Guest Editorial Machine Learning for Resilient Industrial Cyber-Physical Systems

I. Introduction

WITH the rapid development of information technologies, the computing, networking, and physical elements in industrial environments are becoming tightly amalgamated with each other, resulting in the formation of the so-called Industrial Cyber-Physical Systems (ICPS). These systems forge the core of current real-world networked industrial infrastructures, having a cyber-representation of physical assets through digitalization of data across the enterprise, along the value stream and process engineering life cycle, along the digital thread, and along the supply chain. Typical applications of ICPS include smart grids, digital factory, cognitive and collaborative robots, freight transportation, process control, plant-wide systems, medical monitoring, etc. ICPS often operate in an unpredictable and challenging environment, where various disturbances, such as unplanned natural events, human faults or malicious behaviors, software and hardware failures, etc., may occur during the automation process at runtime. Moreover, ICPS can exhibit strong reconfigurability and evolve structurally for many purposes. During this evolution, new and unforeseen possibilities in the service-oriented business process may appear among various ICPS components. In particular, new "emergent" behaviors may arise that need to be monitored, understood, managed and controlled. When there are significant uncertainties, such emergent behaviors could make the evolved ICPS unstable and unable to meet the quality/performance targets, even resulting in hazards. Well-designed machine-learning techniques have the potential to effectively address the uncertainties and disturbances in the automation of ICPS. They can also facilitate the automated discovery of valuable underlying rules and patterns to improve the performance of ICPS in all phases of their life cycles.

This Special Issue on Machine Learning for Resilient Industrial Cyber-Physical Systems of the IEEE TRANSACTIONS ON AUTOMATION SCIENCE AND ENGINEERING (TASE) is oriented to the dissemination of the state-of-the-art research of leveraging machine learning to handle uncertainties and disturbances for the automation in ICPS. Many papers have been submitted to this Special Issue, while due to the space limitation, only eight papers are accepted after a rigorous peer-review process. We hope that these eight selected papers will produce long-lasting impacts to the research community and stimulate more work in this exciting area.

II. Summaries of Accepted Papers

In [A1], Zhang et al. consider the challenges in ICPS network identification brought by changing network, and limited and noisy data. To address these challenges, a temporal network identification technique is designed, which includes an analysis model based on the state equation and the observation equation, and a model-free method for solving undirected temporal network identification problems with a small amount of contaminated data.

In [A2], Zhou et al. aim to optimize the soft-error reliability of embedded platforms in ICPS that simultaneously integrated CPU and GPU under the temperature constraint. Using an artificial neural network model, a fast soft-error rate and temperature estimation method is designed. To solve the problem, a feedback control-based task scheduling scheme that can adaptively determine the number of admitted tasks and the number of replicas is developed.

In [A3], Hao et al. consider multiple forms of ICS anomaly events and describe a scalable and efficient solution for real-time network traffic anomaly detection for industrial control system. The proposed model combines a statistical model and a machine learning model to identify anomalous traffic patterns. The statistical model makes a short-term prediction, while the machine learning model characterizes the long-term data traffic patterns with high accuracy. The experiments results illustrate detection accuracy enhancement and computational complexity reduction.

In [A4], Luo et al. consider the problem of assessing the short-term voltage stability (SVS) of smart grids.

They develop a machine-learning scheme for accurate and interpretable online SVS assessment, which explores time-series shapelet transform for extracting key dynamics and models the postfault time series using flat features, followed by the integration with topology information.

In [A5], Ji et al. consider overall production performance optimization in ICPS, and design a framework for machine learning-based edge sensing and control co-design. This framework first analyzes model learning error to bound the actual control performance, and then develops a cloud-edge symphony co-design algorithm that also considers the defects of edge computing units.

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In [A6], Xu et al. study memristive crossbar-based neuromorphic computing systems (NCS) design optimization. They develop a reliability-driven framework for a memristive crossbar-based NCS which includes a general reliability-aware training scheme for improving the robustness and a drop connect-inspired approach for mitigating the stuck-at faults. The experimental results show that it can significantly improve the computation accuracy and robustness of NCS.

In [A7], Laili et al. focus on the precision and speed degradation problems of tailored machine learning models for robot grasping detection considering environmental disturbance and limited data. They develop a robust grasp candidate generation strategy and a region-based predictor to locate the best grasping point-pair for the robot grasping detection.

In [A8], Cui et al. address the problem of excessive bandwidth pressure and heavy cloud loads induced by high noise data in distributed deep neural networks for ICPS. They develop a novel ICPS-based distributed framework, which leverages advanced depthwise separable convolutions to implement a lightweight module of data filtering that identifies and filters out high noise data. The experiments demonstrate that the developed framework can effectively mitigate unnecessary transmission and cloud computing loads.

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Appendix: Related Articles

[A1] Y. Zhang, C. Yang, K. Huang, C. Zhou, and Y. Li, "Robust structure identification of industrial cyber-physical system from sparse data: A network science perspective," *IEEE Trans. Autom. Sci. Eng.*, early access, Mar. 10, 2021, doi: 10.1109/TASE.2021.3062356.

[A2] J. Zhou, L. Li, A. Vajdi, X. Zhou, and Z. Wu, "Temperature-constrained reliability optimization of industrial cyber-physical systems using machine learning and feedback control," *IEEE Trans. Autom. Sci. Eng.*, early access, Mar. 12, 2021, doi: 10.1109/TASE.2021.3062408.

[A3] W. Hao, T. Yang, and Q. Yang, "Hybrid statistical-machine learning for real-time anomaly detection in industrial cyber-physical systems," *IEEE Trans. Autom. Sci. Eng.*, early access, May 6, 2021, doi: 10.1109/TASE.2021.3073396.

[A4] Y. Luo, C. Lu, L. Zhu, and J. Song, "Graph convolutional network-based interpretable machine learning scheme in smart grids," *IEEE Trans. Autom. Sci. Eng.*, early access, Aug. 2, 2021, doi: 10.1109/TASE.2021.3090671.

[A5] Z. Ji, C. Chen, J. He, S. Zhu, and X. Guan, "Learning-based edge sensing and control co-design for industrial cyber-physical system," *IEEE Trans. Autom. Sci. Eng.*, early access, Oct. 13, 2021, doi: 10.1109/TASE.2021.3115937.

[A6] Q. Xu et al., "Reliability-driven memristive crossbar design in neuromorphic computing systems," *IEEE Trans. Automat. Sci. Eng.*, early access, Nov. 12, 2021, doi: 10.1109/TASE.2021.3125065.

[A7] Y. Laili, Z. Chen, L. Ren, X. Wang, and M. J. Deen, "Custom grasping: A region-based robotic grasping detection method in industrial cyber-physical systems," *IEEE Trans. Autom. Sci. Eng.*, early access, Jan. 11, 2022, doi: 10.1109/TASE.2021.3139610.

[A8] Y. Cui, L. Li, Z. Tao, M. Chen, and T. Wei, "Filtering out high noise data for distributed deep neural networks," *IEEE Trans. Autom. Sci. Eng.*, early access, Oct. 3, 2022, doi: 10.1109/TASE.2022.3208027.