Topology of Social Networks and Efficiency of Collective Intelligence Methods

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ABSTRACT

In this work we analyzed the role social networks play in the efficiency of collective problem-solving, evaluating whether the topological characteristics seen in real-world networks yield any performance improvement in such processes. To study this we used the Particle Swarm Optimization as a testbed for social groups performing a collective task, defining the structure of communication between individuals in the swarm through topologies generated by a model for the creation and evolution of social networks. The experimental results indicate that groups using these networks may, indeed, experience better performance in collective problem-solving, so that these groups were able to overcome the results achieved by swarms using classical neighborhoods for PSO and reached results very close to those found by swarms using the topology of DMS-PSO, usually considered to be part of the state-of-the-art of Particle Swarm Optimization.

Categories and Subject Descriptors

I.2.11 [**Artificial Intelligence**]: Distributed Artificial Intelligence—*Multiagent systems*; I.6 [**Simulation and modeling**]: Miscellaneous

Keywords

particle swarm optimization, collective intelligence, complex networks, complex systems

1. INTRODUCTION

Between all vertebrates, primates stand out as a group possessing large brains relative to their bodies, with the humans being the species with largest brain-body size ratio [10]. Despite accounting for only 2% of adult total body weight, human brain is responsible for 25% of glucose consumption, 20% of oxygen demands and 15% of total cardiac

output [18]. Given this high metabolic cost it is hard to imagine that this scenario is only due to a fluke. Therefore, it seems of great relevance to study the evolutionary forces that induced this enlargement of primate brains, evaluating the competitive advantages that compensates such a high demand for energy. There are some hypotheses aiming at explaining encephalization and that are supported by a number of evidences. One family of theories are the ecological hypotheses, proposing that primate species need larger brains due to a more complex set of skills required by their foraging patterns and for manipulating their food (e.g.: extract pulp from fruits or termites from a mound) [4]. Another theory, known as social brain hypothesis, argues that this increase is a consequence of the higher computational demands associated with maintaining larger social groups [4]. Some evidences supporting this idea are the disproportional increase in primates (and specially in humans) of brain areas related to social aspects of cognition, language, forecasting peer actions and affective behavior, like neocortex [6] and orbital prefrontal cortex [21, 26], and the fact that these regions are among the most recent areas to suffer development in human evolution [21].

As recent studies indicate [20], networks of human social contacts have some non-trivial characteristics, like small distances, high clustering and power-law degree distribution, that are also exhibited by social networks of other animal species, as well as by technological and biological networks. Are these widespread characteristics product of optimization, of restrictions inherent to the individuals or to the environment, or of mere chance? Assuming that the social brain hypothesis is true and having in mind not only the energy demand of a larger brain but also the evolutionary cost of adaptation that enables humans to make use of sophisticated language, the individual risks of cooperation with others and the optimizing nature of any evolutionary process, it is reasonable to imagine that groups making use of these structures were positively selected by evolution. The rationale behind this supposition is mainly associated with the fact that fitness improvement arises due to a better communication structure, a view corroborated by evidence long known in Psychology indicating that the structure of networks of contacts between agents affects group performance in problem-solving situations [2, 14]. For instance, human groups with sparse connections between their members score better than highly connected groups at solving

complex problems [9], as groups with excessive communication tend to converge too quickly, but to the wrong answer. In easy problems, however, highly connected groups perform better than sparse groups [17].

In this work we intend to analyze the optimality of realistic social networks when applied to shape communication between a group of individuals dealing with real-world problems. With this aim, we evaluated the impact of different structures of communication within a group on the effectiveness of collective problem-solving, focusing primarily on structures that exhibit characteristics consistent with those observed in real networks of social relationships. We used the Particle Swarm Optimization as a model, comparing results achieved by swarms based on classical, complex and state-of-the-art PSO topologies, subject to different rules for interaction between individuals in a swarm. In a previous study [8], we found evidence of how beneficial the application of scale-free networks to particle swarms can be. However, although capable of providing some important features present in many real-world structures, scale-free networks lack other relevant characteristics, such as a high node clustering, as well as more realistic formation processes. Furthermore, in this previous work, we compared the performance of a more restricted set of neighborhoods subject to a small number of experimental arrangements. In the present study, we delve deeper into the subject, getting stronger evidence suggesting that realistic social networks are able to yield good results, indicating that they may be a product of evolutionary processes and situating them as potentially beneficial structures to be used to regulate communications between artificial agents in Swarm Intelligence methods.

