Unveiling Swarm Intelligence with Network Science—the Metaphor Explained

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***Abstract*—Self-organization is a natural phenomenon that emerges in systems with a large number of interacting components. Self-organized systems show robustness, scalability, and flexibility, which are essential properties when handling real-world problems. Swarm intelligence seeks to design nature-inspired algorithms with a high degree of self-organization. Yet, we do not know *why* swarm-based algorithms work well and neither we can compare the different approaches in the literature. The lack of a common framework capable of characterizing these several swarm-based algorithms, transcending their particularities, has led to a stream of publications inspired by different aspects of nature without much regard as to whether they are similar to already existing approaches. We address this gap by introducing a network-based framework—the interaction network—to examine computational swarm-based systems via the optics of *social dynamics*. We discuss the social dimension of several swarm classes and provide a case study of the Particle Swarm Optimization. The interaction network enables a better understanding of the plethora of approaches currently available by looking at them from a general perspective focusing on the structure of the social interactions.**

***Index Terms*—self-organization; complex systems; network science; swarm intelligence; particle swarm optimization**

I. Introduction

SWARM INTELLIGENCE refers to the global order that emerges from simple social individuals interacting among themselves [1]–[6]. In the past three decades, swarm intelligence has inspired many computational models, allowing us to understand social phenomena and to solve real-world problems [6]. The field of computational intelligence has witnessed the development of various swarm-based techniques that share the principle of social interactions while having different natural inspirations such as ants [7], fishes [8], fireflies [9], birds [10], to name a few. Though researchers have studied such techniques in detail, the lack of general approaches to assess these systems prevents us from uncovering what makes them intelligent and understanding the differences between techniques beyond their inspirations.

Much research has been devoted to understand and improve these bio-inspired algorithms [5], [6], [11]. In the literature, researchers often examine the techniques from the perspective of their natural inspirations. For instance, in some flocking models that mimic bird flocks, the velocities of individuals are usually used to understand the system behavior [11]. In these systems, the lack of spatial coordination or the excess of coordination among individuals generally leads to poor performance in solving problems. In the case of foraging-based models inspired by ant colonies, many studies attempt to understand the performance of these models by examining the pheromone that agents deposit on the environment [12]. This usual approach of analyzing models via their inspiration has helped to improve algorithms by building new procedures [13]–[16].

These analyses, however, are confined to the specific niches that have their metaphor (e.g., ants following pheromone, birds searching for food, fireflies trying to synchronize) and jargon (e.g., pheromone, velocity, fish weight). The broad variety of natural inspirations makes it challenging to find interchangeable concepts between swarm-intelligent techniques [17]. The absence of niche-free analyses restricts the findings of a model to its own narrowed sub-field. Such myopia leads us to miss the underlying mechanisms driving a system to the imbalanced states that new techniques (or procedures) endlessly try to avoid. In this scenario, we need agnostic quantitative approaches to analyze swarm intelligence in a general manner and thus provide the means to understand and improve algorithms in whatever niche.

The field lacks general methodologies to analyze swarms because of the absence of a generic framework to examine their main similarity: the social interactions (see Fig. 1). Indeed, the concept of *social interaction* is fundamental in swarm intelligence; it refers to the exchange of information through diverse mechanisms [3], [5]. In this definition, social interactions are not only the mere exchange of information

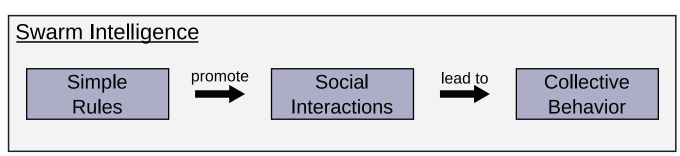

Fig. 1. The social interaction at the mezzo level is still overlooked by researches who often devote considerable efforts to understand how changing the simple rules at the micro level (e.g., procedures, equations) directly affects the collective behavior of the system at the macro level. In fact, these micro-level rules create the conditions to social interaction at the *mezzo level* which in turn enables the necessary swarm dynamics to solve complex problems at the macro level.

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between peers but also have the potential to change individuals [5]. The sophisticated behavior emerging from social interactions enables the system to adjust itself to solve problems [5]. In swarm-intelligent techniques, individuals process information and locally interact among themselves, spreading knowledge within the swarm which results in the emergent system ability. In this sense, examining the social mechanisms is fundamental to understand intelligence in these systems. This general perspective also helps us to assess swarms with different natural inspirations. Instead of relying on the complete understanding of the micro-level properties (e.g., velocity, pheromone, weight), we can assess the swarm via the structure and dynamics of the social interactions [3].

Notably, the field of Network Science has shown that every complex system has an underlying network encoding the interactions between the components of the system and that the understanding of the structure of this network is *sine qua non* for learning the behavior of the system itself [18]. Network Science advocates that the complex systems comprehension can be reached by observing the structure and dynamics of their underlying networks [19]–[21]. Though the idea of using networks as frameworks for understanding complex phenomena dates back to Moreno's use of sociograms in the 1940s [22], it has popularized after two seminal papers from Watts and Strogatz [23], and Barabási and Albert [24] in the late 1990s. Recent works in the field have demonstrated that even small variations in fundamental structural properties, such as the degree distribution, can significantly influence the behavior of the system described by the network [25], [26].

Here we propose a network-based framework—the interaction network—for the general assessment and comparison of swarm intelligence techniques. In the following sections, we start by describing the importance of understanding swarm-based algorithms and explaining the definition of the interaction network. We show how the interaction network can be defined for other swarm-based metaphors using a system categorization proposed by Mamei et al. [27]. Then, we demonstrate a complete case study using the concept of flocking and show the relationship between the interaction network and the swarm behavior.

