Guest Editorial Machine-Learning-Assisted Evolutionary Computation

EVOLUTIONARY computation has been highly effective in solving complex problems. However, designing high-performance algorithms remains challenging, requiring collaborations between different communities. A promising direction is developing hybrid systems that integrate optimization and learning. While recent research in optimization for machine learning, such as neural architecture search and evolutionary reinforcement learning, has achieved great success, there is still a vast potential to exploit the reverse direction, that is, incorporating machine learning into evolutionary computation to enhance its performance.

Recent literature has shown promising results in evolutionary computation enhanced by data-driven techniques and machine learning. However, much of this rich knowledge is often discarded, left unexplored, and not acted on. These learning and knowledge-assisted effective algorithms analyze features of the problem and solutions, effective settings, operators or heuristics, and findings and evaluations of the search and fitness landscape, to inform or drive the evolution and optimization. All this information can be collected and processed as data systematically, serving as an excellent new problem domain and challenge for the machine learning community to further inform and enhance evolutionary computation. Despite the challenges of fostering, reusing, and interpreting this rich knowledge, these investigations are highly rewarding to further advance human-designed or automatically designed evolutionary algorithms.

This special issue aims to showcase the latest advancements in machine-learning-assisted evolutionary computation for optimization. In response to the open call, 34 submissions were received. Each paper underwent a rigorous peer-review process, evaluating the originality, technical quality, presentational, and overall contribution. The following four outstanding articles were accepted, presenting state-of-the-art research and promising future directions, as described below.

The article [A1] by Yu et al. investigates the computation-intensive multitask robot allocation problem, where the low-level path planning problem is nested in the high-level task allocation problem. The proposed multiobjective evolutionary algorithm (MOEA) at the high level focuses on allocating the tasks, the routing of which is then optimized at the low level using an end-to-end approach that hybridizes large neighborhood search with deep reinforcement learning (DRL). This challenging problem is efficiently tackled by balancing high-level powerful exploration of task allocation and low-level quick exploitation of routing, leveraging the complementary strengths of MOEA and DRL. The proposed algorithm shows its effectiveness in both a real-world scenario and benchmark instances of varying distributions, providing equivalent multimodal solutions for decision makers. While challenges remain, such as time and payload constraints and computational demands, this research successfully demonstrates an effective integration of machine learning into evolutionary computation, offering a promising approach with potential impact on broad real-world applications.

The article [A2] focuses on a variation of the distributed hybrid flow shop scheduling problem with job working and reworking (DHFRPJM). A hybrid approach combining mixed-integer programming, local search, and reinforcement learning, namely, a proximal policy optimization algorithm, is proposed to solve the problem. The novelty of the research lies in a new mixed integer linear programming model that formulates the new problem. Reinforcement learning is used to guide the optimization based on previous experiences, exploring the solution space by a proximal policy to select the operators in an iterated greedy search. A decoding heuristic is also introduced for job merging and reworking, and the search goes through the process of destruction and construction to improve the solutions. The proposed approach was evaluated on 225 generated DHFRPJM problem instances. The approach was found to outperform state-of-the-art algorithms, including an artificial bee colony algorithm, a genetic algorithm, a co-evolutionary memetic algorithm, a dual population evolutionary framework, and two variations of the iterated greedy algorithm, at a lower computational cost.

The article [A3] addresses the challenges of identifying gene subsets to improve cell classification accuracy. The article proposes several innovations. First, a novel surrogate-assisted optimization framework is developed to jointly minimize the number of selected genes and classification errors, using the surrogate model to reduce the number of real function evaluations. Second, a two-phase initialization method is proposed to replace the typical randomized approach found in most evolutionary algorithms. Finally, a new method for gene selection that mixes global and local multiobjective optimization is used to find gene subsets via a method named GLoMoGS which employs a binary competitive swarm optimization algorithm. A local search method is embedded to eliminate irrelevant genes from the current optimal solution, which minimizes both

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classification errors and the number of genes. A comparison of eight state-of-the-art gene-selection methods on eight scRNA-seq datasets shows that GLoMoGS efficiently identifies gene subsets in accurate classification from scRNA-seq data.

