Guest Editorial Special Issue on Learning Theories and Methods With Application to Digitized Process Manufacturing

THE digitization of process manufacturing involves converting information and knowledge into a digital format through technologies, such as artificial intelligence (AI), the Internet of Things (IoT), blockchain, and digital twins. This transformation promotes extension and optimization within the industrial, supply, and value chains, aiming to enhance decision-making efficiency, enable agile operations, and ensure information security and privacy. However, the current learning and operational approaches in the process industry remain rooted in traditional informatization, falling short of the vision for digital transformation. To address this gap, it is crucial to implement fusion analysis, deepen understanding, adopt autonomous learning, and enable intelligent optimization based on life-cycle data. Therefore, it is of fundamental importance to realize the transformation of process manufacturing toward digitalization and intelligentization, i.e., the use of artificial intelligence with decision-making capability, via new learning theories, methods, and algorithms.

The aim of this special issue is to provide a collection of most recent research advances dedicated to both academic research and industrial applications in the domain of digitized process manufacturing by means of learning theories, methods, and algorithms. After a rigorous and comprehensive review of the submitted manuscripts, we have selected seventeen articles to be included in this special issue. A summary of these articles is provided as follows.

The diverse sampling rates of sensors, coupled with challenges such as communication failures and cyberattacks in the manufacturing process, highlight the significance of addressing incomplete or insufficient data, which may involve missing values or limited samples. This scenario emerges as a pivotal aspect in the digital transformation of process manufacturing. Deep learning methods are employed to thoroughly understand data patterns and reveal relationships in information from incomplete or insufficient manufacturing process data. In [A1], Kang et al. combine the cross-modal data fusion technique and the deep adversarial generation technique to impute the completely missing data in the digital industry, allowing for multimodal data fusion analysis on long-term time-series data. To obtain quality variables of different sampling rates from soft sensors, in [A2], this work proposes a deep learning model based on a multitemporal channel convolutional neural network (MC-CNN). The model contains a shared network used to extract the temporal feature and a parallel prediction network used to predict each quality variable. In [A3], a target-related Laplacian autoencoder (TLapAE) is proposed to leverage information from partially labeled data. Incorporating a target-related Laplacian regularizer and a stacked TlapAE (STLapAE) for extracting deep feature representations, the method improves prediction accuracy compared to soft sensors using labeled data only and other modeling methods based on partially labeled data. To identify unseen objects in the digital transformation of process manufacturing, in [A4], a tensor-based zero-shot learning framework termed "MetaEvolver" is proposed for improving recognition accuracy and unseen-domain generalizability for process manufacturing. MetaEvolver learns to evolve the dual prototype distributions for each generating uncertainty domain from seen classes and then generalizes to unseen classes.

Inevitable factors, including the dynamic work environment, component performance degradation, and heterogeneity among similar automation systems, highlight the significance of digitizing sensor data to evaluate the health and safety status of process manufacturing. Leveraging learning methods, such as neural networks, offers reliable approaches to detecting faults and anomalies, and assessing system safety. In [A5], Chen et al. provide a comprehensive review of transfer learning-motivated fault detection methods, categorizing them into two subclasses: either based on knowledge calibration or based on knowledge compromise. This survey focuses on the utilization of previous knowledge for fault diagnosis tasks. From this perspective, three principles and a new classification strategy for transfer learning-motivated fault diagnosis techniques are introduced. To separate temporal and spatial information and learn appropriate representation, in [A6], a framework is introduced for explicit representation and customized fault isolation. This approach addresses both temporal and spatial characteristics, allowing for the identification and localization of anomalies impacting various dependencies. Moreover, in [A7], a spatial–temporal variational graph attention autoencoder (STVGATE) is proposed for fault detection to effectively capture the spatial and temporal features of the interconnected unit processes. The results demonstrate that the proposed method dramatically increases the fault detection rate and reduces the false alarm rate. To achieve real-time safety assessment in nonstationary environments, in [A8], a dynamic submodular-based learning strategy is proposed to

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address the safety assessment in imbalanced drifting streams. The method incorporates an incremental update procedure with the structure of the broad learning system and a dynamic submodular-based annotation using an activation interval strategy. This approach achieves better assessment accuracy than typical existing approaches.