2. NETWORKS AND SOCIAL SYSTEMS

Until recently, networks representing relations in complex systems, like social networks, were considered too complex and were, thus, modeled as resulting from a totally random process. However, with the increasing data availability and computing power, as well as better analytical tools, it was possible to formalize many concepts on these systems and to notice that some characteristics of real-world networks were significantly different from those expected for completely random structures or for regular networks, as lattices or full graphs. These differences became more evident in 1998 and 1999, when two seminal papers were published studying average distances between nodes[1] and degree distributions[2] in these so called complex networks. In the first work, Duncan Watts and Steven Strogatz [25] pointed out that many real-world networks, as power grids and the neural network of the worm *Caenorhabditis elegans*, exhibit the "small-world effect", a combination of small average distance and high clustering[3] that no existent model for the origin of complex networks had been able to provide. Analogously, in the second paper Albert-László Barabási and Réka Albert
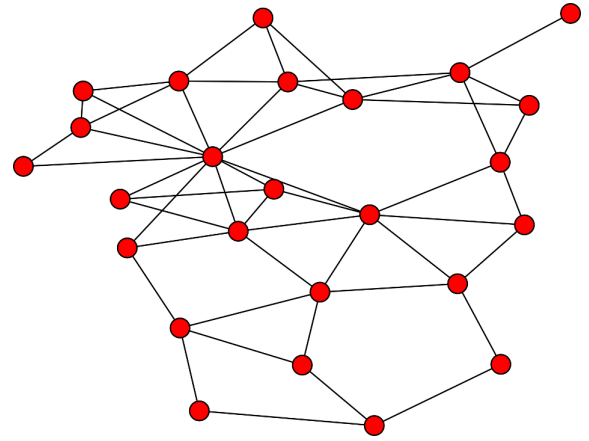

Figure 1: Network with 25 nodes and 50 edges generated using the model proposed by Davidsen, Ebel and Bornholdt.

[1] showed that networks as those formed by citations between scientific publications, links between web pages, and electric power grids have nodes with degrees distributed according to a power-law[4], a property incompatible with any model so far[5].

To address the inadequacy of the existing models, Watts and Strogatz presented the Small-World network model that, unlike random networks, is able to generate networks displaying small-world properties from an initially highly structured network based only on local connections, as ring or lattice topologies, with the addition of a few connections between random nodes. On the other hand, Barabási and Albert proposed the Scale-Free model, which combines addition of new nodes and edges to the network with preferential attachment, a mechanism that selects ends for the added edges with probability proportional to the number of connections a node already has, in a rich-gets-richer fashion.

Despite generating networks with specific characteristics observed in the real-world, these models fail to provide structures combining the small-world effect with a degree distribution following a power-law. One mechanism combining both these features was presented by Davidsen, Ebel and Bornholdt [3] and focused on modeling acquaintance networks (see Figure 1 for an example of a network generated using this model). In this model at each step one individual is randomly selected to introduce two random acquaintances of hers, creating a direct connection between them. If the selected individual has less than two social contacts, then she introduces herself to other random person. At the end of this step, with probability p one random person dies (i.e., is removed from the network) and another one is born with one connection to a randomly selected acquaintance. The parameter p defines the shape of the degree distribution when a stationary state is achieved, varying from a power-law, when $p \ll 1$ (which makes the linking mechanism the

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dominant ingredient), to a Poisson distribution when $p \sim 1$ (which makes the random death-birth process dominant). It is worth noting that the preferential attachment mechanism is indirectly present in this model through the linking mechanism, as the probability of a person being introduced to a new social contact is larger if she has more acquaintances. This model is more consistent with what is seen in natural systems, once it explains the small-world effect not from regular networks, as Watts and Strogatz model, but from a random structure. Also, these acquaintance networks can provide a power-law degree distribution with no need for any global information on the network (such as the current degree distribution, necessary to the preferential attachment step in the original Scale-Free model), making this model compatible with self-organization principles expected to be present in social networks.