II. Understanding Swarm Systems

In the field of Swarm Intelligence, scholars often analyze algorithms via their performance on given problems [17]. In many cases, innovation means better results on a set of benchmark functions. These improvements, however, tend to arise without much explanation. Researchers often use jargons to justify their approaches and to describe the improvements [17]. This black-box approach sidetracks us from the underlying mechanisms in these systems. We lack a general interpretability of results. The case occurs because of the lack of a comprehensive view of swarm-based algorithms. Though some efforts have been made to understand swarm systems from a general perspective, they tend to be qualitative in nature.

Mamei et al. have proposed to look at the swarm as a system processing information [27]. From this perspective, the way a swarm handles information defines its underlying self-organization mechanism. We can describe a system using three aspects of information: (i) the definition of information, (ii) how individuals use information, and (iii) how information flows within the system (see Fig. 2). This approach *classifies* swarm systems but fails to examine them quantitatively.

In fact, the literature has various approaches to classify swarm systems [28]–[30] and metaheuristics in general [31]–[33]. These efforts are essential to organize the field. They are necessary initial steps to understand current and new algorithms. Still, the absence of quantitative approaches prevents us from characterizing the particularities of methods and quantifying their differences.

In some cases, researchers measure the swarm diversity to understand the technique [30]. This diversity is often the diversity of the candidate solutions when solving a given problem [11], [12], [34]–[37]. With such approach, however, we focus on the final outcome of the swarm dynamics, neglecting the underlying mechanism leading to these dynamics. We lack a framework enabling us to examine the system from an intermediate perspective.

A. The Social Interactions in Swarm Systems

The dynamics of swarm-based systems depend on social interaction. The system lacks coordination without enough interaction among the individuals and looses adaptability with the excess [38]. The local rules in such systems promote or undermine the level of interaction within the swarm (Fig. 1). In this sense, the social interactions are halfway between the micro and macro behavior of the system. The network emerging from these complex interactions is a natural universal mezzo-level perspective of swarms.

Previous research has used the network paradigm to examine the emergent behavior in social animals and its un-

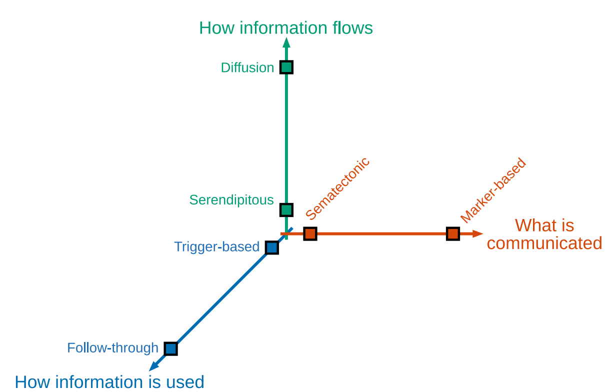

Fig. 2. Three dimensions define the self-organized mechanism in a swarm system: how information flows, how information is used, and the definition of information. The *diffusion* flow occurs when individuals passively receive information that other individuals spread in the environment whereas *serendipitous* flow occurs when individuals need to search information left in the environment by other individuals. When using information in a *trigger-based* system, individuals act in the environment by performing specific, mostly one-off, actions, while in a *follow-through*, they are guided by what they find, and the action can be more long-lasting. The *marker-based* information is explicitly defined for interaction purposes (e.g., pheromone), while individuals implicitly share *sematectonic* information as the current state of the population (figure adapted from [27]).

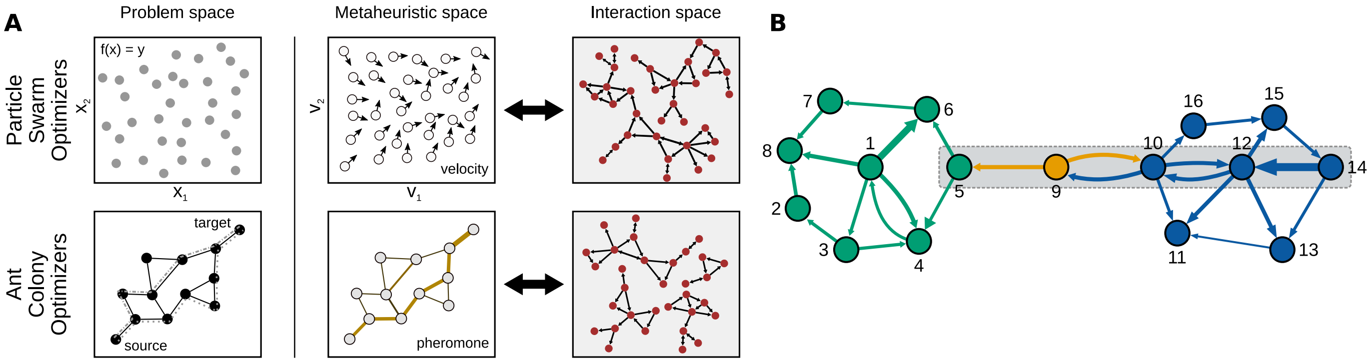

Fig. 3. Different viewpoints of swarm systems. We highlight that the interaction space is a general way of viewing these systems. (**A**) Models of swarm intelligence are commonly used to solve continuous (top) and discrete (bottom) problems that can be represented in the *problem space* (left). Each model incorporates metaphor-specific aspects such as velocities (first row) and pheromone (second row) in PSO and ACO, respectively, that can be represented in the *metaheuristic space* (middle). However, regardless the problem and the metaphor, the actions of individuals are interdependent and depend on the social interactions. The use of the interaction network allows us to represent these social interactions in the *interaction space* (right), enabling a unified assessment of metaheuristics. (**B**) A general illustration of an interaction network for swarm systems where each node is an individual in the population and each link represents the direction and the extent of the individuals' influence. Each color depicts a distinct sub-network to which members are highly integrated and tightly connected when compared to nodes outside the sub-network. For instance, individuals 1, 4 and 5 belong to the leftmost sub-network depicted in red whereas individuals 10, 11 and 12 belong to the rightmost sub-network depicted in blue, while individual 9 act as a bridge between the sub-networks.

derlying mechanisms [39]–[42]. Some developments in the computational intelligence field have also taken advantage of networks [43]–[49]. They have been used to understand swarm systems [50], [51] and their respective collective behaviors such as flocking [52]–[59] and foraging [49], [60]. In this regard, Oliveira et al. proposed one of the first approaches to examine interactions within the swarm in the Particle Swarm Optimization [52]. Yet, these preliminary efforts have focused on specific techniques, missing the fact that social interaction is the common feature driving swarm intelligence.

