Guest Editorial Special Issue on Reinforcement Learning-Based Control: Data-Efficient and Resilient Methods

As an important branch of machine learning, reinforcement learning (RL) has proved its efficiency in many emerging applications in science and engineering. A remarkable advantage of RL is that it enables agents to maximize their cumulative rewards through online exploration and interactions with unknown (or partially unknown) and uncertain environments, which is regarded as a variant of data-driven adaptive optimal control methods. However, the successful implementation of RL-based control systems usually relies on a good quantity of online data due to its data-driven nature. Therefore, it is imperative to develop data-efficient RL methods for control systems to reduce the required number of interactions with the external environment. Moreover, network-aware issues, such as cyberattacks, dropout packet and communication latency, and actuator and sensor faults, are challenging conundrums that threaten the safety, security, stability, and reliability of network control systems. Consequently, it is significant to develop safe and resilient RL mechanisms.

This special issue focuses on promoting the development of cutting-edge RL and intelligent control systems, including theoretic studies, controller design, algorithm development, applications, and experimental validations, and encouraging the collaboration between researchers from diverse fields, such as computational intelligence, control systems, RL, and cybersecurity. We have received a large number of submissions to this special issue. After the peer-review process, 22 articles were accepted for publication that cover a wide variety of RL-based control topics from both theoretical and practical points of view. We separate these articles into four groups based on their research objectives.

The first group of articles aims at ameliorating the data efficiency of traditional RL methods based on the exploitation of historical data, prior knowledge, and replayed experience. Among them, Gao et al. [A6] built a transfer RL framework that enables the learning of controllers to employ the prior knowledge extracted from previously learned tasks and data, which improves the learning performance and data efficiency. In order to boost the sample efficiency of soft actor–critic, which is an off-policy RL strategy, Banerjee et al. [A3] applied a mixture of prioritized off-policy data with the latest on-policy data to train the policy and the value function networks. Yang et al. [A19] presented a composite critic learning mechanism, which combines the instantaneous data with the historical data, leading to an efficient, experience-replay-based RL approach. Li et al. [A5] have studied the adaptive optimal tracking control problem and developed a model-free Q-learning algorithm with a high efficiency of data utilization. Xu and Wu [A18] proposed a data-efficient off-policy RL approach for distributed output tracking control problems of heterogeneous multiagent systems with uncertain exosystem dynamics. Considering the grid emergency voltage control problem in electric power systems, a multiagent graph-attention-based deep RL algorithm is proposed to improve the decision accuracy in a data-efficient manner [A20].

The second group attempts to guarantee the resiliency, safety, and robustness of the closed-loop systems in terms of RL. Xie et al. [A17] investigated the problems of communication-efficient and resilient multiagent RL. They considered the scenario that some agents are adversarial captured by the Byzantine attack model and established the trade-off between optimality and resilience where Byzantine agents are present. Jiang et al. [A9] studied the adaptive optimal control problem of networked nonlinear systems and proposed an RL-based control approach so that the closed-loop system can handle stochastic sensor and actuator dropouts. Kokolakis and Vamvoudakis [A10] developed a safe pursuit-evasion game to enable finite-time capture, optimal performance, and adaption to an unknown cluttered environment in terms of Gaussian processes and RL. Modares et al. [A13] proposed a data-driven safe RL algorithm for discrete-time nonlinear systems to ensure both safety and stability of closed-loop systems. Yu et al. [A21] investigated the fault-tolerant formation control problem of networked fixed-wing unmanned aerial vehicles (UAVs) based on the integration of RL and fractional-order adaptive control.