3. PARTICLE SWARM OPTIMIZATION

The Particle Swarm Optimization [13] is a population-based metaheuristic for global optimization of continuous functions. As a Swarm Intelligence method, this technique uses social cognition as a metaphor, following the idea that, through culture, local positive innovations are transported to larger groups and that multiple innovations are combined in order to obtain better results [11]. Each particle (individual) in the swarm has its own set of characteristics (for instance, psychological traits, beliefs or parts of a solution to a given problem) which can be represented as a point in a multidimensional space. The particle can, then, evaluate the quality of its current set and then compare it to the quality of its previous configurations and, also, compare its own success to the success achieved by a defined subset of its peers (also called "neighbors"). This neighborhood can be static throughout the search process or be dynamically updated using some criterion. After the comparison step, each particle can update its characteristics set in order to achieve a higher quality solution, for which it may imitate its successful neighbors and use its own previous experiences. The pseudocode for the standard PSO is presented in Algorithm 1. The particle i moves through the space with a velocity v_i, which is calculated by combining the inertial speed (ωv_i) and the particle's cognitive and social influences. These influences are usually implemented as two attractors (p_i and p_{g_i}) whose intensities are weighted in each dimension by a random variable that assumes values between 0 and c_1 or c_2, the individual and social coefficients, respectively.

As observed in human groups, an adequate communication structure, combined with a good parameter setting, can greatly improve results achieved by a particle swarm. While too sparse topologies can make the particles to waste much computational effort on low quality regions, a highly connected swarm can propagate information too fast, making the system to collapse quickly to a suboptimal solution, trapping it in a local optima [5]. Therefore, many topologies have been proposed when implementing PSO, starting with the canonical global and local neighborhoods (see Figure 2). The global neighborhood consists of a fully connected swarm, in which every particle receives information from all its peers, while the local neighborhood is based on a ring-like structure, where each particle communicates with its nearest neighbors to the left and to the right. Beyond the canonical structures, the von Neumann neighborhood is also widely used and is known for usually promoting a nice

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> **input**: ω, c_1, c_2, N and neighborhood
> Initialize position x_i, velocity v_i and personal best position p_i for each of the N particles;
> **while** *stop criterion is not satisfied* **do**
>   **for** $i \leftarrow 1$ **to** N **do**
> $g_i \leftarrow \arg\min_{j \in neighbors(i)} f(p_j)$;
> $v_i \leftarrow \omega v_i + c_1 r_1 (p_i - x_i) + c_2 r_2 (p_{g_i} - x_i)$;
> $x_i \leftarrow x_i + v_i$;
>   **if** x_i *is within search range and* $f(x_i) < f(p_i)$
>   **then**
> $p_i \leftarrow x_i$;
>   **end**
>   **end**
> **end**

Algorithm 1: Particle Swarm Optimization for minimization

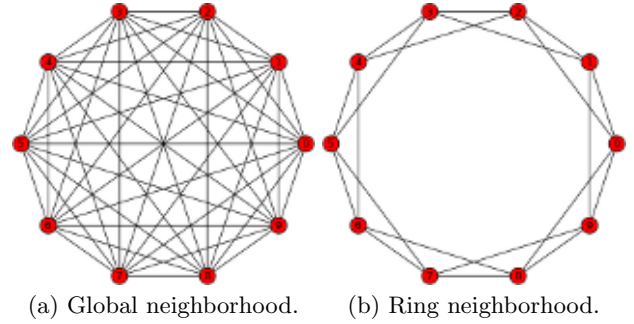(a) Global neighborhood.   (b) Ring neighborhood.

Figure 2: Canonical topologies for PSO with 10 particles.

balance between exploration and exploitation. In von Neumann topologies the particles are organized in a grid and can communicate only with those peers adjacent to them in the structure. Whereas these three neighborhoods are static, there are also well known dynamic neighborhoods, as that of DMS-PSO [15], which organize the particles in small temporary subswarms with equal sizes that are totally rearranged at regular intervals (see Figure 3). A particle, then, can exchange information only with other particles in the same subswarm. When the search process is near its final iterations the topology is replaced by a global neighborhood, focusing mainly on refining the best solution found so far instead of looking for new solutions. DMS-PSO can delay the collapse of the swarm, giving it enough time to explore the search space, and can nowadays be considered a topology in the state-of-the-art.

4. EXPERIMENTS

4.1 Method

The main hypothesis to be tested in this study was whether complex networks yield better results while mediating collective problem-solving in groups of natural or artificial agents. To test this, we adopted the Particle Swarm Optimization as model of social groups, as explained in previous sections. Despite its simplification, it is considered a sound model of interaction within human groups [16]. We compared the effectiveness of such swarms in solving a series of optimization problems while using global, local and von
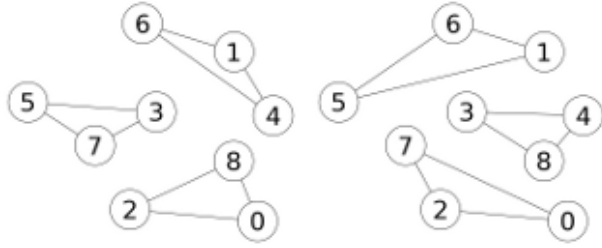
(a) Subswarms before the rearragement.