In this work, we argue that the social dynamics in swarm-based algorithms should be more analyzed and explored to provide insights into the *dynamic network* behind the rules and inspirations, which may lead to a possible meta-classification of the systems but from the dynamics of social interactions rather than the natural inspiration for the social system. In Section III, we define the interaction network and use the categorization proposed by Mamei et al. to elaborate on the plausibility of describing and employing the interaction network to assess models of swarm intelligence inspired by different mechanisms of self-organization. Though different mechanisms, an interaction network can be built to characterize the system over a common space: the interaction space. In the interaction space, the interaction network becomes a general framework that allows for the unified assessment of swarm-intelligent models with distinct inspirations.

III. The Network of Social Interaction

We propose to examine the social interactions within a swarm as a way to assess the behavior of swarm-intelligent systems. Here we develop the concept of *interaction network* to represent the interdependencies of the actions of the individuals. For a given swarm system, the interaction network $\mathbf{I}$ consists of nodes that represent its individuals and edges $\mathbf{I}_{ij}$ that indicate the extent to which individual i influences the action of the individual j. As social interactions are dynamic and so the swarm, we use $\mathbf{I}(t)$ to describe the influence that individuals exert on each other at time t.

The interaction network is a representation of the swarm and the result of the rules that define the swarm system. However, the network $\mathbf{I}$ belongs to the *interaction space* $\mathcal{I}$ (see Fig. 3A). This is an agnostic space exempt from the particularities of the swarm algorithm or problems being solved by the algorithm. Note that both the algorithm (i.e., rules) and problem modify the social dynamics within the system and have an impact on $\mathbf{I}$. Yet, when we look at algorithms from this general framework, we have the potential to assess different algorithms that are, at their surface, completely distinct (i.e., inspired by distinct natural phenomena).

The analyses of the network structure—at both global- and individual-levels—enable us to assess different aspects of the swarm, and aspects across different swarm approaches. For instance, Fig. 3B depicts a conceptual interaction network for swarm systems. At the individual-level, the network positions occupied by individuals indicate the types of interdependencies that were created by the swarm and the influence individuals may exert on one another. The individuals with a high degree centrality (e.g., individuals 1 and 12) typically exert higher influence when compared to other individuals. Similarly, individuals that connect different groups (e.g., individual 9) act as bridges between subgroups of individuals and control the cascade of influence between sub-networks. Thus, some individuals in a swarm system can develop important roles as bridges and hubs. Lastly, at a global-level, the interaction network indicates the extent of local and global exploration by providing the relationship between natural niches formed by individuals (e.g., green and blue sub-networks).

In order to analyze a swarm using the interaction network, we need to understand the rules and mechanisms that allow individuals to influence the action of each other within each swarm system. For this, we employ the dimensions described in Fig. 2 to guide our understanding of algorithms and thus to define its network. For a given algorithm, we have to

TABLE I
SOCIAL INTERACTIONS OF THE EIGHT SWARM-INTELLIGENT CATEGORIES AS ORGANIZED BY MAMEI ET AL. [27].

Name	Inspiration	Heuristic	Communication	Social interaction	Example
Quorum	bacteria	decision-making	Direct	Triggered based on the passively perceived current arrangement of their local environment	BSO [61]
Embryogenesis	cells [62]	self-assembling	Direct	Triggered based on the passively perceived markers of social interaction diffused in the environment	GSO [63]
Molding	slime mold amoebas [64]	swarm coordinated aggregation	Direct	Passively perceived markers of social interaction they diffuse in the environment	Graduate Routing [65]
Flocking	birds [5]	swarm coordinated motion	Direct	Continuously self-propel based on the current arrangement of their passively perceived environment	PSO [10]
Brood sorting	worker ants [3]	sorting of items	Indirect	Triggered based on the actively found current arrangement of their local environment	SMOA [66]
Nest Building	termites [67]	coordinated construction of complex structures	Indirect	Triggered based on the actively found markers of social interaction left in the environment	MBO [68]
Foraging	ants [3]	coordinated exploration of the environment	Indirect	Continuously self-propel based on the actively found markers of social reinforcement left in the environment	ACO [7]
Web Weaving	spiders [69]	coordinated construction of complex structures	Indirect	Continuously self-propel based on the actively found current arrangement of their local environment	RIO [70]

identify how each individual uses information after it received information from other individuals. It is clear that first we need to characterize what information is in the system then describe how information exchange influences individuals. Table I describe how the interaction network can be constructed for the approaches proposed by Mamei et al. [27]. In Section IV, we provide a detailed case study of a well-known flocking technique, the Particle Swarm Optimization, for which we use a definition of $\mathbf{I}$ to analyze the swarm behavior.

IV. THE SOCIAL INTERACTION IN THE PARTICLE SWARM OPTIMIZATION

The Particle Swarm Optimization (PSO) is a population-based optimization method that relies on the interactions of individuals sharing the best positions they found during the search process [10]. The method—inspired by the social behavior in flocks of birds—consists of a population of simple reactive agents (particles) that explore the search space by locally perceiving the environment and interacting among themselves to improve their solutions.

