Guest Editorial: Special Issue on Theory, Algorithms, and Applications for Hybrid Intelligent Dynamic Optimization

DYNAMIC optimization problems are pervasive in various fields, ranging from chemical process control to aerospace, autonomous driving, physics, robotics, and beyond. These problems involve optimizing a dynamic system considering inputs, parameters, constraints, and a cost function. For dynamic optimization, two broad classes of strategies emerge: deterministic and heuristic methods. Deterministic optimization methods leverage the analytical properties of the problem, generating a sequence of points that converge to the optimal solution. These techniques are suitable when explicit models and constraints are available and easy to evaluate. On the other hand, heuristic approaches treat the problem as a black box, relying on iterative improvements to a fitness function. They are employed for complex problems with challenging system models or significant uncertainty.

In industrial applications, some aspects of the problem are accurately known, making deterministic optimization methods viable. However, other parts may be highly complex or rely on input–output data, hence favoring heuristic optimization methods or machine learning approaches. Recognizing this, hybrid dynamic optimization methods have emerged, aiming to leverage the complementary characteristics of deterministic, heuristic, and machine-learning techniques.

In light of this, the aim of this Special Issue is to call for the most advanced research that is dedicated to the interplay and fusion of deterministic, heuristic, and learning-based hybrid intelligent optimization methods. We received a large number of submissions from both academic and industrial communities. Finally, we select 20 outstanding papers to be published in this Special Issue, which can be categorized into three groups, namely, theory, algorithms, and applications. A summary of these papers is given as follows.

Several results have been proposed to bridge the gap between hybrid intelligent optimization theories. For complex uncertain multiagent systems, it is challenging to model the uncertainties and exploit the cooperative learning ability of the systems. Chen et al. [A1] propose a novel convex temporal convolutional network-based distributed cooperative learning control for uncertain discrete-time nonlinear multiagent systems. This method has high control accuracy, strong robustness, and anti-interference ability. With the development of artificial intelligence, model-free fault detection (FD) strategies have been widely investigated over the past 20 years. Ran et al. [A2] develop a data-driven and model-free hybrid FD design approach for nonlinear dynamic systems without information. This approach can exploit the complementary advantages of the model-based and that data-driven methods, and has a strong ability to deal with nonlinear dynamic systems with unknown information. Lin et al. [A3] investigate the long-term challenge of solving the finite-horizon Hamilton–Jacobi–Bellman equation. This work establishes the relationship between the partial time derivative and the terminal-time utility function. An approximate dynamic programming algorithm in the actorcritic framework is developed for solving continuous-time finite-horizon optimal control problems. Mallick and Chen [A4] consider a trajectory optimization approach for dynamical systems subject to measurement noise. A reformulation of stochastic control is proposed in a reinforcement learning setting where a stochastic optimal control–expectation maximization algorithm is proposed. With the extension of just-in-time (JIT) production research to construction management, much attention has been paid to bringing JIT production into prefabricated production scheduling. Xie et al. [A5] propose a JIT precast production scheduling model and develop an optimal shifting algorithm to locate the optimal starting time of each batch and minimize the batch cost. This work also develops a genetic algorithm based on dominance rules to solve the early/tardy scheduling problem and find a more reasonable and feasible production schedule with higher efficiency. Meng et al. [A6] investigate how to use the supermodularity to reduce the action space and derive the incremental optimal solution set and the incremental optimal selection. Accordingly, a monotonicity cut is proposed to remove unpromising actions from the action space. The results show that the monotonicity cut can effectively improve the performance of reinforcement learning.

