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

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.

Author details

Eneko Osaba[1*], Esther Villar[1] and Javier Del Ser[1,2]

1 TECNALIA Research and Innovation, Derio, Spain

2 University of the Basque Country (UPV/EHU), Bilbao, Spain

*Address all correspondence to: eneko.osaba@tecnalia.com

References

[1] Del Ser J, Osaba E, Molina D, Yang XS, Salcedo-Sanz S, Camacho D, et al. Bio-inspired computation: Where we stand and what's next. Swarm and Evolutionary Computation. 2019;**48**: 220-250

[2] Yang XS, Cui Z, Xiao R, Gandomi AH, Karamanoglu M. Swarm Intelligence and Bio-Inspired Computation: Theory and Applications. London: Newnes; 2013

[3] Kennedy J. Particle swarm optimization. In: Encyclopedia of Machine Learning. London: Springer; 2010. pp. 760-766

[4] Dorigo M, Di Caro G. Ant colony optimization: a new meta-heuristic. In: Proceedings of the 1999 congress on evolutionary computation-CEC99 (Cat. No. 99TH8406), Vol. 2. IEEE; 1999. pp. 1470-1477

[5] Fogel LJ, Owens AJ, Walsh MJ. Artificial Intelligence Through Simulated Evolution. New York: Wiley IEEE Press; 1998

[6] Schwefel HPP. Evolution and Optimum Seeking: The Sixth Generation. New York: John Wiley & Sons, Inc.; 1993

[7] Rechenberg I. Evolution Strategy: Optimization of Technical Systems by Means of Biological Evolution. Vol. 104. Stuttgart: Frommann-Holzboog; 1973. pp. 15-16

[8] Holland JH. Adaptation in Natural and Artificial Systems: An Introductory Analysis with Applications to Biology, Control, and Artificial Intelligence. Massachusetts: MIT press; 1992

[9] Dorigo M. Optimization, learning and natural algorithms [PhD thesis]. Milan, Italy: Politecnico di Milano; 1992

[10] Eberhart R, Kennedy J. A new optimizer using particle swarm theory. In: Proceedings of the Sixth International Symposium on Micro Machine and Human Science (MHS'95). IEEE; 1995. pp. 39-43

[11] Ertenlice O, Kalayci CB. A survey of swarm intelligence for portfolio optimization: Algorithms and applications. Swarm and Evolutionary Computation. 2018;**39**:36-52

[12] Brezočnik L, Fister I, Podgorelec V. Swarm intelligence algorithms for feature selection: A review. Applied Sciences. 2018;**8**(9):1521

[13] Gao K, Cao Z, Zhang L, Chen Z, Han Y, Pan Q. A review on swarm intelligence and evolutionary algorithms for solving flexible job shop scheduling problems. IEEE/CAA Journal of Automatica Sinica. 2019;**6**(4): 904-916

[14] Eskandar H, Sadollah A, Bahreininejad A, Hamdi M. Water cycle algorithm—A novel metaheuristic optimization method for solving constrained engineering optimization problems. Computers & Structures. 2012;**110**:151-166

[15] Passino KM. Biomimicry of bacterial foraging for distributed optimization and control. IEEE Control Systems. 2002;**22**(3):52-67

[16] Yang XS. Flower pollination algorithm for global optimization. In: International Conference on Unconventional Computing and Natural Computation. Springer; 2012. pp. 240-249

[17] Simon D. Biogeography-based optimization. IEEE Transactions on Evolutionary Computation. 2008;**12**(6): 702-713

[18] Yang XS. A new metaheuristic bat-inspired algorithm. In: Nature Inspired

Cooperative Strategies for Optimization (NICSO 2010). Springer; 2010. pp. 65-74

[19] Yang XS, Deb S. Cuckoo search via l'evy flights. In: World Congress on Nature & Biologically Inspired Computing. IEEE; 2009. pp. 210-214

[20] Karaboga D, Basturk B. A powerful and efficient algorithm for numerical function optimization: Artificial bee colony (ABC) algorithm. Journal of Global Optimization. 2007;**39**(3): 459-471

[21] Yang XS. Firefly algorithm, stochastic test functions and design optimisation. International Journal of Bio-Inspired Computation. 2010;**2**(2): 78-84

[22] Ahmadi-Javid A. Anarchic society optimization: A human-inspired method. In: IEEE Congress on Evolutionary Computation (CEC). IEEE; 2011. pp. 2586-2592