In process manufacturing, where intricate and interdependent variables influence production outcomes, predictive models play a pivotal role in decision-making by anticipating future outcomes and trends in manufacturing processes. In [A9], a time-series encoding temporal convolutional network (TSE-TCN) is proposed for guiding the real-time adjustment of treatment devices and preventing the excessive emission of pollutants. The effectiveness of the proposed method is verified through the industrial cracking and regeneration parts of a fluid catalytic cracking unit. In [A10], Shi et al. propose a weakly reinforced k-nearest neighbor classifier combined with expert knowledge (DR-KNN/CE) for abnormity forecast of the synthetical material and energy balances (AF-SBME). By including expert knowledge as external assistance and enhancing self-ability to mine and synthesize data knowledge, the proposed method has a more advanced performance compared with other existing high-performance data-driven classifiers.

Given the complexity of situations in process manufacturing, making decisions that are adaptable to changing circumstances and resilient to future situations is vital for cost reduction, efficiency improvement, and safety. Reinforcement learning provides a robust framework, allowing systems to learn optimal decision strategies through interactions with the environment. To make optimal decisions with strict safety requirements in blast furnace operation, in [A11], an offline reinforcement learning approach is designed to ensure safety, maximize return, and address issues of partially observed states. Experiments show that the proposed method improves the safety and return in the blast furnace melting process. For handling job scheduling in flexible scenarios, particularly on a single machine out of multiple machines, in [A12], Song et al. utilize deep reinforcement learning to learn priority dispatching rules (PDRs). Moreover, a heterogeneous-graph-neural-network-based architecture is proposed to capture complex relationships among operations and machines. To address the recovery of train operation order in reordering and retiming strategies during disturbances, in [A13], a deep reinforcement learning (DRL) approach is introduced to minimize the average total delay for all trains along the railway line. The learning agent is responsible for adjusting running times, dwell times, and departure sequences for trains while simultaneously resolving conflicts. The method effectively reduces the average total delay, as demonstrated on an adapted timetable implemented on the Beijing–Shanghai high-speed railway line. To make control decisions adaptable to changing operating conditions, it is necessary to make predictive control by identifying the system model from process data. Therefore, in [A14], an error-triggered adaptive sparse identification for predictive control (ETASI4PC) method is proposed. The method creates an initial model using sparse identification and implements a real-time prediction error-triggered mechanism to monitor changes in operating conditions. The proposed method can rapidly adapt itself to frequent changes in operating conditions and achieve real-time control effects even for unknown operating conditions.

In the improvement of the decision-making process in digitalized process manufacturing, optimization algorithms play a vital role in enhancing efficiency, resource utilization, and overall performance. They achieve this by systematically identifying the most optimal solutions to complex problems. To tackle multiobjective optimization problems (MOPs) with expensive constraints, in [A15], a multigranularity surrogate modeling framework for evolutionary algorithms is developed. The method adaptively determines the approximation granularity of constraint surrogates based on the position of the population in the fitness landscape and uses a dedicated model management strategy to prevent the population from getting trapped into local optima. Experimental results on a large number of test problems show that the proposed framework is superior to seven state-of-the-art competitors. In [A16], in order to solve the plant-wide energy-saving problem of an ethylene plant, a new distributed consensus algorithm is proposed to dynamically adjust the step size and automatically abandon the irrational evolutionary route while eliminating the dependence of optimization algorithms on model gradient information. The algorithm can reduce the total energy consumption of an ethylene plant with less computing time and assured consensus. To enhance the effectiveness and efficiency of subspace clustering in visual tasks, in [A17], Zhang et al. propose a method embedded in the subspace clustering framework of low-rank representation (LRR) methods, along with the computationally factored formulation of Schatten p-norm. The proposed approach utilizes tractable and scalable factor techniques, effectively mitigating the drawbacks associated with higher computational complexity, especially in the context of large-scale coefficient matrices. The experimental results demonstrate the effectiveness and efficiency of the proposed nonconvex clustering approaches.

