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Chapter

Introductory Chapter: Swarm Intelligence - Recent Advances, New Perspectives, and Applications

Eneko Osaba, Esther Villar and Javier Del Ser

1. Introduction

Swarm intelligence has emerged as one of the most studied artificial intelligence branches during the last decade, constituting today the most high-growing stream on bioinspired computation community [1]. A clear trend can be deduced by analyzing some of the most renowned scientific databases available, showing that the interest aroused by this branch has been in crescendo at a notable pace in the last years [2]. Undoubtedly, the main influences behind the conception of this stream are the extraordinarily famous particle swarm optimization (PSO, [3]) and ant colony optimization (ACO, [4]) algorithms. These meta-heuristic lighted the fuse of the success of this knowledge area, being the origin and principal inspiration of their subsequent research. Such remarkable success has led to the proposal of a myriad of novel methods, each one based on a different inspirational source such as the behavioral patterns of animals, social and political behaviors, or physical processes. The constant proposal of new methods showcases the capability and adaptability of this sort of solvers to reach a near-optimal performance over a wide range of high-demanding academic and real-world problems, being this fact one of the main advantages of swarm intelligence-based meta-heuristics.

2. Brief history of swarm intelligence

The consolidation of swarm intelligence paradigm came after years of hard and successful scientific work and as a result of the proposal of several groundbreaking and incremental studies, as well as the establishment of some cornerstone concepts in the community.

In this regard, two decisive milestones can be highlighted in swarm intelligence history. First of these breakthrough landmarks can be contextualized on horseback between the 1960s and 1970s. Back then, influential researchers such as Schwefel, Fogel, and Rechenberg revealed their first theoretical and practical works related to evolving strategies (ES) and evolutionary programming (EP) [5–7]. An additional innovative notion came to the fore some years later from John H. Holland's hand. This concept is the genetic algorithm (GA, [8]), which was born in 1975 sowing the seed of the knowledge field today known as bioinspired computation. All the three outlined streams (i.e., ES, EP, and GA) coexisted in a separated fashion until the

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1990s, when they all erected as linchpin elements of the unified concept evolutionary computation.

The second milestone that definitely contributed to the birth of what currently is conceived as swarm intelligence is the conception of two highly influential and powerful methods. These concrete algorithms are the ACO, envisaged by Marco Dorigo in 1992 [9], and the PSO [10], proposed by Russell Eberhart and James Kennedy in 1995. Being more specific, the PSO was the method that definitely lit the fuse of the overwhelming success of swarm intelligence, being the main inspiration of a plethora of upcoming influential solvers. Therefore, since the proposal of PSO, algorithms inheriting its core concepts gained a great popularity in the related research society, lasting this acclaim until the present day [11–13]. For the modeling and design of these novel approaches, many inspirational sources have been considered, commonly categorized by (able to collect these sources in three recurring groups):

- Patterns found in nature: we can spotlight two different branches that tie (fall) together within this category. The first one is related to biological processes, such as the natural flow of the water (water cycle algorithm, [14]), chemotactic movement of bacteria (bacterial foraging optimization algorithm, [15]), pollination process of flowers (flower pollination algorithm, [16]), or geographical distribution of biological organisms (biogeography-based optimization, [17]). The second inspirational stimulus is the behavioral patterns of animals. This specific trend is quite outstanding in recent years, yielding a design based on creatures such as bats (bat algorithm, [18]), cuckoos (cuckoo search, [19]), bees (artificial bee colony, [20]), or fireflies (firefly algorithm, [21]).

- Political and social behaviors: several human conducts or political philosophies have also inspired the proposal of successful techniques. Regarding the former, we can find promising adaptations of political concepts such as anarchy (anarchic society optimization, [22]) or imperialism (imperialist competitive algorithm, [23]). With respect to the latter, social attitudes have been also served as inspiration for several methods such as the one coined as society and civilization [24], which emulates the mutual interactions of human and insect societies, or the hierarchical social meta-heuristic [25], which mimics the hierarchical social behavior observed in a great diversity of human organizations and structures.

- Physical processes: physical phenomena have also stimulated the design of new swarm intelligence algorithmic schemes, covering a broad spectrum of processes such as gravitational dynamics and kinematics (gravitational search algorithm, [26]), optic systems (ray optimization, [27]), or the electromagnetic theory (electromagnetism-like optimization, [28]). A recent survey published by Salcedo-Sanz [29] revolves around in this specific sort of methods.

In addition to the above-defined categories, many other fresh branches spring under a wide range of inspirations such as business tools (brainstorming optimization, [30]) or objects (grenade explosion method, [31]).

It is also worth mentioning that besides these monolithic approaches aforementioned, there is an additional trend which prevails at the core of the research activity: hybridization of algorithms. Since the dawn of evolutionary computation, many efforts have been devoted to the combination of diverse solvers and functionalities aiming at enhancing some capabilities or overcoming the disadvantages

of well-established meta-heuristic schemes. Obviously, memetic algorithms (MAs), conceived by Moscato and Norman in the 1980s in [32, 33], beat this competition. Despite MAs were initially defined as hybridization of GAs and local search mechanisms, MAs rapidly evolved to a broader meaning. Related to SI, today is straightforward to find hybridization of SI meta-heuristic schemes with separated local improvement and individual learning mechanisms in the literature. Some examples of this research trend can be found in [34–38].

Finally, up to now, SI methods have been applied to a wide variety of interesting topics along the years. Being impossible to gather in this introductory chapter all the applications already addressed by SI paradigms, we refer the reader to some remarkable and highly valuable survey works specially devoted to outline the application of SI algorithms in specific domains. In [39] a survey dedicated to geophysical data inversion was published. In [11] the latest findings of portfolio optimization are studied. An additional interesting work can be found in [12] focused on summarizing the intensive work done related to the feature selection problem. Intelligent transportation systems are the crossroads of the works gathered in [40], while in [41] authors conducted a comprehensive review of SI meta-heuristics for dynamic optimization problems. We acknowledge that the literature focused on all these aspects is immense, which leads us to refer the interested readers to the following significant and in-depth surveys [42–44].

3. Motivation behind the book edition

With reference to the scientific production, SI represents the most high-growing stream in today's related community, with more than 15,000 works published since the beginning of the twenty-first century. Analyzing the renowned Scopus® database, a clear upward trend can be deduced. Specifically, scientific production related to SI grows at a remarkable rate from nearly 400 papers in 2007 to more than 2000 in 2018. In fact, the interest in SI has been in crescendo at such a pace that the number of published scientific material regarding this field is greater than other classical streams such as evolutionary computation every year since 2012.

Thus, and taking advantage of the interest that this topic arises in the community, the edited book that this chapter is introducing gravitates on the prominent theories and recent developments of swarm intelligence methods and their application in all the fields covered by engineering. This material unleashes a great opportunity for researchers, lecturers, and practitioners interested in swarm intelligence, optimization problems, and artificial intelligence as a whole.

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