The third group focuses on extensions of existing RL-based control methods, and combinations of RL and advanced control techniques, such as model predictive control (MPC) and distributed control. To be more specific, Jiang et al. [A22] introduced a λ-policy iteration method for optimal control problems of discrete-time linear systems in order to relax the reliance on an initial admissible control policy. A value iteration method is developed to solve the optimal control problem of discrete-time nonlinear systems with constrained cost [A16]. Wang et al. [A4] proposed a supplementary control approach for discrete-time nonlinear systems in the framework of goal representation heuristic dynamic programming. For the sake of realizing coordination of multiagent systems in an adaptive optimal sense, Wang et al. [A8] developed distributed controllers via RL to address semiglobal output regulation

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problems in the presence of input saturation. Lan et al. [A12] proposed a distributed time-varying optimal formation control protocol for nonlinear uncertain multiagent systems. Lian et al. [A11] proposed a distributed minimax strategy for multiplayer games via RL, and the stability and robustness of the closed-loop systems have been discussed. The combination of RL and MPC appears in [A14] where the MPC serves as a policy generator and the RL is leveraged to evaluate the policy.

The fourth group is related to applications of RL-based control methods, including UAVs, industrial processes, and robotics. Bøhn et al. [A1] showed that deep RL can successfully learn to perform attitude control of fixed-wing UAVs with nonlinear dynamics. They have developed a data-efficient learning framework that yields flight-worthy attitude controllers within minutes of learning time. Li et al. [A2] modeled the temperature field control problem in roller skin via partial differential equations (PDEs) and proposed an event-triggered adaptive dynamic programming method for PDE systems. Liu et al. [A15] studied a dynamic operation optimization problem for a steelmaking process in terms of deep RL. Regarding the multirobot efficient search problem, Guo et al. [A7] proposed a distributional RL-based researcher with respect to moving targets.

We would like to express our sincere gratitude to all the authors and reviewers for their great dedication to this special issue. This special issue would not have been successful without their efforts. Finally, we highly appreciate the strong support from the Editor-in-Chief, Prof. Yongduan Song, the past Editor-in-Chief, Prof. Haibo He, and the IEEE TRANSACTIONS ON NEURAL NETWORKS AND LEARNING SYSTEMS's Editorial Office.

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APPENDIX: RELATED ARTICLES

[A1] E. Bohn, E. M. Coates, D. Reinhardt, and T. A. Johansen, "Data-efficient deep reinforcement learning for attitude control of fixed-wing UAVs: Field experiments," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 35, no. 3, pp. 3168–3180, Mar. 2024.

[A2] B. Li, N. Chen, B. Luo, J. Chen, C. Yang, and W. Gui, "ADP-based event-triggered constrained optimal control on spatiotemporal process: Application to temperature field in roller kiln," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 35, no. 3, pp. 3229–3241, Mar. 2024.

[A3] C. Banerjee, Z. Chen, and N. Noman, "Improved soft actor-critic: Mixing prioritized off-policy samples with on-policy experiences," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 35, no. 3, pp. 3121–3129, Mar. 2024.

[A4] X. Wang, D. Ding, X. Ge, and Q.-L. Han, "Supplementary control for quantized discrete-time nonlinear systems under goal representation heuristic dynamic programming," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 35, no. 3, pp. 3202–3214, Mar. 2024.

[A5] C. Li, J. Ding, F. L. Lewis, and T. Chai, "Model-free Q-learning for the tracking problem of linear discrete-time systems," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 35, no. 3, pp. 3191–3201, Mar. 2024.

[A6] X. Gao, J. Si, and H. Huang, "Reinforcement learning control with knowledge shaping," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 35, no. 3, pp. 3156–3167, Mar. 2024.

[A7] H. Guo, Q. Peng, Z. Cao, and Y. Jin, "DRL-searcher: A unified approach to multirobot efficient search for a moving target," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 35, no. 3, pp. 3215–3228, Mar. 2024.

[A8] B. Wang, L. Xu, X. Yi, Y. Jia, and T. Yang, "Semiglobal suboptimal output regulation for heterogeneous multi-agent systems with input saturation via adaptive dynamic programming," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 35, no. 3, pp. 3242–3250, Mar. 2024.