We hope that these 17 articles in this special issue are beneficial for promoting the further development and application of learning theories and methods to digitized process manufacturing. We would like to thank all the authors who submitted their work to this special issue and all the reviewers for their great efforts in assessing the submissions. Finally, we also extend our gratitude to the Editor-in-Chief and the Editorial Office for their timely guidance and consistent support.

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APPENDIX: RELATED ARTICLES

[A1] M. Kang, R. Zhu, D. Chen, X. Liu, and W. Yu, “CM-GAN: A cross-modal generative adversarial network for imputing completely missing data in digital industry,” *IEEE Trans. Neural Netw. Learn. Syst.*, early access, Jun. 23, 2023, doi: 10.1109/TNNLS.2023.3284666.

[A2] Y. Zhou, B. Song, H. Shi, Y. Tao, and S. Tan, “A soft sensor for multirate quality variables based on MC-CNN,” *IEEE Trans. Neural Netw. Learn. Syst.*, accepted.

[A3] B. He, X. Zhang, and Z. Song, “Deep learning of partially labeled data for quality prediction based on stacked target-related Laplacian autoencoder,” *IEEE Trans. Neural Netw. Learn. Syst.*, early access, Nov. 28, 2023, doi: 10.1109/TNNLS.2023.3321691.

[A4] B. Ren, L. T. Yang, X. Deng, J. Feng, X. Nie, and C. Zhu, “A tensor-based zero-shot recognition for process manufacturing via learning uncertain domain prototype alignment,” *IEEE Trans. Neural Netw. Learn. Syst.*, accepted.

[A5] H. Chen, H. Luo, B. Huang, B. Jiang, and O. Kaynak, “Transfer learning-motivated intelligent fault diagnosis designs: A survey, insights, and perspectives,” *IEEE Trans. Neural Netw. Learn. Syst.*, early access, Jul. 19, 2023, doi: 10.1109/TNNLS.2023.3290974.

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[A7] M. Lv, Y. Li, H. Liang, B. Sun, C. Yang, and W. Gui, “A spatial–temporal variational graph attention autoencoder using interactive information for fault detection in complex industrial processes,” *IEEE Trans. Neural Netw. Learn. Syst.*, early access, Nov. 8, 2023, doi: 10.1109/TNNLS.2023.3328399.

[A8] Z. Liu and X. He, “Dynamic submodular-based learning strategy in imbalanced drifting streams for real-time safety assessment in nonstationary environments,” *IEEE Trans. Neural Netw. Learn. Syst.*, early access, Jul. 26, 2023, doi: 10.1109/TNNLS.2023.3294788.

[A9] H. Jiang, S. Zhang, W. Yang, X. Peng, and W. Zhong, “Integration of encoding and temporal forecasting: Toward end-to-end NO_x prediction for industrial chemical process,” *IEEE Trans. Neural Netw. Learn. Syst.*, early access, May 29, 2023, doi: 10.1109/TNNLS.2023.3276593.

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[A11] K. Jiang, Z. Jiang, X. Jiang, Y. Xie, and W. Gui, “Reinforcement learning for blast furnace ironmaking operation with safety and partial observation considerations,” *IEEE Trans. Neural Netw. Learn. Syst.*, early access, Jan. 17, 2024, doi: 10.1109/TNNLS.2023.3340741.

[A12] W. Song, X. Chen, Q. Li, and Z. Cao, “Flexible job-shop scheduling via graph neural network and deep reinforcement learning,” *IEEE Trans. Ind. Informat.*, vol. 19, no. 2, pp. 1600–1610, Feb. 2023.

[A13] L. Ning, Y. Li, M. Zhou, H. Song, and H. Dong, “A deep reinforcement learning approach to high-speed train timetable rescheduling under disturbances,” in *Proc. IEEE Intell. Transp. Syst. Conf. (ITSC)*, Oct. 2019, pp. 3469–3474.

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