(b) Subswarms after rearragement.

Figure 3: Example of topology in DMS-PSO with 9 particles and subswarms of size 3.

Neumann static neighborhoods – classical topologies used not only in metaheuristics but widely adopted to shape communication between processes in computational systems –, the neighborhood of Dynamic Multi-Swarm Particle Swarm Optimizer (DMS-PSO), and two complex topologies (one static and the other dynamic) that will be presented in subsection 4.2. The main set of problems to be solved in this work is the test suite for the IEEE Congress on Evolutionary Computation (CEC) 2005 Special Session on real-parameter optimization [23], which comprises 25 functions with real parameters, with 10, 30 and 50 dimensions, ranging from simple functions with a single local optima (unimodal function) to highly complex ones – sometimes noisy, non-separable, non-continuous or non-differentiable – with a huge number of local optima (multimodal). As we intended to check the presence of trends toward improvement or deterioration in the performance of any tested topology in higher dimensional problems, we also used the test suite developed for the IEEE CEC 2008 Special Session on large scale global optimization [24] for 100-dimensional problems, which is formed by 7 functions, including unimodal and multimodal ones. Possible drawbacks of using these benchmarks as proxies for real-world problems are their focus only on optimization tasks and the fact that they are artificial, what could make them improper representations for relevant problems in this investigation. However, as well as locating food may be formulated as minimizing distance to food sources, many other real-world tasks can be reduced to optimization problems. Also, the selected benchmarks were developed aiming to display specific characteristics present in real problems, so that we considered these test suites as an adequate form of emulating multiple real challenges at a reasonable effort, allowing us to test a wide range of tasks with different complexities much more effectively than it would be possible with real problems.

To extend our comparisons beyond the classical individual dynamic of PSO, in which each particle uses only one influence (its best social contact) at a time and there is only attraction (positive feedback) and no repulsion (negative feedback) between individuals, we also tested three other dynamics present on PSO literature: the Fully Informed Particle Swarm (FIPS) [19], the Bare Bones PSO [12] and the Attractive and Repulsive PSO (ARPSO) [22]. These dynamics are described bellow:

- The FIPS implements a "fully informed" particle, i.e. a particle that uses as attractor not only information

from its best neighbor but a combination of personal attractors of all its neighbors. The speed update equation from the classical PSO is, thus, changed to the following rule:

$$v_i \leftarrow \omega v_i + \phi \left(\frac{\sum_{k \in \mathcal{N}} \mathcal{W}(k) \phi_k p_{g_k}}{\sum_{k \in \mathcal{N}} \mathcal{W}(k) \phi_k} - x_i \right)$$

in which ϕ_k is a random variable that assumes values in $[0, \phi_{max}]$ (ϕ_{max} is a parameter defined by the user), and the function $\mathcal{W}(k)$ defines the strength of each attractor, using for this any information considered to be relevant (e.g.: the best fitness achieved by particle k).

- ARPSO introduces a simple negative feedback mechanism in PSO aiming to increase diversity when the particles in a swarm are too close to each other. If this diversity is below a predefined threshold (d_{low}), then the particles are no longer attracted to their social influences and become repelled by them. This repulsion lasts until the diversity reaches a value d_{high}.

- Bare Bones Particle Swarm, on the other hand, changes the way a particle combines its influences to define the next point to visit by selecting it according to a Gaussian probability density function with center and variance calculated using the particle's personal and social influences. The position update rule is, thus, changed to:

$$x_i \leftarrow N \left(\frac{p_i + p_{g_i}}{2}, |p_i - p_{g_i}| \right)$$

where $N(\mu, \sigma)$ returns a random value sampled from a normal distribution with center μ and standard deviation σ.

The effectiveness of using complex networks was compared to that of using each of the other topologies, checking whether it was possible to achieve results significantly better (or significantly worse) while using them to shape communication between agents. For each pair of topologies to be compared we follow the steps bellow:

1. Given one experimental condition – i.e. one test function, its dimensionality and the individual dynamic to be used:

   (a) We used the PSO (with the defined individual dynamic) to search for the best solution of the specified test function, applying as neighborhood each topology to be compared;

   (b) We compared the best values obtained when using each topology: if the value obtained by the first was better, then we increased by one the number of wins of the first topology, however, if this value was worse, we incremented the number of wins of the second topology.