To address algorithmic issues in hybrid intelligent dynamic optimization and to achieve higher computational performance, several novel algorithms have been proposed. Jiang et al. [A7] propose a distributed stochastic algorithm with variance reduction for a general smooth nonconvex finite-sum optimization. The convergence rate of the proposed algorithm is $O((1/k))$. Compared with some existing excellent

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algorithms, this algorithm has lower iteration complexity. Lin et al. [A8] give a fuzzy chance-constrained dynamic optimization formulation. An improved fuzzy simulation technique is proposed, which transforms fuzzy chance constraints to their deterministic equivalent constraints, and a data-driven state transition algorithm based on deep neural networks is proposed to achieve stable, global, and robust optimization performance. Yang et al. [A9] introduce Thompson Sampling (TS) to solve the unimodal bandits (UB) problem and propose a TS–UB algorithm with Gaussian prior, which matches the optimal regret of the same order and achieves $O(\log T)$. Decomposing data matrix into low-rank matrix plus additive matrix is a commonly used strategy in pattern recognition and machine learning. Zhang et al. [A10] study the alternating direction method of multiplier (ADMM) with two dual variables and apply it to optimize the generalized nonconvex nonsmooth low-rank matrix recovery problems. This work shows the boundedness of dual variables, and the sufficient descent condition along with the boundedness of primal variables. It also provides the global convergence of the subsequence. Furthermore, they prove that the supergradient of the potential function is upper bounded and obtain the global convergence property of the generated variable sequence. Ma et al. [A11] present a local learning-enabled constrained iLQR algorithm for trajectory planning based on hybrid dynamic optimization and machine learning. More importantly, this algorithm attains the key advantage of circumventing the requirement of system identification and refines the optimal strategy and neural network system to complete the trajectory planning task at the same time under the iterative framework. Xia et al. [A12] propose an alternating minimization method based on meta-learning, whose goal is to minimize part of the global loss in the iterative process, rather than minimizing each sub-problem, it tends to learn an adaptive strategy to replace similar methods designed by hand, so as to get better performance in advance. The learned algorithm has been verified to have a faster convergence speed and better performance than existing alternating minimization-based methods. Nonnegative matrix factorization (NMF) has been widely used to learn low-dimensional representations of data. However, NMF pays the same attention to all attributes of data points, which inevitably leads to inaccurate representations. Wei et al. [A13] propose a new entropy-weighted NMF (EWNMF), which uses an optimizable weight for each attribute of each data point to emphasize their importance.

In practice, the successful implementation of hybrid intelligent optimization methods depends on the integration of various techniques and considerations to meet the challenges of the real-world. Zhang et al. [A14] propose an economic data-driven tabulation algorithm for fast combustion chemistry integration. The proposed framework makes use of Recurrent Neural Networks (RNNs) to construct the tabulation from a series of current and past states to the next state, which takes full advantage of RNNs in handling long-term dependencies of time series data. Li et al. [A15] present their experience of rate limit for the containers in CompanyX, one of the largest e-commerce services in the world. They designed Noah, a dynamic rate limiter that can automatically adapt to the specific characteristic of each container without human effort. Noah has been deployed in CompanyX for two years. It serves more than 50 000 containers and 300 types of applications. It brings benefits in various aspects such as resource utilization and user experience. For operational optimal control problems, they often have the characteristics of high-dimensional, nonlinear, and strongly coupled variables. To address this problem, Chen et al. [A16] propose a dimension-reducible data-driven optimization control framework for the wastewater treatment process. Kong et al. [A17] propose an asymmetric double-stream generative adversarial network (ADS-GAN) for portrait style transfer. From the qualitative comparison, their method has a significant effect in maintaining the complete contour of the portrait and the learning of the target style is sufficient. From quantitative analysis, their results outperform other methods in all metrics. Bai et al. [A18] propose to combine the artificial potential field method and reinforcement learning for online motion planning. The neural motion planner can avoid obstacles in a wide range; meanwhile, the artificial potential field method is exploited to adjust the partial position. Zeng et al. [A19] propose an approach for robotic compliant grasping and manipulation based on the adaptive force control strategy through teleoperation. Their approach has shown more reliable performance than the current widely used position control mode for obtaining compliant grasping and manipulation behaviour. Chen et al. [A20] formulate event-triggered optimal load dispatching in HVAC and electric power systems as cardinality-constrained global optimization problems, and the proposed ETCNO-LD method is able to find the global minimal solutions.