In the particle-swarm perspective, exploration and exploitation refer to the ability of individuals to broadly explore the whole search space or specifically focus on a particular area [5]. Similar to other optimization techniques [71], the PSO suffers from premature convergence [72]: the swarm reaches a local optimum solution because of an early equilibrium state. This undesired situation often results from an exploration–exploitation imbalance that leads to a poorly explored search space.

In order to understand the behavior of a swarm (as in the PSO) and properly balance the aforementioned two properties, researchers tend to look at diversity within the swarm. The literature often focuses on the *spatial* diversity [34]–[37]. From this viewpoint, researchers are interested on the outcomes of social interactions such as the positions (i.e., solutions) or velocities of the particles in the search space. Indeed, a poor trade-off between exploration and exploitation affects the diversity of solutions found by the swarm. For instance, researchers have developed different metrics that quantify swarm diversity as the degree of dispersion of particles around a given spatial centroid [35]–[37], [73]. These approaches have succeed in developing novel mechanisms (e.g., adaptive swarm [74]) to improve the performance of the algorithm. Yet, with these approaches, we fail to understand the *underlying social interactions* driving the swarms to particular imbalanced states that new mechanisms try to avoid.

Still, a few works have attempted to analyze the particles' interactions in order to examine the swarm behavior. Some of these efforts analyzed the impact of the infrastructure of the swarm communication on the swarm performance [59], [75], [76]. Though these studies neglected the actual interactions between particles, they showed that bounding social interactions influences the swarm behavior. Oliveira et al. were the first ones to examine the actual interactions among particles in order to assess the swarm [52]. They proposed the analysis of the swarm using a network in which the nodes (particles) are connected if they share information in a given iteration, and later extended the concept to capture historical information [53], [54], [56]. Later on, Pluhacek et al. provided visualizations of the interactions in the swarm [58].

In the next sections, we briefly describe the PSO technique and define the *interaction network* $\mathbf{I}$ to assess the swarm using the methods developed by Oliveira et al. [55]. With the definition of $\mathbf{I}$, we are able to uncover relationships between the swarm dynamics, the swarm performance, and the social interactions. The understanding of such relationships demonstrates that one can understand and assess swarm approaches from the meta-level of social interactions.

A. Particle Swarm Optimization

In the standard definition of the PSO, each particle i consists of four vectors in a d-dimensional search space: its current position $\vec{x_i}(t)$, its best position found so far $\vec{p_i}(t)$, its velocity $\vec{v_i}(t)$, and the best position found by its neighbors $\vec{n_i}(t)$ [77]. The position of each particle represents a candidate solution to a d-dimensional continuous optimization problem and the swarm moves through the problem search space seeking for better solutions. To enable this capability, all particles change their positions, at each iteration t, according to their velocities $\vec{v_i}(t)$ which are updated based on the personal best position $\vec{p_i}(t)$ and the social best position $\vec{n_i}(t)$.

In the first definition of the algorithm, the swarm could be in the so-called explosion state in which the particles indefinitely increase their velocities [78]. Some approaches have been proposed to prevent this state [78]–[80]. Clerc and Kennedy developed the constricted PSO in which the velocities are constricted by a constriction factor that avoids the explosion state. This factor, χ, is defined as follows:

$$\chi = \frac{2}{\left|2 - \varphi - \sqrt{\varphi^2 - 4\varphi}\right|}, \quad \text{where} \quad \varphi = c_1 + c_2, \tag{1}$$

which adjusts the influence of the previous particle velocities during the optimization process. The constricted PSO employs the following update equation:

$$\begin{aligned} \vec{v_i}(t+1) = \chi \cdot \Bigg\{ \vec{v_i}(t) + \vec{r}_1 c_1 \cdot \Big[\vec{p_i}(t) - \vec{x_i}(t)\Big] \\ + \vec{r}_2 c_2 \cdot \Big[\vec{n_i}(t) - \vec{x_i}(t)\Big] \Bigg\}. \end{aligned} \tag{2}$$

$$\vec{x_i}(t+1) = \vec{x_i}(t) + \vec{v_i}(t+1), \tag{3}$$

where $\vec{r}_1$ and $\vec{r}_2$ are random vectors generated from a uniform probability density distribution in the interval [0,1] for each particle; while c_1 and c_2 are the cognitive and the social acceleration constants that weigh the contribution of the cognitive and social components [5].

The particles in the swarm only interact with a subset of the swarm. The swarm topology defines the infrastructure through which particles communicate and thus enables the particles to retrieve information from other particles (i.e., their neighbors). At each iteration t, each particle i seeks for its best neighbor $n_i(t)$ in its neighborhood (i.e., the one with the best solution so far). Note that each particle i uses information only from $n_i(t)$ at each iteration t.

In the original PSO paper, the implicit communication scheme is defined over a global topology in which all particles of the swarm have the same neighborhood [10]. The information shared among particles is the same for each particle. In local topologies, however, particles have different subsets of neighbors, implying different social information within the swarm [77]. For instance, the ring topology—the most popular local topology—has a structure in which particles communicate with only two other particles using a labeling approach [77]. The topology influences the social interaction within the swarm and has been shown to impact the swarm performance [75]–[77], [81].

Clerc proposed a somewhat different definition of swarm topology—the so-called *graph of influence*—which explicitly includes the social information and presents directed edges [82]. Still, regardless of definition, the swarm topology only refers to the structure for a potential exchange of information and neglects effective interaction among particles.

B. A Network for the Particle Swarm Optimization

To examine a swarm system from the perspective of its social interactions, we need to build the interaction network to capture the structure and dynamics of the social influence exerted among individuals. In the case of the PSO, a social interaction occurs when a particle i updates its position based on the position of a particle j. This happens when j is the best neighbor of i at a given iteration; that is, $n_i(t) = j$.

