Machine Learning for Industry 4.0

By Mengchu Zhou, Yan Qiao, Bin Liu, Birgit Vogel-Heuser, and Heeyoung Kim

The Fourth Industrial Revolution, also known as Industry 4.0, marks the technological shift from traditional manufacturing systems to smart cyberphysical systems. It leads to an improvement in overall productivity and a reduction in environmental impact and promotes sustainable economic development. Industry 4.0 has been driven by emerging technologies such as the Internet of Things (IoT), also called the Industrial Internet of Things; digital twins; artificial intelligence; cloud computing; and edge/fog computing [1], [2], [3], [4], [5]. It is a hot topic in both academia and industry. The implementation of IoT connects physical assets to cybernetworks and captures a significant amount of data. These data, often "big", are then fed to AI-based mission-critical systems to perform production monitoring, quality inspection, fault root cause analysis, quality prediction, and process control. The proper adoption of relevant Industry 4.0 technologies should lead to significant efficiency improvements and cost reductions in various industrial sectors.

> "THE PROPER ADOPTION OF RELEVANT INDUSTRY 4.0 TECHNOLOGIES SHOULD LEAD TO SIGNIFICANT EFFICIENCY IMPROVEMENTS AND COST REDUCTIONS IN VARIOUS INDUSTRIAL SECTORS."

The goal of this special issue is to provide a forum for discussing industrial automation research on smart manufacturing and machine learning. It aims to address the needs and challenges for integration with efficient machine learning algorithms and engineering solutions and provides a vision for future research and development in the area of intelligent automation. The main theme of the special issue is machine learning for Industry 4.0. Topics of interest include, but are not limited to, machine learning for advanced automation; incremental and transfer learning; smart and digital factories; smart logistics and warehouses; robot vision and applications in automation; fault diagnosis, prediction, and prognostics; Industrial Internet of Things; edge computing-based machine learning for automation; big data analytics for forecasting and planning; integrated productivity and quality analysis; production planning, scheduling, and control algorithms; digital twin for automation; data mining and data-driven decision making; AI methods customized for different industries; online real-time data anomaly detection framework; sustainable manufacturing and remanufacturing; 3D printing and additive manufacturing; and Industry 4.0 case studies.

There are five papers accepted in this special issue. Each paper proposes innovative solutions to improve the efficiency and productivity of various industrial sectors.

Zhang et al. [A1] investigate the important issue of automatic defect inspection for the development of smart factories in the era of Industry 4.0. The types of defects may vary in the production process, making it challenging for the old model to adapt to new types of defects directly. To address this problem, Zhang et al. propose an industrial defect classification framework based on lifelong learning, which continuously updates the defect classification model to adapt to different industrial scenarios as new defects appear. Specifically, they present a novel recursive gradient optimization lifelong learning method to train the defect classification model. This method only requires a fixed network capacity and does not need data replay. The authors perform extensive experiments to demonstrate that their proposed framework can effectively alleviate the catastrophic forgetting problem in lifelong learning, compared with other state-of-the-art methods.

Fu et al. [A2] present a fault detection system for intelligent semiconductor manufacturing. Semiconductor manufacturing relies on a long and complex production line for wafer fabrication. Due to the data processing capacity limitation in the current fault detection and classification (FDC) system, the system's fault diagnosis efficiency is limited, and some undesired events cannot be

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detected in time, leading to significant economic loss. With the development of big data technology, this work studies a new FDC framework based on a Hadoop ecosystem to deal with the data processing limitation and improve fault diagnosis efficiency. The authors provide a migration path such that the current FDC system can be smoothly migrated to a Hadoop ecosystem-based one without shutting down a wafer fabrication line, which is crucial for fabrications. The experimental results show that the proposed FDC framework can run safely and stably.

> THE GOAL OF THIS SPECIAL ISSUE IS TO PROVIDE A FORUM FOR DISCUSSING INDUSTRIAL AUTOMATION RESEARCH ON SMART MANUFACTURING AND MACHINE LEARNING.