2. The previous steps were performed 30 times for all the 328 experimental conditions.

3. We, then, calculated the difference between the ratio of the total number of runs (for all experimental conditions) the first network performed better and the ratio the second one obtained better results, checking whether this difference was statistically significant.

As the computational cost of repeating all optimizations specifically for each comparison was very high, we decided to perform the optimizations for each topology and experimental condition 30 times and store the results in a memory. When comparing a pair of topologies, instead of running all optimizations again, we approximated it by drawing samples (without replacement) from the memory respective to the topology and the experimental condition, making it possible to reduce the required running time by two thirds. To make these results more robust, we calculated the studentized confidence intervals for each mean difference between success ratios using a stratified bootstrapping with 1000 repetitions and defining each experimental condition as a different stratum.

The parameters relative to PSO and its individual dynamics were set following recommendations from literature whenever such recommendations were available. This was the case for the standard PSO parameters, c_1, c_2 and ω – which were set, respectively, to 1.496, 1.496 and to vary linearly from 0.9, in the first iteration, to 0.4, at the end of the search –, and for the dynamics and topologies specific parameters, as DMS-PSO subswarm size ($m = 3$) and period between regroupings ($R = 5$), ARPSO upper ($d_{high} = 0.25$) and lower bounds ($d_{low} = 5 * 10^{-6}$) for swarm diversity and FIPS weight function ($\mathcal{W}(x) = 1, \forall x$). Other parameters, as swarm sizes and specifications for the complex topologies, were defined through a preliminary test for each pair of topology and individual dynamic, selecting those parameters that yielded the best results on a simple set of 7 functions, all with 30 dimensions, as used in [7]. As stop criterion it was used the limit of fitness evaluations, as specified for CEC2005 and CEC2008 benchmarks [23, 24]. Full experimental data, as well as the source code for simulations and statistical analysis, are available at http://www.dca.fee.unicamp.br/~godoy.

4.2 The CNPSO+ algorithm

As basis to test the performance of complex neighborhoods on problem-solving we selected the model proposed by Davidsen, Ebel and Bornholdt (introduced on section 2), since this model was developed after social networks and is capable of generating networks with both small-world effect and scale-free degree distribution, two of the main features of complex networks.

Real-world social networks are highly dynamical structures, being common for people to change all their social connections throughout their lives. Thus, it is important to check whether the dynamicity of connections is an important factor in the ability to solve problems in social groups. Particularly, this sort of study can be specially interesting for PSO as, with this knowledge, it may be possible to design mechanisms that enhance swarm intelligence techniques, better equipping them to deal with multimodal problems, a class of problems on which PSO has poor performance. Aiming to explore this possibility, we developed the Complex Neighborhood Particle Swarm Optimizer 2 (CNPSO+), a PSO applying a complex network as initial neighborhood and implementing a simple topolog-

ical adaptation mechanism, loosely based on Davidsen, Ebel and Bornholdt model. Periodically, each particle checks if it has improved its personal best since the last adaptation. If the particle is stagnant then it creates a direct connection to one of its second degree neighbors chosen at random (or to a random individual if the particle has no second degree neighbor), otherwise the particle disconnects itself from its neighbor with the worst personal history. The main idea behind this procedure is that if a particle has recently improved its results it may be in a promising region and therefore must concentrate its efforts on local search. If the particle is stagnant, however, it may be necessary to locate a new promising region, for which the particle could use information obtained from a new neighbor. Furthermore, this procedure was designed with the intention of maintaining a strong element of self-organization, so that the decision is made by each particle based on local information and not by a centralized controller, keeping consistency with what is observed in real social networks and helping to minimize computational costs of the algorithm in distributed environments.

When using the acquaintances network model three parameters need to be set: the swarm size, the average node degree and the probability p of a node to die. Besides them, in CNPSO+ a new parameter is necessary, the number of topological adaptations throughout the search. We set $p = 0.01$ to kept the degree distribution in the scale-free region, whereas the other parameters were defined following the same preliminary tests explained at the end of the previous subsection.