We express our sincere gratitude to all the authors who have contributed their valuable research papers to this Special Issue. The diverse range of perspectives and insights presented in these submissions will undoubtedly inspire further advancements in the field of hybrid intelligent dynamic optimization. We would also like to extend our heartfelt appreciation to the reviewers for their dedicated efforts in rigorously evaluating the submissions. In addition, we would like to thank the Editor-in-Chief and the editorial office for their unwavering support and commitment.

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APPENDIX: RELATED ARTICLES

[A1] S. Chen, Y. Kang, J. Di, P. Li, and Y. Cao, "Convex temporal convolutional network-based distributed cooperative learning control for multiagent systems," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 34, no. 9, pp. 5234–5243, Sep. 2023.

[A2] G. Ran, H. Chen, C. Li, G. Ma, and B. Jiang, "A hybrid design of fault detection for nonlinear systems based on dynamic optimization," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 34, no. 9, pp. 5244–5254, Sep. 2023.

[A3] Z. Lin et al., "Policy-iteration-based finite-horizon approximate dynamic programming for continuous-time nonlinear optimal control," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 34, no. 9, pp. 5255–5267, Sep. 2023.

[A4] P. Mallick and Z. Chen, "Stochastic optimal control for multivariable dynamical systems using expectation maximization," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 34, no. 9, pp. 5268–5282, Sep. 2023.

[A5] Y. Xie, H. Wang, G. Liu, and H. Lu, "Just-in-time precast production scheduling using dominance rule-based genetic algorithm," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 34, no. 9, pp. 5283–5297, Sep. 2023.

[A6] Y. Meng, F. Shi, L. Tang, and D. Sun, "Improvement of reinforcement learning with supermodularity," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 34, no. 9, pp. 5298–5309, Sep. 2023.

[A7] X. Jiang, X. Zeng, J. Sun, and J. Chen, "Distributed stochastic gradient tracking algorithm with variance reduction for non-convex optimization," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 34, no. 9, pp. 5310–5321, Sep. 2023.

[A8] F. Lin, X. Zhou, C. Li, T. Huang, and C. Yang, "Data-driven state transition algorithm for fuzzy chance-constrained dynamic optimization," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 34, no. 9, pp. 5322–5331, Sep. 2023.

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[A10] H. Zhang et al., "Generalized nonconvex nonsmooth low-rank matrix recovery framework with feasible algorithm designs and convergence analysis," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 34, no. 9, pp. 5342–5353, Sep. 2023.

[A11] J. Ma, Z. Cheng, X. Zhang, Z. Lin, F. L. Lewis, and T. H. Lee, "Local learning enabled iterative linear quadratic regulator for constrained trajectory planning," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 34, no. 9, pp. 5354–5365, Sep. 2023.

[A12] J. Xia, S. Li, J. Huang, Z. Yang, I. M. Jaimoukha, and D. Gündüz, "Metalearning-based alternating minimization algorithm for nonconvex optimization," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 34, no. 9, pp. 5366–5380, Sep. 2023.

[A13] J. Wei et al., "An entropy weighted nonnegative matrix factorization algorithm for feature representation," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 34, no. 9, pp. 5381–5391, Sep. 2023.

[A14] Y. Zhang, Q. Lin, W. Du, and F. Qian, "Data-driven tabulation for chemistry integration using recurrent neural networks," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 34, no. 9, pp. 5392–5402, Sep. 2023.

[A15] Z. Li et al., "Noah: Reinforcement-learning-based rate limiter for microservices in large-scale e-commerce services," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 34, no. 9, pp. 5403–5417, Sep. 2023.

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[A20] Z. Chen, J. Wang, and Q. Han, "Event-triggered cardinality-constrained cooling and electrical load dispatch based on collaborative neurodynamic optimization," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 34, no. 9, pp. 5464–5475, Sep. 2023.