the tables shows that some partially connected Neumann structures are able to improve the von Neumann configuration in the majority of the problems. The structure with size 9×9, for instance, improves the standard configuration fitness in functions f_1, f_2, f_3. In f_4 the standard structure is better, while in f_5 the result is the same. As for the average iterations to a solution, the 9×9 structure is faster in every function except f_2.

The 9×9 grid holds 81 nodes, which is approximately twice the number of particles in the swarm. This ratio gave good results throughout the test set. The ratio can also be adjusted for optimal performance. However, in order to avoid introducing extra parameters that require tuning, it is better to analyze the results and establish a consistent size that performs well throughout a wide range of scenarios. For the moment, and according to the results attained in the five-function benchmark, we suggest a $1:2$ relation between the size of the swarm and the size of the grid.

Non-parametric Mann–Whitney U statistical tests (with 0.05 level of significance) comparing the fitness values attained by each configuration in each function return the following results: the 9×9 structure is significantly better than the standard configuration on function f_1; in the remaining problems the two configurations are statistically equivalent.

	f_1	f_2	f_3	f_4	f_5
lbest	2.61e-25 4.33e-25	1.40e+01 3.53e+01	1.07e+02 2.23e+01	4.93e-04 1.99e-03	3.89e-04 1.92e-03
gbest	4.00e+03 6.06e+03	4.91e+00 1.26e+01	1.05e+02 2.89e+01	5.42e+01 6.82e+01	2.33e-03 4.19e-03
VN (9×9)	9.13e-37 ±2.10e-36	9.72e+00 ±1.88e+01	6.89e+01 ±1.71e+01	7.68e-03 ±9.56e-03	1.94e-04 ±1.37e-03

Table 5. *lbest*, *gbest* and 9×9 partially connected von Neumann topology. Best fitness values averaged over 50 runs.

	f_1	f_2	f_3	f_4	f_5
lbest	662.30 ±21.81 (50)	1800.69 ±1650.07 (49)	2014.77 ±2331.92 (22)	618.22 ±31.87 (50)	708.08 ±849.52 (50)
gbest	489.86 ±18.55 (50)	891.42 ±1066.82 (50)	211.13 ±77.46 (23)	315.08 ±56.67 (24)	395.05 ±795.04 (40)
VN (9×9)	474.96 ±22.60 (50)	1589.56 ±2137.00 (50)	314.43 ±81.37 (49)	450.56 ±54.45 (50)	264.80 ±395.90 (49)

Table 6. *lbest*, *gbest* and 9×9 partially connected von Neumann topology Iterations to a solution averaged over 50 runs and number of successful runs.

Applying the Mann–Whitney U tests to the iterations metrics, the conclusions are that the 9×9 structure is statistically better on f_1, f_3, f_4 and f_5. The algorithms are statistically equivalent in f_2. Therefore, the partially connected structure significantly improves the performance of the standard von Neumann configuration in every function except f_2 (in which no statistically significant difference in either fitness and convergence speed could be found among the two algorithms).

Table 5 and Table 6 compare the 9×9 partially connected von Neumann structures with the lbest and gbest strategies. The proposed structure is able to improve lbest fitness values in f_1, f_2, f_3 and f_5; in f_1 and f_3 the differences are statistically significant. The differences in f_4 are also significant but in this case lbest is better. As for the average iterations for a solution, the partially structured von Neumann structure improves lbest in every function, with statistical differences between the results.

The differences between the best fitness values attained by *gbest* and 9×9 structure are statistically different for every function. von Neumann 9×9 is better in f_1, f_3, f_4 and f_5, while *gbest* is better in f_2. Comparing the proposed structure with *gbest* is not trivial because *gbest* fails very often in meeting the stop criteria. It is faster in three functions (f_2, f_3, f_4) but in f_3 and f_4 the topology fails to meet the criteria in more 50% of the runs. Therefore, we may conclude that von Neumann 9×9 performs more consistently than *gbest* throughout the test set.