The article [A4] by Lin et al. examines multiobjective problems with structure constraints, which impose common patterns in optimal solutions, such as specific relations among decision variables or constraints on the shape of the Pareto set. They propose an evolutionary Pareto set learning method that builds upon MOEA/D., where a parametric model (e.g., a neural network) is trained to approximate the Pareto front using a relatively small number of Pareto-optimal solutions. The model takes as input a point on the simplex representing the Pareto front, and outputs a Pareto-optimal solution. The article proposes an evolutionary stochastic gradient descent method that optimizes the learned Pareto set model considering preferences and structure constraints simultaneously. It has applications in personalized manufacturing, engineering design, and other domains, where constraints on individual solutions are insufficient. The research provides an effective approach by enabling the decision-maker to impose constraints on the shape of the Pareto front and the relationships of solutions along the front.

In summary, the selected papers for this special issue showcase the diverse ways machine learning enhances evolutionary computation. Reinforcement learning is used to assist end-to-end routing and select operators, neural network approximates the Pareto front, and surrogate models substitute the expensive forecast of classification accuracy. These interdisciplinary evolutionary algorithms successfully integrate computational intelligence techniques and have been successfully applied to task allocation and routing, flow shop scheduling, engineering design optimization, and cell classification. Interesting challenges remain, particularly regarding the generalization and efficiency of the hybrid evolutionary algorithms in tackling real-world applications with complex and diverse constraints.

The Guest Editors would like to thank all the authors who submitted their work to the special issue, and all the reviewers for their hard work in completing timely and constructive reviews. Special thanks go to the Editor-in-Chief, Prof Carlos A. Coello Coello and the members of the editorial team for their support during the editing process of this special issue. They worked closely with the Guest Editors to ensure the excellent quality of this issue and guarantee its success.

APPENDIX: RELATED ARTICLES

[A1] Y. Yu, Q. Tang, Q. Jiang, and Q. Fan, “A deep reinforcement learning assisted multimodal multiobjective bi-level optimization method for multi-robot task allocation,” *IEEE Trans. Evol. Comput.*, early access, Jan. 28, 2025, doi: 10.1109/TEVC.2025.3535954.

[A2] X.-R. Tao, Q.-K. Pan, and L. Gao, “An iterated greedy algorithm with reinforcement learning for distributed hybrid flow shop problems with job merging,” *IEEE Trans. Evol. Comput.*, early access, Aug. 14, 2024, doi: 10.1109/TEVC.2024.3443874.

[A3] J. Lin, C. He, H. Jiang, Y. Huang, and Y. Jin, “Surrogate-assisted multi-objective gene selection for cell classification from large-scale singlecell RNA sequencing data,” *IEEE Trans. Evol. Comput.*, early access, Jan. 24, 2025, doi: 10.1109/TEVC.2025.3533490.

[A4] X. Lin, X. Zhang, Z. Yang, and Q. Zhang, “Dealing with structure constraints in evolutionary pareto set learning,” 2024, *arXiv:2310.20426*.

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Prof. Qu is among the World’s Top 2% Scientists 2020–2024 by Standford University and Elsevier. She has been serving on several editorial boards at international journals, including IEEE TRANSACTIONS ON EVOLUTIONARY COMPUTATION, *IEEE Computational Intelligence Magazine*, and *Journal of the Operational Research Society*. At IEEE CIS, she served as the Chair/Vice-Chair of several task committees and task forces on automated algorithm design and evolutionary computation. She has guest edited seven special issues in journals, including IEEE TRANSACTIONS ON EVOLUTIONARY COMPUTATION, *IEEE Computational Intelligence Magazine*, and IEEE TRANSACTIONS ON PATTERN ANALYSIS AND MACHINE INTELLIGENCE.

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Dr. Pillay is currently an Associate Editor of IEEE TRANSACTIONS ON EMERGING TOPICS IN COMPUTATIONAL INTELLIGENCE, *IEEE Computational Intelligence Magazine*, *ACM Transactions on Evolutionary Learning and Optimization*, and *Genetic Programming and Evolvable Machines*.

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Prof. López-Ibáñez is an Elected Member of the ACM SIGEVO Executive Board and the Business Committee of the Genetic and Evolutionary Computation Conference (GECCO), the Editor-in-Chief of *ACM Transactions on Evolutionary Learning and Optimization*, an Associate Editor of the *Evolutionary Computation*, and an Editorial Board Member of the *Artificial Intelligence Journal*.