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Editorial

Special Issue "Advanced Process Monitoring for Industry 4.0"

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Industry 4.0 is continually and progressively changing the landscape of manufacturing throughout the world and across different industrial sectors. This movement is catalyzed by the concurrence of three key drivers that, synergistically combined, create the conditions to push forward the performance and effectiveness of plant operations, positively impacting process efficiency, safety, the environmental fingerprint, and the economic outcome through faster and better decision-making processes. These drivers are: the facilitated access to unprecedented amounts of data (both structured and unstructured), new technological developments (smart sensors, IoT, cloud storage, and high-performance computing), and a new wave of advanced analytical solutions (machine learning, artificial intelligence, free programming platforms, and commercial software). As happens in other activities, the key drivers are also impacting Process Monitoring, creating the capability to handle complex processes that generate "extreme data", i.e., data collected at high sampling rates, possibly asynchronously, in large amounts with a variety of structures and variable quality, arising from different places across the value chain.

This Special Issue aims to bring together recent advances in the broad field of Advanced Process Monitoring for Industry 4.0, including all the activities related to fault detection, diagnosis, and prognosis.

All process monitoring activities are critically dependent upon the capability to collect informative data about the state of plant operations and equipment condition. Therefore, new sensors are developed and deployed, transforming quality monitoring from an offline activity conducted in the plants laboratories to a real-time activity made online, in the process, enabling fast product release and decision making, with all the consequent benefits on productivity, quality, inner logistics, and plant economy. Reyes et al., used spectral data in the visible–near infrared (VIS–NIR) range to monitor a combustion process [1], while Hotait et al., reported the use of piezoelectric sensors together with an advanced feature extraction methodology, called AOC-OPTICS [2], for fast and automatic condition monitoring.

Batch processes are always challenging scenarios for process monitoring given their intrinsic non-stationarity and natural tensorial arrangement of data (batch $\times$ variables $\times$ time). These processes become even more difficult to handle when batch operations take place in multiple phases, as covered by Palací-Lopez et al. [3], and show multiple normal operation modes, as addressed by Zhao et al. [4]. Both studies make use of Latent Variable Models as the analytical backbone to address batch modeling. The extreme case of a multistep process (semiconductors) is also covered by Espadinha-Cruz et al. [5], where quality control, monitoring, and diagnosis and other critical tasks are revised under the general umbrella of data mining.

On the other hand, machine learning (ML) and artificial intelligence (AI) methodologies have also been increasingly brought to the process monitoring arena. The papers by Xing Wu et al. [6], Xin Wu et al. [7], and Yumin Liu et al. [8] report applications of convolutional neural networks (CNN) and recurrent neural networks (RNN) for process

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monitoring and diagnosis, exploring their ability to learn new data representations that efficiently represent the normal operation conditions of the process.

The integration of existing knowledge about the processes for process monitoring and diagnosis through digital twins, is also a current trend in Process Monitoring. Rato et al., present a framework where accurate models for the process common cause variation are used to mitigate the scarcity of data for high-dimensional process monitoring, especially during early monitoring periods, also enhancing the diagnosis activity once the fault is detected [9]. On the other hand, de Menezes et al., use a steady-state model to perform data reconciliation, an operation that is instrumental for the estimation of unmeasured variables in the proposed online monitoring scheme, playing the role of a soft sensor, and paving the way for the future adoption of an accurate digital twin [10].

The adaptation of Quality Engineering [11] and Six-Sigma [3] to the new types of measurements, data structures, processes, and the growing analytical body of knowledge, are opportunely covered in the contributions by Ramezani et al., and Palací-López et al., respectively. Similarly, Sader et al. [12] explored the use of modern methods of machine learning to assist in the implementation of Failure Mode and Effect Analysis (FMEA), and exemplify the proposed methodology in a dataset that includes a one-year historic of over 1500 failures with their respective description.

For all these valuable and insightful contributions, the Guest Editors are deeply grateful to the authors and their teams. We hope this rich and diverse collection of contributions fuel and inspire new developments on Statistical Process Monitoring and related fields, keeping up with the accelerating pace of the technological progress, data resources, and complexity of modern processes.

Finally, we would like to express our deepest gratitude and appreciation to the Section Managing Editor, Ms. Shirley Wang, for all the continuous and diligent support throughout all the phases of preparation of this Special Issue of *Processes*. We are also thankful to all the reviewers for their unconditional generosity in the time and effort dedicated to improve all the contributions with their knowledge, insights, and critical reasoning. The Special Issue "Advanced Process Monitoring for Industry 4.0" is available at https://www.mdpi.com/journal/processes/special_issues/Monitoring_Industry (accessed on 3 August 2021).

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