In the above reported statistical tests on the averaged iterations to a solution, when a configuration meets the criterion on less runs that the other configuration, the r best results are selected and compared, where r is the number of runs in which the least successful configuration (of two) met the criterion. When considering the results of the four configurations in each function, and select only the r best iterations results, where r is the number of runs in which the least successful configuration of all four met the criterion, different iteration to solution values are obtained, which are given in Table 7. Under these criteria, the 9×9 partially connected von Neumann structure still performs better than *lbest* and von Neumann in the majority of the scenarios. The *gbest* is the fastest configuration in four functions but its fitness values and success rates, as already stated, are very poor when compared to the other algorithms.

	f_1	f_2	f_3	f_4	f_5
lbest	6.50e+02	1.80e+03	2.01e+03	5.94e+02	3.87e+02
gbest	3.53e+02	8.05e+02	2.02e+02	3.15e+02	3.95e+02
VN	4.79e+02	1.32e+03	2.78e+02	4.36e+02	2.40e+02
VN (9×9)	4.63e+02	1.40e+03	2.51e+02	4.20e+02	1.51e+02

Table 7. Iterations to a solution averaged over 50 runs and number of successful runs.

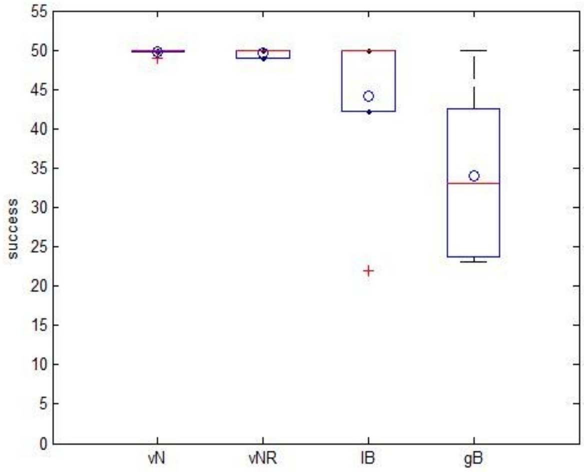

Figure 1. Rank by success rates. von Neumann (vN), von Neumann random partially connected structure (vNR), *lbest* (lB) and *gbest* (gB).

The boxplot in Figure 1 summarizes the results of the algorithms according to the *success* metrics. The *gbest* configuration is clearly the worst algorithm in the test set under this criterion. The standard von Neumann configuration is the most consistent (in the total 250 runs, it only failed in one run), but the 9×9 von Neumann attains similar results: in 250 runs it only failed twice.

A general evaluation of the four topologies according to fitness results in the following ranking: 9×9 von Neumann (1.7), standard von Neumann (2.1), lbest (3.0) and gbest (3.2). The proposed structure ranks first. Figure 2 shows the boxplot of the ranking.

As demonstrated above, the proposed partially connected structures are able to improve the standard configuration and the classical *lbest* and *gbest* topologies. The question that arises now is what makes these random structures better. The differences to the standard configuration are the candidates for explaining the differences: different average connectivity, dynamic connectivity and neighborhood, and memory (please remember that a particle retains the p_g value, even if the informant is no longer in the neighborhood, until a better p_g is transmitted by a neighbor).

Some tests with non-memory versions of the dynamic structures showed that the memory version performs generally better. However, non-memory structures do not necessarily perform worst and this strategy may be useful under higher connectivity partially connected structures (with Moore neighborhood, for instance). This study is beyond the scope of this paper and the main conclusion at this moment is that the memory scheme is beneficial for the purposes of the von Neumann structure.

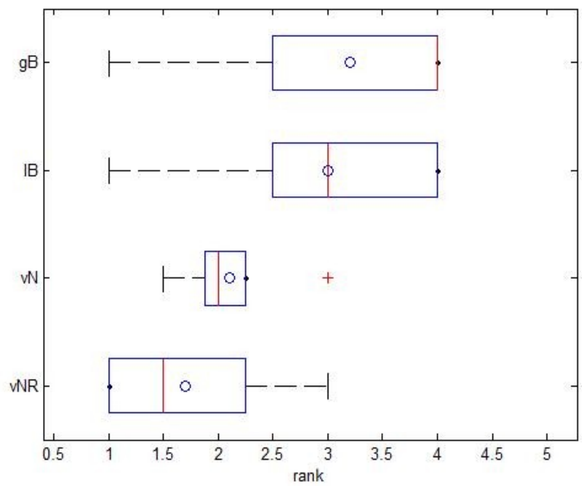

Figure 2. Rank by overall performance.

Although the connectivity degree is significant for the performance (experiments with larger grid sizes caused degradation in the performance), the results in Tables 3 and 4 show that the structure is robust to the grid size.

