

Editorial

Preface to “Swarm and Evolutionary Computation—Bridging Theory and Practice”

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Swarm and evolutionary computation (SEC) [1] is a broad and growing area of modern computer sciences, dealing with nature-inspired systems that are capable of displaying intelligent behaviour, thus optimising a vast range of challenging real-world scenarios that cannot be addressed via the direct application of purely theoretical exact approaches (e.g., [2]).

For decades, the swarm intelligence and evolutionary computation communities worked independently and, despite having common goals, progressed as two separate fields. Currently, advances in these research topics have generated highly hybrid, interconnected, and self-adaptive frameworks, displaying and employing ideas from both fields. This calls for more collaborative and joint efforts to be made by SEC researchers and practitioners from all relevant fields, e.g., engineering and robotics.

Indeed, SEC research is highly applicable to several real-world domains, from engineering to finance, as well as other scenarios in which optimisation is needed to either make an intelligent decision or minimise/maximise costs/profits.

Not to be underestimated, SEC systems currently play a key role in related computer science areas, such as machine learning (ML) and deep learning (DL), where hybrid methods can either make use of SEC algorithms to optimise, train, and design ML and DL systems or, vice versa, make use of ML to increase the efficiency of nonconforming SEC and help its users overcome undesired algorithm behaviours, e.g., premature convergence, lack of selection pressure, and difficulties in preserving an adequate level of population diversity.

This Special Issue collects articles reflecting the latest developments within the SEC community, in terms of both successful real-world applications and state-of-the-art algorithmic design. This volume contains the 11 articles accepted for publication in the ‘Swarm and Evolutionary Computation—Bridging Theory and Practise’ Special Issue of the MDPI *Mathematics* journal. The articles of this Special Issue are included in the following order.

The paper by Villuendas-Rey et al. [3] addresses, as one of the central ML tasks, the problem of clustering data with missing values and mixed features by applying swarm intelligence techniques.

The study by Khishe et al. [4] used automatically designed classifiers for the early detection of COVID-19 from chest X-ray images by evolving convolutional neural networks (CNNs) to efficiently find the optimal hyperparameters of CNNs.

The works in Refs. [5,6] present feature selection techniques based on genetic algorithms (GAs) in ML. Cho et al. [5] studied the prediction of a stock market index and cryptocurrency price in finance, and Lee et al. [6] performed Android malware detection.

Shenoy and Pai [7] theoretically establish the relationship between the magnification of a search space and the mixing time of the reversible Markov chain induced by local search-based metaheuristics. The usefulness of the results obtained was illustrated in the 0/1 knapsack problem. This work constitutes a good starting place from which the



Citation: Kim, Y.-H.; Caraffini, F. Preface to “Swarm and Evolutionary Computation—Bridging Theory and Practice”. *Mathematics* **2023**, *11*, 1209. <https://doi.org/10.3390/math11051209>

Received: 27 January 2023
Accepted: 18 February 2023
Published: 1 March 2023



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performance of SEC regarding combinatorial optimisation problems using search spaces can be analysed.

The paper authored by Yang et al. [8] presents the use of a memetic algorithm (MA) on the multidimensional knapsack problem by introducing a novel repair heuristic based on the tendency function and a genetic search for the function approximation.

In the study by Moon and Yoon [9], the authors propose a genetic mean reversion strategy that evolves a population of portfolio vectors using an MA for online portfolio selection in financial engineering.

Kim and Lee [10] suggest an interactive GA system that can allow users to easily create and experiment with desired mechanical assemblies, which are encoded as undirected graphs, via direct manipulation interfaces in virtual reality, and to intuitively explore design space by repeatedly applying the proposed crossover operator.

In the paper by Jovanovic et al. [11], the authors propose a hybrid ML and swarm intelligence approach to address credit card fraud detection. In their work, the enhanced firefly algorithm was used to tune a support vector machine and extreme gradient-boosting ML models.

In the work of Niccolai et al. [12], the authors introduce a specific procedure to bridge demand-side management from the theoretical application scenario to the practical industrial scenario. In particular, toroidal correction was used in the differential evolution to prevent the local optima from worsening the effectiveness of their method.

To reduce the high simulation costs of optimising agents approximated by deep neural networks (DNNs), Shin and Kim [13] present surrogate-assisted GAs whose surrogate models are used for fitness evaluation in GAs, where the surrogates predict cumulative rewards for an agent's DNN parameters.

As the Guest Editors, we would like to thank all the authors and reviewers involved in the production of this Special Issue. The aim of this Special Issue was to collect novel, high-quality papers in the field of SEC. We hope that the selected research articles will prove to be significant for the SEC communities and motivate the conduction of further studies.

Author Contributions: Conceptualization, Y.-H.K. and F.C.; methodology, Y.-H.K. and F.C.; validation, Y.-H.K. and F.C.; formal analysis, Y.-H.K. and F.C.; investigation, Y.-H.K. and F.C.; writing—original draft preparation, Y.-H.K.; writing—review and editing, F.C.; supervision, Y.-H.K. and F.C.; project administration, Y.-H.K. and F.C.; funding acquisition, Y.-H.K. All authors have read and agreed to the published version of the manuscript.

Funding: Y.-H.K. acknowledges the support provided by the National Research Foundation (NRF) grant funded by the Korea Government (MSIT) (No. 2021R1F1A1048466) and the support provided by the “Establishing a smart response platform for marine accidents” project of the Korea Institute of Marine Science & Technology Promotion (KIMST) funded by the Korea Coast Guard Agency (KIMST-20220463).

Acknowledgments: We would like to thank the MDPI publishing editorial team, all the peer reviewers, and all the authors who contributed to this Special Issue.

Conflicts of Interest: The authors declare no conflict of interest.

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