4.3 Results and discussion

The comparisons between results achieved when using complex topologies and those obtained when using classical static neighborhoods are reported on Table 1. For a better analysis, we show also comparisons for partial results, grouped according to benchmark dimension, function multimodality and individual dynamics used in PSO. According to the obtained data, static complex topologies provide better overall results than all other static topologies. The dynamic complex neighborhood used in these experiments, despite exhibiting better general performance than global and local neighborhoods, produced worse results than von Neumann topology. Looking into the partial data it is noticeable that, while both complex topologies have significantly better results when using the regular individual rule from PSO (only with positive feedback) and the rule from ARPSO (which displays both positive and negative feedback), their performance when combined with fully informed particle swarms (FIPS) is weak when compared to von Neumann and local topologies. In fact, after analyzing the experimental data in detail it was possible to trace the bad results of dynamic complex topology against von Neumann topology only to its inefficiency when combined with FIPS since, for all dimensionalities, complex topologies have consistently much lower performance when applied to a fully informed swarm whereas they display the best results when applied to regular PSO and ARPSO individual rules and mixed results when combined with Bare Bones PSO (however, as the reader can see in Table 1, the overall results of complex topologies when applied to the Bare Bones PSO rule are better than those of von Neumann with this same rule).

The poor performance of complex topologies when com-

Table 1: Comparison between complex and classical communication topologies. The table shows the difference (95% confidence interval) between the proportion of tests in which swarms using complex neighborhoods yielded better results and the proportion in which the classical topologies were better than their complex counterparts. Conditions in which complex neighborhoods were better are marked in bold.

Complex network	Compared with	Dimensions			
		10	30	50	100
Static	Global	**[25.7%, 25.9%]**	**[22.0%, 22.2%]**	**[32.3%, 32.4%]**	**[47.6%, 47.9%]**
	Von Neumann	**[2.8%, 3.0%]**	**[8.1%, 8.3%]**	**[6.7%, 6.9%]**	[−9.4%, −9.0%]
	Local	**[9.9%, 10.1%]**	**[24.2%, 24.4%]**	**[32.9%, 33.0%]**	**[17.1%, 17.5%]**
Dynamic	Global	**[14.1%, 14.3%]**	**[7.3%, 7.4%]**	**[24.6%, 24.8%]**	**[44.5%, 45.0%]**
	Von Neumann	[−6.1%, −5.9%]	[−5.9%, −5.7%]	**[5.4%, 5.5%]**	[−4.4%, −4.1%]
	Local	[−1.7%, −1.6%]	**[15.2%, 15.4%]**	**[26.8%, 26.9%]**	**[18.2%, 18.5%]**

Complex network	Versus	Individual dynamic			
		Regular	FIPS	Bare Bones PSO	ARPSO
Static	Global	**[39.6%, 39.8%]**	**[39.7%, 39.8%]**	[−5.3%, −5.1%]	**[39.8%, 40.0%]**
	Von Neumann	**[10.9%, 11.1%]**	[−17.4%, −17.3%]	**[4.1%, 4.3%]**	**[17.0%, 17.2%]**
	Local	**[37.6%, 37.8%]**	[−19.9%, −19.8%]	**[22.0%, 22.2%]**	**[47.6%, 47.8%]**
Dynamic	Global	**[44.1%, 44.3%]**	**[7.2%, 7.3%]**	**[0.9%, 1.1%]**	**[18.3%, 18.5%]**
	Von Neumann	**[22.1%, 22.3%]**	[−41.1%, −40.9%]	**[8.3%, 8.5%]**	**[3.5%, 3.7%]**
	Local	**[38.1%, 38.3%]**	[−42.1%, −42.0%]	**[23.1%, 23.3%]**	**[38.2%, 38.3%]**

Complex network	Compared with	Function type		
		Unimodal	Multimodal	Complete
Static	Global	**[18.2%, 18.4%]**	**[30.5%, 30.6%]**	**[28.3%, 28.3%]**
	Von Neumann	**[12.1%, 12.3%]**	**[3.1%, 3.2%]**	**[4.7%, 4.9%]**
	Local	**[21.5%, 21.6%]**	**[22.2%, 22.3%]**	**[21.8%, 21.9%]**
Dynamic	Global	[−3.5%, −3.4%]	**[23.1%, 23.2%]**	**[17.4%, 17.5%]**
	Von Neumann	[−2.5%, −2.3%]	[−3.0%, −2.8%]	[−2.7%, −2.6%]
	Local	**[11.9%, 12.1%]**	**[14.9%, 15.0%]**	**[13.7%, 13.8%]**