Here we use a simple (yet powerful) definition of interaction network $\mathbf{I}(t)$ in which the weight of an edge (i, j) is the number of times the particle i was the best neighbor of the particle j or vice-versa until the iteration t [53]. This network represents the social interactions that systematically affect the swarm. We can use a time window t_w to control the recency of the analysis, thus the interaction network at iteration t with window t_w is defined as the following:

$$\mathbf{I}_{ij}(t) = \sum_{t'=t-t_w+1}^{t} \Big[\delta_{i,n_j(t')} + \delta_{j,n_i(t')}\Big], \tag{4}$$

with $t \geq t_w \geq 1$ and where $\delta_{i,j}$ is Kronecker delta. In this definition, nodes (i.e., particles) are connected by an edge with weight equals to the number of times two particles shared information in at most t_w iterations before the iteration t [53]. The time window t_w tunes the frequency–recency balance in the analysis. High t_w makes the network dominated by most frequent interactions; low t_w only includes most recent interactions and when $t_w = 1$ we have instantaneous interactions.

Note that the definition of an interaction network for a swarm system depends on the rules that promote social interaction in the system. Here we pinpointed that, in PSO, a social interaction between i and j occurs when the particle i updates its velocity $\vec{v_i}$ using the position of a particle j. Yet, this definition of $\mathbf{I}$ is a simple one that includes only the occurrence of social interaction between particles. More complex definitions may include edge direction or other aspects of the algorithm such as the social constant c_2 or the realizations of $\vec{r_2}$. Nevertheless, with this simple definition, we can already better understand the swarm [52]–[56]. Other swarm systems, however, have different rules and distinct forms of social interactions, as we pointed out in Section II-A and showed in Table I.

C. Examining the Social Interactions with $\mathbf{I}$

The formation of structures in the interaction network arises from the way information flow within the swarm which, in

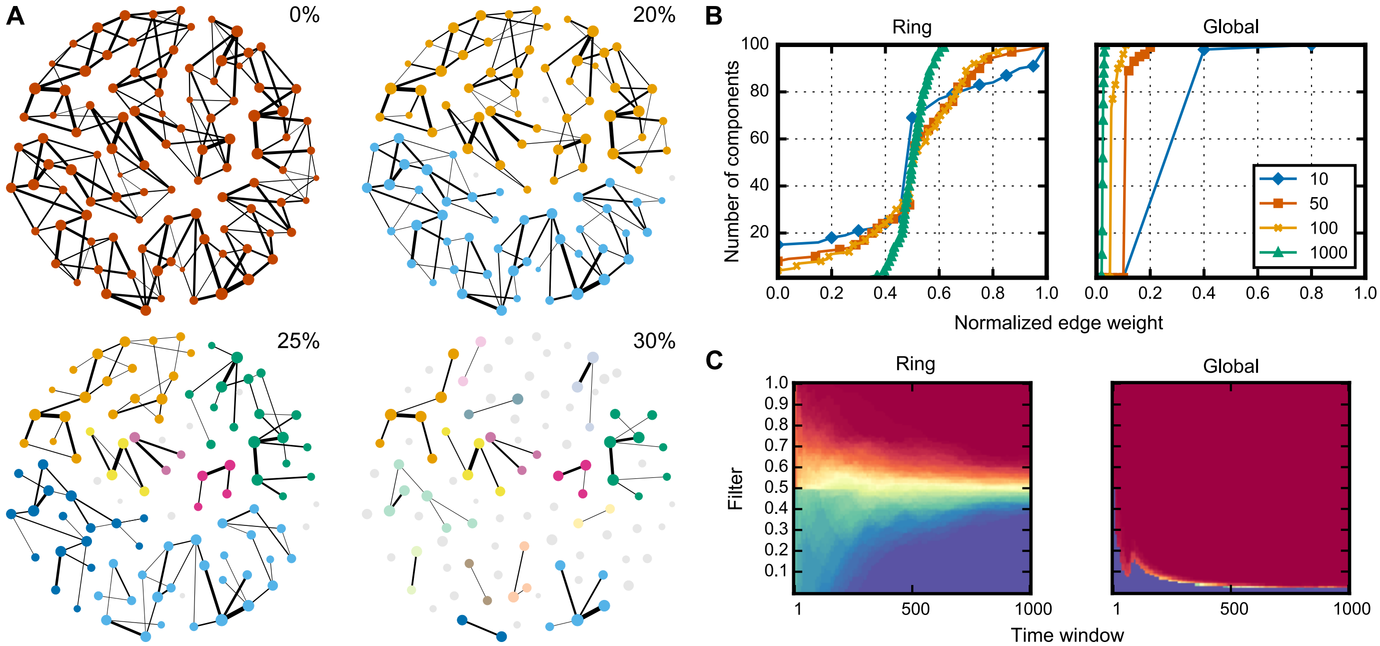

Fig. 4. The pace at which components emerge while edges are gradually removed from **I** is associated with the search mode of the swarm. An exploration mode is characterized by a slow increase in the number of components due to the different information flows present in the swarm. The network, however, is rapidly destroyed in a swarm that depends only on a small set of individuals, a behavior related to an exploitation search mode. In the PSO, (**A**) the weighted interaction network of a run with the swarm using a von Neumann topology has edges removed based on their weight: below 20% of the highest possible weight, 25% and 30%. The colors represent components with more than one node. In this process, edges with lowest weights are removed first. (**B**) The impact of the edges removal on the growth of the number of components depends on the structure of the swarm topology. The different colors/markers in the plot represent the time window t_w. The normalized weight is the weight value divided by $2t_w$ which is the highest possible weight in the network. The rapidly increasing in the number of components of the global topology leads to a behavior related to the exploitation search mode. In the ring topology, the number of components increases slowly, indicating the existence of sub-swarms searching more independently through the search space [53]. In all cases, the swarm consists of 100 individuals. (**C**) Each topology leads to distinct interaction diversity that can be described by the number of components emerging (color intensity) as edges are removed (y-axis) of the interaction network with different time windows (x-axis).

turn, alters the dynamics of the swarm. The existence of well-connected nodes in **I** indicates frequent information flows in the swarm. The constant interaction among certain individuals leads to their respective nodes in the interaction network to be clustered. To capture these clusters, we can gradually remove the edges of **I** according to their weight; the components that emerge during this network destruction represent the information flows within the swarm (see Fig. 4A). The disconnectivity emerges from the percolation threshold surpassed.

