# Guest Editorial
# Special Issue on Deep Integration of Artificial Intelligence and Data Science for Process Manufacturing

PROCESS manufacturing serves as the pillar of the continuous manufacturing industry such as oil, gas, chemicals, nonferrous metals, iron, and steel, and thus is closely related to almost every aspect of human life. On the one hand, in order to meet several urgent but challenging demands of increasing profits, reducing materials consumption, enhancing safety, and protecting the environment, it is necessary to facilitate the development of process manufacturing with the usage of some novel and advanced techniques such as artificial intelligence (AI) and computation intelligence (CI). On the other hand, with the increasing scale of process manufacturing, another challenge is how to effectively deal with a huge amount of industrial big data in the process industry for environmental perception, modelling, optimization, decision-making, autonomous intelligent control, fault detection, and risk analysis. Therefore, it is of fundamental importance to deeply integrate AI, CI, and data sciences to achieve accurate control and optimal decision-making for process industries.

In view of this, the aim of this Special Issue is to provide a collection of most recent research advances that are dedicated to both academic researches and industrial applications in the domain of process manufacturing by means of deeply integrating AI, CI, and data sciences. After a rigorous and comprehensive review of the submitted manuscripts to this Special Issue, we selected nine articles to be included in this Special Issue. A summary of these articles is provided as follows.

In some specific industrial scenarios such as extreme working environments, it is essential to apply soft sensor techniques for the prediction of the hard-to-measure quality variables based on the easy-to-measure process variables. Considering that deep learning has shown outstanding capability in feature representation of complex data, it is promising to tightly integrate deep learning with soft sensors. In the article "A layer-wise data augmentation strategy for deep learning networks and its soft sensor application in an industrial hydrocracking process," Yuan *et al.* propose a layer-wise data augmentation (LWDA) strategy and develop an LWDA-based stacked autoencoder (LWDA-SAE) for the pretraining of deep learning networks and soft sensor modeling in industrial processes. Compared with traditional deep learning networks, the proposed method can effectively reduce the information loss and generalization degradation of high hidden layers. In order to capture the sequential dependence among different variables in process manufacturing, the article "Dual attention-based encoder-decoder: A customized sequence-to-sequence learning for soft sensor development," by Feng *et al.*, proposes a dual attention-based encoder–decoder for soft sensors based on the long short-term memory network. Their approach can concurrently conduct the feature learning from the variable-wise and time-wise for each quality variable to pursuit an accurate quality prediction. In the article "Data-driven intelligent warning method for membrane fouling," Wu *et al*. design a data-driven intelligent warning method for warning the future events of membrane fouling in membrane bioreactor. It should be mentioned that the proposed method adopts the recurrent fuzzy neural network (RFNN) as a soft sensor technique to measure the membrane permeability of the membrane bioreactor.

In order to guarantee the efficient and safe operation of industrial processes, it is critically important to utilize environmental monitoring techniques to evaluate the operating status of process manufacturing from a holistic perspective. However, in large-scale industrial plants, environmental monitoring is a challenging problem due to the complex features of multi-unit, multi-mode, high-dimension data. Hence, in the article "Hierarchical quality monitoring for large-scale industrial plants with big process data," Yao *et al.* propose a hierarchical quality monitoring (HQM) algorithm based on the distributed parallel semisupervised Gaussian mixture model. Moreover, the proposed method can address plant-wide big process data to realize hierarchical fault detection and diagnosis for plant-wide processes. In the article "Spatiotemporal graph convolution multi-fusion network for urban vehicle emission prediction," Xu *et al.* propose a spatiotemporal graph convolution multi-fusion network (ST-MFGCN) to predict urban vehicle emission. Due to the ability to capture the vehicle emission spatiotemporal variation patterns and learn the effects of complex environmental factors, the proposed method outperforms the other baselines on most vehicle emissions.

The modeling of the chemical process aims to analyze the internal relationship among various variables of process industries and extract their main features by means of mathematical

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formulas. Due to industrial big data and complex process nonlinearity, it is challenging but interesting to balance the tradeoff between modeling accuracy and computation burden. In the article "Local–global modeling and distributed computing framework for nonlinear plant-wide process monitoring with industrial big data," Jiang *et al.* propose a local–global modeling and distributed computing framework to realize the efficient monitoring and fault detection of the nonlinear plant-wide processes. Since the learning process can be implemented in a distributed manner, it is worth mentioning that the proposed method can effectively handle industrial big data so as to reduce the computation burden. In order to effectively reduce both numerical stiffness and model complexity of chemical reaction systems, the article "Intelligent time-scale operator-splitting integration for chemical reaction systems," by Zhang *et al.*, proposes an intelligent time-scale operator-splitting chemistry integration method, which utilizes a pre-trained backpropagation neural network to identify the slow and fast reactions.

As is known to all, advanced control is the key to ensure the high-precision performance of process manufacturing, and many control methods such as model predictive control and fault-tolerant control have been successfully applied in process industries. Considering that manufacturing systems not only involve nonlinearities and disturbances but also are subject to actuation failures, it is enforceable to utilize advanced AI techniques including neural networks for the control of process manufacturing. In the article "Iterative learning model predictive control based on iterative data-driven modeling," Ma *et al.* utilize a control-affine feedforward neural network (CAFNN) to establish an accurate first principal model and then apply the iterative learning model predictive control (ILMPC) to track the reference trajectory in complex nonlinear batch systems. Moreover, the authors theoretically prove the robust stability and convergence of the proposed method. In the article "Neuro-adaptive fault-tolerant control under multiple objective constraints with applications to tire production systems," Cui *et al.* propose a neuro-adaptive fault-tolerant control to cope with the multiple objective constraints, system uncertainties, and the unknown actuation failures. Then, the authors validate the effectiveness of the proposed method via simulation on speed regulation of extruding machines in tire production lines.

We hope that the nine articles selected in this Special Issue are beneficial for promoting the development in the field of 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 ensuring the quality of the selected papers. 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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