bined with FIPS is likely to be result of the chosen weight function $\mathcal{W}$, which assigns equal attractiveness to all influences a particle has. As a fully informed particle does not select only its best neighbor as its social influence but defines this influence by averaging the best position visited by each of its neighbors, the point of the search space towards which the particle will be attracted will not necessarily be located in one of the most promising regions found by the particles' neighbors so far. Imagine that one particle has some of its neighbors personal best located in one basin of attraction and the rest of them located in a second basin of attraction: the resulting attraction force may be directed to a point outside both basins (or located in their peripheries), aggregating the information previously gathered by the swarm in an ineffective fashion and seriously compromising the swarm's ability to perform local search. This disorientation will be stronger the more connections a particle has, an effect particularly harmful to networks with higher average degree or with degree distribution following a power-law, as in the later their connectivity is highly dependent on the hubs. In a scale-free network the role of hubs is to intermediate communication between distant nodes, therefore an efficient hub should aggregate signals from multiple sources and spread potentially beneficial information. If a highly connected particle in PSO is unable to improve its current solution using the knowledge gathered from its peers, its personal best will be stuck in the same position for a long time during which this hub will not send any new information to its less connected neighbors, inducing the deterioration of the informational flow throughout the network. The reader can notice that, unlike what happens in the standard PSO,

in FIPS a stagnant particle is usually not associated with the achievement of a local optimum, which could be solved by providing the particle information about new promising regions. Therefore, it is clear that the topological update mechanism proposed in this work for the dynamic complex network would result in bad performance in a fully informed swarm: stagnant particles would seek more information by connecting to new peers, dislocating even more its social attractor from any promising region such neighbors may have found and worsening the problem.

The combination of complex networks and fully informed particle swarms, however, is not doomed to poor results. A carefully designed combination of weight function and topology creation and update mechanism can greatly improve the performance of this kind of swarm, as is seen in the Scale-free Fully Informed PSO (SFIPSO) [27]. The SFIPSO defines a weighting function $\mathcal{W}$ that makes particles more attracted by influences with better fitnesses and generates the social network between the particles using a method that stimulates the creation of links between particles that are closer in the search space and gives particles with better performance higher probability of receiving new connections, being, thus, more prone to became hubs in this network. According to the experiments performed by the authors of SFIPSO, this algorithm was capable of achieving good performance in each tested function. This result is a strong indicator that the design of new individual rule for processing social information in swarm intelligence techniques may be more efficient if made in line with the selection of the topology that will shape the communication in this system.

When analyzing the relationship between the dimension-

ality of the tested functions and the results for a given topology, it was not possible to detect any clear trend of improvement or degradation of the relative performance of swarms using complex topologies as the size of the search space increased. For the selected parameters, in none of the comparisons the difference of performance was monotonically increasing or decreasing as we added more dimensions to the problem. If we focus on the function multimodality, in problems with only one local optimum global topology exhibits much better performance than in problems with a large number of optima, as expected. Another interesting relation between neighborhoods and function multimodality is observed in the comparison between static complex and von Neumann communication topologies, as the advantage of using the complex one is much reduced in problems with higher number of peaks.

It is also noticeable that, despite having similar behaviors, static and dynamic complex topologies display qualitatively different results. To analyze the differences between these two approaches, we compared the results achieved by each of these topologies under the same experimental conditions. The results of these comparisons is exhibited in Table 2. The difference of performance between static and dynamic complex networks is similar for all tested number of dimensions, providing no evidence that one topology benefits more than the other from the increase in the search space. On the other hand, for different types of function, it was possible to notice that the advantage of static complex networks was reduced for multimodal problems. The most marked difference, however, was observed when comparing the results of static and dynamic topologies when combined with different individual behaviors. Swarms using dynamic complex topologies were able to locate better solutions combined with individual behavior implementing only positive feedback and using only the best social contact as attractor, whereas they performed poorly in comparison with swarms using static topologies if their particles' behavior presented also negative feedback or defined their social attractor by averaging all the information obtained from their peers. These results reinforce the earlier highlighted existence of benefits in the joint design of individual behavior and communication structure between agents (and the method by which this structure is updated) in swarm intelligence techniques, also suggesting that the actual mechanism used by social animals to create (and maintain) contacts may have coevolved with the way these animals aggregate information gathered from their social contacts. This being the case, the behavior of social animals is likely to be an efficient method to solve the problems these animals face, as seeking for food or shelter, and may be a valuable inspiration for Engineering. It is worth to notice, however, that both the coevolution of social behaviors hypothesis and the effectiveness of the current animal behavior ask for more evidence.