Zhou et al. [A3] investigate an integrated order batching and job assignment issue in a smart warehouse. As an essential part of Industry 4.0 facilitated supply chains, smart warehouses can offer smart tips and operational constraints for users, providing growth drivers for logistics companies and retailers. The authors propose a reinforcement-learning-based adaptive iterated local search (RAILS) approach to improve order-picking efficiency for smart warehouses, including a batching algorithm to efficiently handle fluctuating orders. They also design a perturbation mechanism based on reinforcement learning that can adaptively select the perturbation type and determine the perturbation strength. Experimental results show that the proposed approach outperforms several existing ones, with greater superiority as problem scales up.

Ringwald et al. [A4] focus on improving tactile robot-based assembly line adaptation to new products. Currently, manual redesign, manufacturing, and exchange of the end-effector setup limits its adaptation since the gripper fingers must often match the geometry of product components to ensure a successful assembly process. To address this issue, the authors present an automatic finger design, production, and evaluation pipeline. They have implemented two different form-closure-based design principles to automatically generate fingertip geometry. The resulting fingertips are printed via an automatic production unit and experimentally evaluated based on pick and insertion tasks for three different manipulation objects. The authors set up the training and testing process for a neural-network-based design method to demonstrate the potential usage of the introduced design methods for machine-learning-based fingertip design approaches.

In the last article in this special issue article collection, Jiang et al. [A5] focus on using deep reinforcement learning for robot control. Their work proposes an algorithm to train a neural network model with a large amount of data in a simulated environment and then transfer it to the real environment. The algorithm can guide the two-armed robot to complete complex assembly tasks. The proposed algorithm outperforms other algorithms in a large experimental study, and the real robot arm completes the assembly task significantly faster than script and keyboard operations.

We would like to extend our gratitude to Editor in Chief Prof. Yi Guo, the associate editors, and the many anonymous reviewers who have supported this special issue. Our hope is that this issue will motivate researchers and practitioners to develop machine learning and Industry 4.0/5.0 technologies for robotics and automation, benefiting numerous industrial sectors such as semiconductor manufacturing, electronic manufacturing, remanufacturing, and modern agriculture [6].

APPENDIX: RELATED ARTICLES

[A1] J. Zhang, D. Guo, Y. Wu, X. Xu, and H. Liu, "Toward lifelong learning for industrial defect classification," *IEEE Robot. Autom. Mag.*, vol. 30, no. 2, pp. 10–21, Jun. 2023, doi: 10.1109/MRA.2023.3258743.

[A2] H. Fu, Y. Qiao, L. Bai, N. Wu, B. Liu, and Y. He, "Development of fault detection systems: The Hadoop ecosystem implementation," *IEEE Robot. Autom. Mag.*, vol. 30, no. 2, pp. 22–33, Jun. 2023, doi: 10.1109/MRA.2023.3263973.

[A3] L. Zhou, C. Lin, and Z. Cao, "Reinforcement-learning-based local search approach to integrated order batching: Driving growth for logistics and retail," *IEEE Robot. Autom. Mag.*, vol. 30, no. 2, pp. 34–45, Jun. 2023, doi: 10.1109/MRA.2023.3265515.

[A4] J. Ringwald, S. Zong, A. Swikir, and S. Haddadin, "Automatic gripper-finger design, production and application: Towards fast and cost-effective small-batch production," *IEEE Robot. Autom. Mag.*, vol. 30, no. 2, pp. 46–56, 2023, doi: 10.1109/MRA.2023.3269404.

[A5] D. Jiang, H. Wang, and Y. Lu, "Mastering the complex assembly task with a dual-arm robot: A novel reinforcement learning method," *IEEE Robot. Autom. Mag.*, vol. 30, no. 2, pp. 57–66, Jun. 2023, doi: 10.1109/MRA.2023.3262461.

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[5] H. Yuan and M. Zhou, "Profit-maximized collaborative computation offloading and resource allocation in distributed cloud and edge computing systems," *IEEE Trans. Autom. Sci. Eng. (from July 2004)*, vol. 18, no. 3, pp. 1277–1287, Jul. 2021, doi: 10.1109/TASE.2020.3000946.

[6] O. Friha, M. A. Ferrag, L. Shu, L. Maglaras, and X. Wang, "Internet of Things for the future of smart agriculture: A comprehensive survey of emerging technologies," *IEEE/CAA J. Autom. Sin.*, vol. 8, no. 4, pp. 718–752, Apr. 2021, doi: 10.1109/JAS.2021.1003925.