Note that the pace at which these components appear relates to the swarm dynamics. A slow increase suggests an exploration search mode in which individuals share information among distinct groups and thus create social interactions with various levels of tie strength. A rapid increase suggests, however, an exploitation search mode in which individuals interact with few same sources and thus create a center of information with similar levels of tie strength.

With the definition in Eq. (4), we can now examine the search mode in the PSO. For instance, we analyze **I** of swarms using different topology parameters—that are known to lead the swarm to behave differently—while solving the same problem. As shown in Fig. 4B, with the global topology, the particle swarm presents exploitation behavior, whereas the ring topology leads the system to explore different information sources. Note that this analysis differs from the typical analysis on the relationship between fitness and topology structure [75], [76], [81]. Here we focus on the way particles interact during the swarm search when using different structures: the communication topology affects the diversity of the *interactions* in the swarm, generating different interaction networks.

To consider the swarm ability to maintain different frequent information flows, we can analyze the network destruction while varying t_w to include frequency and recency in the analysis of the flows. Fig. 4C depicts the number of components that emerge when edges are removed from **I** with increasing time windows. The interaction network of a particle swarm with global topology seems to be destroyed at the same pace in both perspectives of frequency (i.e., high t_w) and recency (i.e., low t_w). The interactions of the particles within this topology promote a lack of diversity in the information flows in short and long terms.

This diversity regards to the ability of the swarm to have a diverse flow of information—a perspective different from *spatial* diversity in which d-dimensional properties of particles are compared to particular definitions of swarm center [35]–[37], [83]. Note that the lack of diversity in the information flow can decrease the spatial diversity in a swarm. The absence of multiple information flows leads particles retrieving information from few sources and drives particles to move towards the same region of the search space; lack of interaction diversity pushes individuals to the same direction.

To quantify interaction diversity, we measure the destruction pace of interaction networks with different time windows. For a given time window t_w, the area under the destruction curve

A_{t_w} can be seen as a measure of diversity in the information flow. High values of A_{t_w} indicate fast destruction, whereas low values imply in a slower destruction. Hence, we can define the interaction diversity ID (previously called communication diversity [55]) as the mean diversity over a set of time windows T, as the following:

$$\mathrm{ID}(t) = 1 - \frac{1}{|S||T|} \sum_{t'_w \in T} A_{t_w = t'_w}(t), \qquad (5)$$

where $|S|$ is the number of particles in the swarm. Thus, swarms exhibiting high ID (i.e., low values for A_{t_w}) have the ability to have diverse information flows, while low values for ID imply in swarms with only few information flows (i.e., high value for A_{t_w}). An ideal set T would be one taking into account all time windows (i.e., interactions from $t_w = 1$ until $t_w = t$). This procedure, however, can be computationally expensive given the vast number of possible time windows, and a more reasonable approach is to have a sample set of time windows.

1) Experimental Design: To investigate the extent to which the interaction diversity assess the swarm at each iteration, we systematically examined the swarm using different topologies that lead the swarm to behave differently. We employ different connected k-regular graphs (i.e., graphs that nodes have k links) as the swarm communication topology with k equal to 2, 4, 5, 6, 7, 8, 9, 10, 20, 30, 40, 50, 60, 70, 80, 90, and 100 (special cases are: $k = 2$, ring topology; $k = 4$, von Neumann topology; and $k = 100$, global topology). Here we consider a distinct group of four benchmark functions F_2, F_6, F_{14}, and F_{19} from the CEC'2010 set which possess varied characteristics and cover major aspects of optimization problems such as multi-modality and non-separability [84]. In all experiments, we set the number of dimensions to 1000 and, when applicable, the degree of non-separability m to 50; and define the swarm with 100 particles that are updated according to Eq. (2) with $c_1 = 2.05$, $c_2 = 2.05$ [78].

We analyze the relationship between ID and fitness improvement over time; thus we define fitness improvement $f_\Delta(t)$ at iteration t as the speed at which the fitness $f_g(t)$ of the swarm changes between the two immediate iterations t and $t-1$ as follows: $f_\Delta(t) = \frac{f_g(t) - f_g(t-1)}{f_g(t-1)}$, where $f_g(t)$ is the global best fitness of the swarm at iteration t. In the simulations, we set as the stopping criterion whether the maximum number of iterations, $t_{max} = 10000$, is reached or the swarm converged at iteration t_s. We define that a swarm converged at iteration t_s if the global best fitness does not improve, that is, if $f_\Delta(t) < 10^{-5}$, until iteration $t_s + \delta$ with $\delta = 500$. For each considered swarm topology, we run a PSO implementation 30 times while measuring ID and f_Δ at each iteration in each execution.

2) Results: First, we analyze the impact of the infrastructure of communication (i.e., swarm topology) on the diversity of the information flows within a swarm. We found that k-regular topologies promote higher diversity as k decreases when solving the same problem (see Fig. 5 and Table II). With less connected topologies, swarms exhibit greater interaction diversity than with more connected ones. Given previous studies, this is an expected result: short topological distances lead to fast information flow which decreases the diversity [77]. Our results revealed that the interaction diversity in the swarm depends on the problem; the same topology leads to distinct levels of diversity when optimizing different functions (see also Table II). Though the topology bounds the interactions among particles, the swarm organize the way information flow to optimize a function.