Figure 3 shows the connectivity degree k in typical runs with different grids. As expected, the average connectivity decreases with the grid size. However, from 7×7 to 10×10 the connectivity decreases from values above 4 to an average degree near 2.5, and except for function f_1 there are no clear effects on the performance.

Figure 4 shows the number of particles by their averaged connectivity over a typical run, for growing grid size. The distribution of connectivity values is clearly different for each type of grid. In the 9×9 most of the particles have $k = 3$, which is the connectivity of $lbest$. However, as demonstrated, the partially connected von Neumann structure with size 9×9 performs better than the *lbest* PSO in the majority of the scenarios. It is plausible that the efficiency of

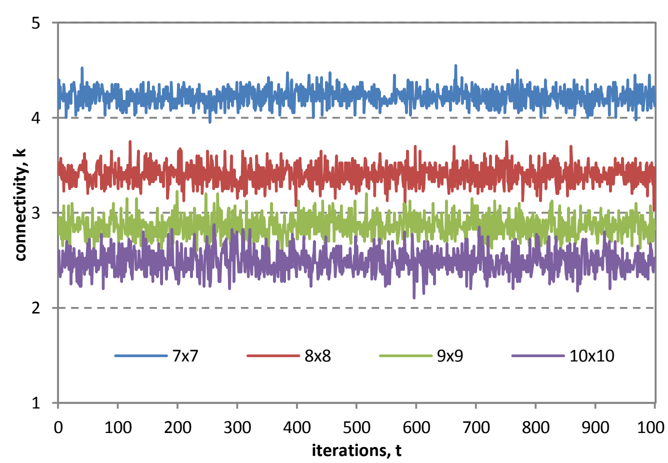

Figure 3. Connectivity degrees observed in typical runs with 7x7, 8x8, 9x9 and 10x10 sized structures.

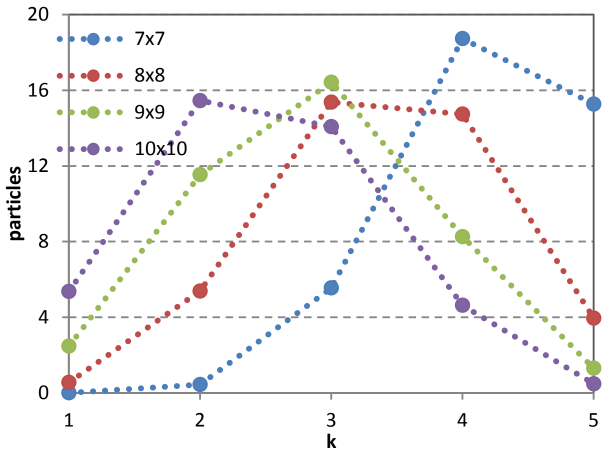

Figure 4. Number of particles by connectivity degree. Values averaged over 1000 iterations of a typical run.

the proposed scenarios may come from a combination of factors, namely, the average connectivity degree, the dynamics of the system and the additional (temporary) connectivity given by the memory scheme. However, further experiments are required in order to understand better the role of each factor in the performance of the topology. Specifically, it is very important to detect what has more impact in the performance of the partially connected von Neumann topologies, if the average connectivity, or the dynamic nature of that connectivity. Understanding the weight of these factors may lead to the design of more efficient dynamic structures, based on the interaction of the particles and their particular status (fitness, velocity and position).

5. CONCLUSIONS

This paper describes an investigation on the effects of alternative population structures on the behavior of the Particle Swarm Optimization (PSO) algorithm. Dynamic and partially connected structures were tested by placing the particles on a 2-dimensional grid of nodes larger than the swarm size. The particles move randomly on the grid and the network of information is defined in each iteration by the particle's position in the grid and by their von Neumann neighborhood.

Structures with growing sizes were tested on a classical test set and compared to standard topologies. The results demonstrate that the proposed structure performs consistently throughout the test set, improving the performance of other topologies in the majority of the scenarios and under different performance evaluation criteria. The structure is robust to the ratio between the grid size and the swarm size and a fixed size with ratio 1:2 performs well on every function.

In the future, the five functions test set will be extended with other problems. The performance of the partially connected von Neumann topology with different dimensionality will be also investigated in order to understand how the system scales. A dynamic structure with Moore neighborhood will also be implemented and tested. Finally, non-random strategies for the movement based on the fitness and the Euclidean distance between the particles are also under consideration.

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