[A9] Y. Jiang, L. Liu, and G. Feng, "Adaptive optimal control of networked nonlinear systems with stochastic sensor and actuator dropouts based on reinforcement learning," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 35, no. 3, pp. 3107–3120, Mar. 2024.

[A10] N. T. Kokolakis and K. G. Vamvoudakis, "Safety-aware pursuit-evasion games in unknown environments using Gaussian processes and finite-time convergent reinforcement learning," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 35, no. 3, pp. 3130–3143, Mar. 2024.

[A11] B. Lian, V. S. Donge, W. Xue, F. L. Lewis, and A. Davoudi, "Distributed minmax strategy for multiplayer games: Stability, robustness, and algorithms," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 35, no. 3, pp. 3265–3277, Mar. 2024.

[A12] J. Lan, Y.-J. Liu, D. Yu, G. Wen, S. Tong, and L. Liu, "Time-varying optimal formation control for second-order multiagent systems based on neural network observer and reinforcement learning," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 35, no. 3, pp. 3144–3155, Mar. 2024.

[A13] A. Modares, N. Sadati, B. Esmaeili, F. A. Yaghmaie, and H. Modares, "Safe reinforcement learning via a model-free safety certifier," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 35, no. 3, pp. 3302–3311, Mar. 2024.

[A14] M. Lin, Z. Sun, Y. Xia, and J. Zhang, "Reinforcement learning-based model predictive control for discrete-time systems," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 35, no. 3, pp. 3312–3324, Mar. 2024.

[A15] C. Liu, L. Tang, and C. Zhao, "A novel dynamic operation optimization method based on multiobjective deep reinforcement learning for steelmaking process," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 35, no. 3, pp. 3325–3339, Mar. 2024.

[A16] Q. Wei and T. Li, "Constrained-cost adaptive dynamic programming for optimal control of discrete-time nonlinear systems," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 35, no. 3, pp. 3251–3264, Mar. 2024.

[A17] Y. Xie, S. Mou, and S. Sundaram, "Communication-efficient and resilient distributed Q-learning," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 35, no. 3, pp. 3351–3364, Mar. 2024.

[A18] Y. Xu and Z.-G. Wu, "Data-efficient off-policy learning for distributed optimal tracking control of HMAS with unidentified exosystem dynamics," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 35, no. 3, pp. 3181–3190, Mar. 2024.

[A19] Y. Yang, Y. Pan, C.-Z. Xu, and D. C. Wunsch, "Hamiltonian-driven adaptive dynamic programming with efficient experience replay," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 35, no. 3, pp. 3278–3290, Mar. 2024.

[A20] Y. Zhang, M. Yue, J. Wang, and S. Yoo, "Multi-agent graph-attention deep reinforcement learning for post-contingency grid emergency voltage control," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 35, no. 3, pp. 3340–3350, Mar. 2024.

[A21] Z. Yu, J. Li, Y. Xu, Y. Zhang, B. Jiang, and C.-Y. Su, "Reinforcement learning-based fractional-order adaptive fault-tolerant formation control of networked fixed-wing UAVs with prescribed performance," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 35, no. 3, pp. 3365–3379, Mar. 2024.

[A22] H. Jiang, B. Zhou, and G.-R. Duan, "Modified λ-policy iteration based adaptive dynamic programming for unknown discrete-time linear systems," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 35, no. 3, pp. 3291–3301, Mar. 2024.

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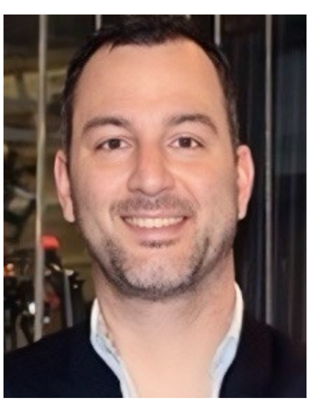

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