Indeed, swarm-intelligent systems have the capability to self-organize during the optimization process; they can adapt their behavior towards an optimal behavior to solve a given problem. Hence, to assess the relationship between swarm search and interaction diversity, we examine the pace f_Δ at which a swarm improves and the interaction diversity at each iteration. We found that ID exhibits a non-trivial relationship with f_Δ, as seen in Fig. 6(A) for the function F_2. The average f_Δ increases with the average ID until reaches a maximum pace after which f_Δ decreases with ID. The increase of diversity in the social interactions of the swarm leads to faster swarm pace only until a certain level of diversity; then the swarm starts to slow down—swarm dynamics that impacts the overall swarm performance, as seen in Fig. 6(B). We also found a non-trivial association between k-regular topologies and the best fitness found at the end of the optimization process. From global to 30-regular topologies, the fitness decreases from 8.06×10^3 and improves down to 6.77×10^3, then deteriorates up to 1.01×10^4.

3) Discussion: Our results demonstrate the capability of interaction diversity ID to explain the behavior of the swarm during the optimization process in the Particle Swarm Optimization technique. ID enables us to identify changes in the way information flow within the swarm depending on the type of problem. The leverage capability of proposed analysis procedure brings on the possibility to identify imbalance during the search process and further understand the flow of information within the swarm. More than using this to select which is the best topology for a particular problem, one can

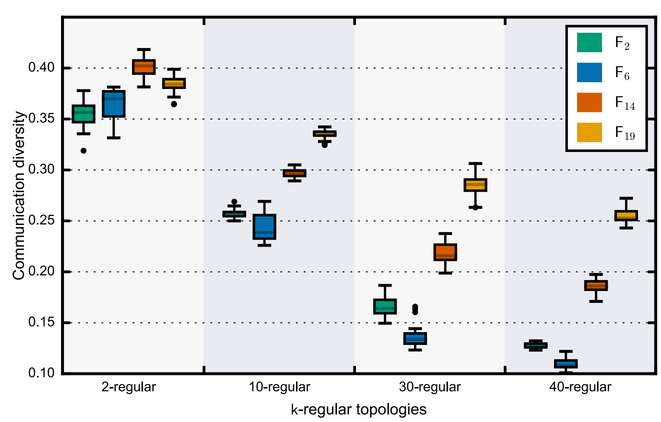

Fig. 5. The characteristic interaction diversity of the swarm regarding different topologies of communication and benchmark functions. Each box-plot represents 30 repeated simulations. The interaction diversity is typically higher for less connected topologies (i.e., 2-regular and 10-regular) when compared to highly connected topologies (i.e., 30-regular and 40-regular). Similarly, some functions appear to consistently present higher interaction diversity when compared to other regardless of the underlying communication topology.

TABLE II

INTERACTION DIVERSITY (95% CONFIDENCE INTERVALS) AND THE FINAL FITNESSES FOR DIFFERENT k-REGULAR TOPOLOGIES.

	k-regular topologies							
	Ring	Neumann	5	6	7	8	9	10
F_2	$(0.350, 0.359)$	$(0.325, 0.329)$	$(0.345, 0.356)$	$(0.328, 0.332)$	$(0.329, 0.333)$	$(0.283, 0.287)$	$(0.285, 0.288)$	$(0.255, 0.258)$
	1.0184×10^4	8.9214×10^3	1.0297×10^4	9.0308×10^3	9.0245×10^3	8.3778×10^3	8.4711×10^3	8.2141×10^3
F_6	$(0.359, 0.370)$	$(0.317, 0.321)$	$(0.360, 0.369)$	$(0.316, 0.320)$	$(0.318, 0.322)$	$(0.268, 0.274)$	$(0.268, 0.275)$	$(0.238, 0.249)$
	1.7889×10^6	1.4784×10^6	1.5871×10^6	1.5463×10^6	1.4926×10^6	1.3893×10^6	1.4189×10^6	1.0583×10^6
F_{14}	$(0.397, 0.404)$	$(0.363, 0.366)$	$(0.399, 0.405)$	$(0.360, 0.363)$	$(0.361, 0.364)$	$(0.320, 0.323)$	$(0.321, 0.325)$	$(0.295, 0.298)$
	1.2450×10^{10}	1.0920×10^{10}	1.2628×10^{10}	1.0686×10^{10}	1.0823×10^{10}	1.0007×10^{10}	9.8929×10^9	9.2693×10^9
F_{19}	$(0.381, 0.387)$	$(0.387, 0.391)$	$(0.373, 0.381)$	$(0.382, 0.384)$	$(0.383, 0.386)$	$(0.353, 0.355)$	$(0.352, 0.356)$	$(0.333, 0.336)$
	8.6326×10^6	7.3515×10^6	8.5287×10^6	7.4901×10^6	7.5940×10^6	7.0125×10^6	6.8728×10^6	6.7804×10^6
	20	30	40	60	70	80	90	Global
F_2	$(0.195, 0.200)$	$(0.162, 0.169)$	$(0.127, 0.129)$	$(0.098, 0.100)$	$(0.090, 0.091)$	$(0.082, 0.083)$	$(0.073, 0.074)$	$(0.057, 0.058)$
	7.1551×10^3	6.7687×10^3	6.9666×10^3	7.2088×10^3	7.2479×10^3	7.2293×10^3	7.4163×10^3	8.0666×10^3
F_6	$(0.165, 0.175)$	$(0.132, 0.140)$	$(0.108, 0.112)$	$(0.083, 0.087)$	$(0.076, 0.079)$	$(0.069, 0.071)$	$(0.062, 0.065)$	$(0.055, 0.058)$
	1.2550×10^6	1.6004×10^6	1.6119×10^6	1.7215×10^6	2.1324×10^6	2.0674×10^6	2.6710×10^6	2.6931×10^6
F_{14}	$(0.241, 0.246)$	$(0.215, 0.222)$	$(0.183, 0.188)$	$(0.153, 0.159)$	$(0.142, 0.147)$	$(0.129, 0.134)$	$(0.119, 0.124)$	$(0.096, 0.099)$
	7.9751×10^9	7.0154×10^9	7.9144×10^9	9.0796×10^9	1.0001×10^{10}	1.0116×10^{10}	1.0436×10^{10}	1.1396×10^{10}
F_{19}	$(0.294, 0.300)$	$(0.281, 0.288)$	$(0.252, 0.257)$	$(0.211, 0.214)$	$(0.197, 0.200)$	$(0.183, 0.186)$	$(0.166, 0.169)$	$(0.127, 0.128)$
	6.0334×10^6	5.7086×10^6	5.6747×10^6	5.3514×10^6	5.4846×10^6	5.5568×10^6	5.4663×10^6	5.3245×10^6

even deploy this to propose adaptive mechanisms to avoid imbalance during search processes [81].