[23] Atashpaz-Gargari E, Lucas C. Imperialist competitive algorithm: An algorithm for optimization inspired by imperialistic competition. In: IEEE Congress on Evolutionary Computation (CEC). IEEE; 2007. pp. 4661-4667

[24] Ray T, Liew KM. Society and civilization: An optimization algorithm based on the simulation of social behavior. IEEE Transactions on Evolutionary Computation. 2003;**7**(4): 386-396

[25] Duarte A, Fernández F, Sánchez Á, Sanz A. A hierarchical social metaheuristic for the max-cut problem. In: European Conference on Evolutionary Computation in Combinatorial Optimization. Springer; 2004. pp. 84-94

[26] Rashedi E, Nezamabadi-Pour H, Saryazdi S. Gsa: A gravitational search algorithm. Information Sciences. 2009; **179**(13):2232-2248

[27] Kaveh A, Khayatazad M. A new meta-heuristic method: Ray optimization. Computers & Structures. 2012;**112**:283-294

[28] Birbil SI, Fang SC. An electromagnetism-like mechanism for global optimization. Journal of Global Optimization. 2003;**25**(3):263-282

[29] Salcedo-Sanz S. Modern meta-heuristics based on nonlinear physics processes: A review of models and design procedures. Physics Reports. 2016;**655**:1-70

[30] Shi Y. An optimization algorithm based on brainstorming process. In: Emerging Research on Swarm Intelligence and Algorithm Optimization. Pensilvania: IGI Global; 2015. pp. 1-35

[31] Ahrari A, Atai AA. Grenade explosion method—A novel tool for optimization of multimodal functions. Applied Soft Computing. 2010;**10**(4): 1132-1140

[32] Moscato P. On Evolution, Search, Optimization, Genetic Algorithms and Martial Arts: Towards Memetic Algorithms. Technical Report 826. Pasadena: California Institute of Technology; 1989

[33] Moscato P, Norman M. A Competitive and Cooperative Approach to Complex Combinatorial Search. In: Proceedings of the 20th Informatics and Operations Research Meeting. Citeseer; 1991. pp. 3-15

[34] Mortazavi A, Toğan V, Moloodpoor M. Solution of structural and mathematical optimization problems using a new hybrid swarm intelligence optimization algorithm. Advances in Engineering Software. 2019;**127**:106-123

[35] Osaba E, Ser JD, Panizo A, Camacho D, Galvez A, Iglesias A. Combining bioinspired meta-heuristics

and novelty search for community detection over evolving graph streams. In: Proceedings of the Genetic and Evolutionary Computation Conference Companion. ACM; 2019. pp. 1329-1335

[36] Govindan K, Jafarian A, Nourbakhsh V. Designing a sustainable supply chain network integrated with vehicle routing: A comparison of hybrid swarm intelligence metaheuristics. Computers & Operations Research. 2019;**110**:220-235

[37] Shareef SM, Rao RS. Optimal reactive power dispatch under unbalanced conditions using hybrid swarm intelligence. Computers and Electrical Engineering. 2018;**69**:183-193

[38] Osaba E, Del Ser J, Sadollah A, Bilbao MN, Camacho D. A discrete water cycle algorithm for solving the symmetric and asymmetric traveling salesman problem. Applied Soft Computing. 2018;**71**:277-290

[39] Yuan S, Wang S, Tian N. Swarm intelligence optimization and its application in geophysical data inversion. Applied Geophysics. 2009;**6**(2):166-174

[40] Del Ser J, Osaba E, Sanchez-Medina JJ, Fister I. Bioinspired computational intelligence and transportation systems: A long road ahead. IEEE Transactions on Intelligent Transportation Systems. 2019:1-30

[41] Mavrovouniotis M, Li C, Yang S. A survey of swarm intelligence for dynamic optimization: Algorithms and applications. Swarm and Evolutionary Computation. 2017;**33**:1-17

[42] Yang F, Wang P, Zhang Y, Zheng L, Lu J. Survey of swarm intelligence optimization algorithms. In: 2017 IEEE International Conference on Unmanned Systems (ICUS). IEEE; 2017. pp. 544-549

[43] Parpinelli RS, Lopes HS. New inspirations in swarm intelligence: A survey. International Journal of Bio-Inspired Computation. 2011;**3**(1):1-16

[44] Yang XS. Swarm intelligence based algorithms: A critical analysis. Evolutionary Intelligence. 2014;**7**(1): 17-28