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Editorial

Editorial for Special Issue "Artificial Intelligence Energizes Process Manufacturing"

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Process manufacturing is a pillar of modern economy; it is the dominant mode of production in many industries, including oil and gas, chemicals, nonferrous metals, iron, steel, and more. In order to address the problems of resource constraints, energy efficiency, and environmental protection in process manufacturing, it is necessary to develop systems and methods to make process manufacturing more efficient, greener, and smarter. From another perspective, artificial intelligence has been successfully applied in various fields, such as autonomous vehicles, image analysis, robotic manipulators, real-time assistants, and smart recommendation, and has demonstrated its powerful strengths in knowledge representation, cognitive comprehension, and autonomous learning. Therefore, a deep and tight integration between artificial intelligence and process manufacturing is a promising direction toward "smart process manufacturing." Smart process manufacturing has become a hot research topic in recent years, and various governments have released strategic plans for smart process manufacturing with the aim of upgrading and transforming the process industry.

Considering that process industries must confront a number of challenges, including multiscale integration, human–cyber–physical interaction, and multi-objective optimization with tight constraints, there are strong research interests in developing and applying artificial intelligence technologies for smart process manufacturing. Therefore, this special issue focuses on how to solve bottleneck problems in operating management, production operations, efficiency, security, and information integration. Meanwhile, this issue aims to promote the applications of artificial intelligence in process manufacturing from various perspectives, including modeling, optimization, intelligent perception, autonomous control, and smart decision-making.

With strong support from the Chinese Academy of Engineering, it has been our great honor to invite academicians and renowned researchers from many countries including Belgium, Canada, China, Denmark, Germany, the Republic of Korea, Singapore, Sweden, and the United States to report on ideas, theories, and technologies related to smart process manufacturing. Through a rigorous and careful peer-review process, we have selected nine papers for publication. A brief summary of these articles is provided below.

By developing chemical product modeling tools and methods, researchers can intuitively understand the internal relationship among various variables in process manufacturing, and capture the main properties of such relationships through mathematical modeling. In general, modeling is the first step to realize functions in process manufacturing such as process monitoring, decision-making, autonomous control, and fault detection. In this special issue of *Engineering*, Teng Zhou et al. aim to tackle the complex design problems caused by the strong interaction between material selection and process operation. They emphasize that hybrid modeling is beneficial in the design of multiscale materials and processes, since the material properties should be described by data-driven models, while the process-related principles should be based on mechanistic models. By connecting three aspects, including data-driven manufacturing, decentralized manufacturing, and integrated blockchains, Manu Suvarna et al. present a holistic perspective on the role of cyber–physical production systems (CPPSs) in driving next-generation manufacturing. Furthermore, they propose that, through the application of data-driven modeling, CPPS can aid in transforming manufacturing to become more intuitive and automated. Maarten R. Dobbelaere et al. summarize the strengths, weaknesses, opportunities, and threats of applying machine learning to achieve chemical modeling in process engineering, and present three recommendations to improve the credibility of machine-learning-based modeling methods. They also point out that machine learning is especially suitable for time-limited applications such as real-time optimization and planning.

Due to the harsh environment of real industrial process, the measurements sampled by sensing devices are always subject to many undesirable factors, such as a varying operating environment, variation in raw materials and product quality indexes. Hence, it is necessary to develop novel process-monitoring techniques to evaluate the operating status of process manufacturing. Zhaohui Zeng et al. propose the sub-band instantaneous energy spectrum (SIEP) to quantitatively represent the

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characteristics of designated frequency bands of the cell voltage under various cell conditions. Based on the SIEP, they further propose a cell-condition-sensitive frequency segmentation method, so that aluminum-based electrolysis cell voltage can be monitored more reliably and accurately. Because the distribution of measurement data changes over time in a varying operating environment, process-monitoring models based on historical training data cannot fulfill the task of monitoring online streaming data accurately. Hence, Chunhua Yang et al. propose a robust transfer dictionary learning method, which is a synergistic framework of representative learning and domain adaptive transfer learning, to eliminate the distribution divergence caused by environmental interference and maintain the monitoring performance for the industrial process. Oguzhan Dogru et al. adopt a type of reinforcement learning method called the actor–critic policy to address real-time object-tracking problems in the process industry. This approach can not only improve the robustness of the monitoring system under environmental uncertainties, but also utilize fewer images generated by computer vision to reduce maintenance cost.

It is well known that control is the key to ensuring closed-loop stability and high-precision performance in process manufacturing. As the scale of industrial systems has become increasingly large and the structures of such systems have become more complex in recent years, it is necessary to introduce advanced machine learning techniques to optimize the decision-making process and control strategies for the process industry. Since conventional methods in the ironmaking process cannot meet the requirements of a timely response and elastic computing, Heng Zhou et al. propose a multi-objective optimization framework based on cloud services and a cloud distribution system. On this basis, they further utilize deep learning and evolutionary computation to develop a multi-objective optimization algorithm to optimize the conflicting objects in the blast furnace ironmaking process. From the perspectives of monitoring, control, optimization, and fault detection, Li Sun et al. review the typical applications of machine learning and data-driven control in power-generation systems that are subject to stochastic uncertainties. Finally, they point out that machine learning and data-driven control techniques can help to improve the visibility, maneuverability, flexibility, profitability, and safety of smart power-generation systems, and thus are expected to become an important alternative to traditional model-based methods. Tao Yang et al. review the shortcomings of the existing decision-making, control, and operation management frameworks for the whole production process in the process industry, and suggest that deeply integrating industrial artificial intelligence and the Industrial Internet with the domain knowledge of the process holds potential for realizing intelligent manufacturing in the process industry.

In summary, this issue of *Engineering* presents nine key papers that report on recent advances in smart process manufacturing from the aspects of chemical modeling, process monitoring, and control. We hope that this special issue can help researchers and practitioners in both academia and industry to further understand the roles of artificial intelligence in smart process manufacturing. Finally, we express our sincere thanks to the authors, reviewers, editorial office, and guest editors for their great efforts.