The diversity of interaction is a general measure to assess swarm-based systems because it does not consider peculiarities associated with the swarm metaphor. The approach is defined over the structure of the network—the *interaction space*—which is entirely based on the social interactions. For instance, the results regarding the associations between topology, interaction diversity, and fitness, clearly indicate that interaction diversity can be used to understand the complex behavior exhibited in the PSO (our case study) with different communication topologies. In fact, this approach can help researchers to perform parametric analyses; due to the lack of analytical tools, previous parametric studies tend to consider simplified version of the algorithm [78].

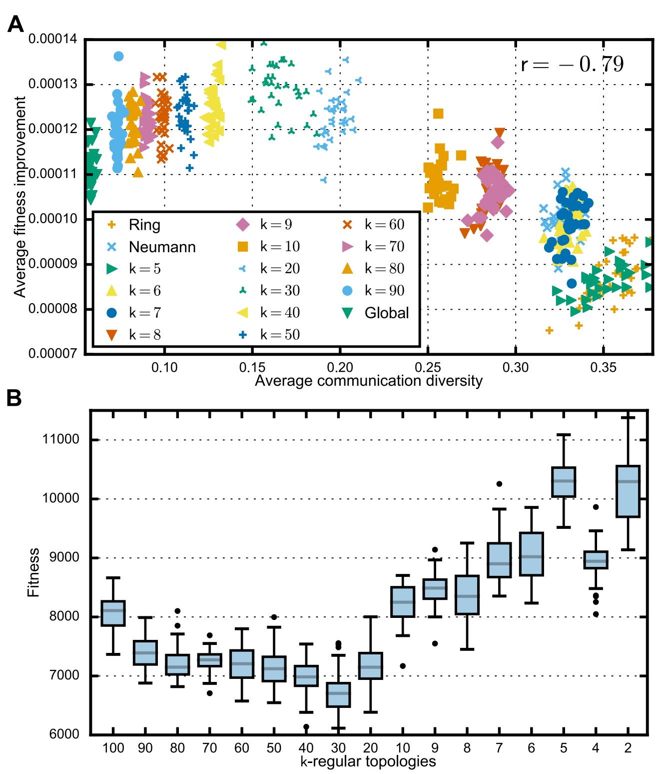

Fig. 6. The interaction diversity, fitness improvement, final fitness and k-topologies are associated in a non-trivial manner. In the results for F_6 function, (**A**) although the correlation of -0.79 indicates a strongly negative linear relationship between the average interaction diversity and the mean fitness improvement, one can easily see that they are associated in a non-monotonic way. (**B**) Similarly, the final quality of the fitness found by the swarm also presents a non-monotonic behavior regarding k-regular topologies and consequently interaction diversity.

V. DISCUSSION

Bees, ants, birds, and many other animals have inspired several swarm-based algorithms, but the literature fails to explain their differences and their complex behavior, losing their full potential. In the field, we often describe the differences between the techniques or their versions via the performance achieved when solving distinct problems. This black-box approach has enabled the area to grow over the years and to develop excellent general-use tools. This approach, however, lacks *interpretability*. How to interpret, for instance, that including a diversity procedure improves the performance of a swarm algorithm? Is this modification the same as using a different algorithm? With this opaque approach, we miss the opportunity to understand swarm intelligence.

The main barrier to understanding the swarm complex behavior is the discontinuity between the micro-level actions of individuals and the macro-level behavior of the swarm. In our work, we argue that the *interaction network* is the necessary mezzo level to explain and understand these systems. With this approach, we can examine a system via an intermediary structure that emerges from the social interactions within the swarm. We can now analyze the patterns of these self-organized interactions. The interaction network also grants an agnostic representation of swarm systems in the *interaction space* which provides us with a more general perspective of swarm-based algorithms.

To verify the plausibility of this network-based approach, we considered the self-organization mechanism of flocking as a case study and investigated its most popular optimization technique, namely, the Particle Swarm Optimization. We also discussed the social interaction in other self-organization mechanisms to guide definitions of their interaction network. In the analysis of the PSO, we found that the interaction network helps us to disentangle complex features of swarm systems. We analyzed its interplay with the quality and improvement of fitness, and we found that some characteristics of the interaction network can be used to explain parametric settings in the algorithm. Specifically, we studied the diversity in the network (i.e., the Interaction Diversity). Our results revealed that different communication topology leads the swarm to distinct search mode that also depends on the problem landscape.

The network-based perspective of swarms unfolds a pathway to researchers to study these systems comprehensively. This perspective creates opportunities on two fronts. First, it brings the required general viewpoint to build an objective classification of swarm-based algorithms. This classification guides the algorithm selection for problem-solving and the development of novel or hybrid methods. Second, the network empowers scholars to examine swarms from an intermediate level that is crucial to understand the complex behavior of these systems. At this mezzo level, we expose the effects of the swarm rules which are hidden in the swarm behavior.

In this study, though we limited our numerical analyses to the PSO, we proposed a general approach that makes possible to perform parametric analyses, quantify differences between methods, balance techniques with hybrid or adaptive versions, and build mezzo-level mechanisms. These are directions for future research.

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