To evaluate the potential of applying the complex topologies discussed in this work to solve Engineering problems, we also compared the static and dynamic complex neighborhoods to a state-of-the-art topology in PSO, the DMS-PSO (presented in section 3), under the classical individual behavior, for which DMS-PSO was developed. The results are exhibited in Table 3. It is noticeable the difference of relative performance between the complex neighborhoods, as the static topology lost much of its competitiveness against DMS-PSO when the size of the search space was increased,

what is not observed for the dynamic topology. The dynamic complex neighborhood, in turn, got mixed results in harder problems, achieving better results in the largest search space tested (100 dimensions) and performing slightly worse than DMS-PSO in rugged surfaces. The overall results show little difference between the dynamic complex topology presented in this work and DMS-PSO, with a narrow advantage to the latter. By the strict point of view of Engineering, this complex topology still needs improvement so it can overcome the results achieved by the DMS-PSO. Despite this, it is remarkable that swarms using a topology made mainly to mimic real societies, which was only adapted for performance improvement through minor parametric adjustments, were able to achieve results so close to those obtained by swarms using a state-of-the-art topology. We wonder whether a mechanism for topological update more similar to those seen in Nature would be able to provide even better results.

5. CONCLUSION AND FUTURE WORKS

In this work we studied complex networks and what is the effect of their use for structuring communication between natural or artificial agents in collective problem-solving. The experimental results brought evidence that the topological characteristics present in real-world social networks may, in fact, provide gain of performance and show that the mechanism used by individuals to create or delete social connections may strongly influence the results obtained by a group. This corroborates with the idea that the current topology of human social networks (and its update mechanism) was positively selected by natural evolution due to the improvement of performance in groups applying these structures of communication. Moreover, the obtained data indicates that the performance of a group of agents using a complex network to define its neighborhood also is highly dependent on how individuals act on the information they got from their peers, suggesting the method social animals establish and manage social ties coevolved with the way these individuals process social information. Furthermore, the obtained results have important implication for the design of multi-agent and distributed systems, as it renders natural societies as a potentially good source of inspiration for such systems based on decentralized agents.

One clear direction for further research is to investigate the effect more realistic individual behaviors have on the collective performance of social groups as well as the interaction between these behaviors and different topologies, specially dynamic ones inspired by the way social networks evolve. Of course, as a technique for solving Engineering problems, the combination of PSO and complex networks still needs some fine-tuning, as the design of an individual rule exploring the characteristics of these networks and of a topological update mechanism that improves the algorithm's ability to tackle multimodal problems. The main goal of this work, however, was not to develop the best optimization method but to explore the relationship between collective behavior and the communication structure within a group, shedding some light on the subject and supposedly inciting other researchers to investigate it.

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Table 2: Comparison between static and dynamic complex neighborhoods in multiple scenarios. The table shows the difference (95% confidence interval) between the proportion of tests in which swarms using dynamic complex neighborhoods returned better results and the proportion in which the static complex topologies were better. Negative values indicates that static topology yielded better results.

Dimensions				Function type	
10	30	50	100	Unimodal	Multimodal
$[-12.0\%, -11.8\%]$	$[-14.9\%, -14.7\%]$	$[-8.3\%, -8.1\%]$	$[-14.8\%, -14.4\%]$	$[-24.5\%, -24.3\%]$	$[-9.0\%, -8.9\%]$

Individual dynamic				
Regular	FIPS	Bare Bones PSO	ARPSO	Complete
$[13.5\%, 13.7\%]$	$[-47.7\%, -47.6\%]$	$[6.3\%, 6.5\%]$	$[-21.9\%, -21.6\%]$	$[-12.1\%, -12.0\%]$

Table 3: Results of complex neighborhoods against DMS-PSO. The table shows the difference (95% confidence interval) between the proportion of tests in which swarms using complex neighborhoods returned better results and the proportion in which DMS-PSO was better. Negative values indicates that DMS-PSO achieved the best results.

Complex network	Dimensions			
	10	30	50	100
Static	$[7.7\%, 8.1\%]$	$[-14.9\%, -14.7\%]$	$[-25.5\%, -25.2\%]$	$[-31.9\%, -31.4\%]$
Dynamic	$[9.6\%, 9.9\%]$	$[-6.8\%, -6.5\%]$	$[-10.3\%, -10.0\%]$	$[6.2\%, 6.7\%]$

Complex network	Function type		
	Unimodal	Multimodal	Complete
Static	$[-12.9\%, -12.5\%]$	$[-14.8\%, -14.6\%]$	$[-12.5\%, -12.3\%]$
Dynamic	$[5.5\%, 5.7\%]$	$[-3.6\%, -3.3\%]$	$[-2.0\%, -1.8\%]$

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