processes

MDPI

Editorial

Special Issue on "Process Monitoring and Fault Diagnosis"

Cheng Ji and Wei Sun *

College of Chemical Engineering, Beijing University of Chemical Technology, North Third Ring Road 15, Chaoyang District, Beijing 100029, China; 18401695565@163.com
* Correspondence: sunwei@buct.edu.cn

The following Special Issue entitled "Process Monitoring and Fault Diagnosis" aims to explore the latest progress and perspectives on the application of data analytic techniques to enhance stable operation and safety in chemical processes and other related process industries.

A fault refers to at least one variable that exists as an unpermitted deviation from the acceptable operable limits [1]. Fault detection aims to determine whether the process is operated within the normal state, and fault diagnosis refers to the identification of the responsible variables and root cause [2]. In general, chemical processes are expected to be operated under an ideal steady state; various random factors during practical production, however, lead to frequent process disturbances, which can be mostly considered as normal conditions. However, the presence of these disturbances poses challenges in the early detection and identification of faults. To address this issue, multivariate data-driven tools have become a popular research focus [3–5]. In recent years, advanced approaches leveraging statistical machine learning [6,7], deep learning [8–10], and hybrid modeling of process information and data have emerged [11–13], with the above approaches demonstrating promising performance in process monitoring and showing significant potential for industrial applications. The aim of the following Special Issue is to encourage scholars in the field to share their latest contributions, thereby fostering communication and the development of advanced process monitoring techniques.

The collection of research papers included in this Special Issue encompasses various aspects, including both traditional signal processing and advanced deep learning methods to handle process safety tasks such as process fault detection, bearing fault diagnosis, remaining useful life prediction, etc. Nine high-quality research papers and one literature review were published as a part of this Special Issue. The accepted publications are all available online at https://www.mdpi.com/journal/processes/special_issues/Process_Monitoring (accessed on 1 February 2024). The accepted papers introduce cutting-edge methodologies, demonstrate the reliability of their techniques through validation, and inspire further exploration of the subject. Below is a concise summary of the key topics and significant contributions of the cited papers.

(1) The first paper by Ji and Sun offers an extensive review of classical and recent research on data-driven process monitoring methods from the perspective of the characterization and mining of industrial data [14]. The authors of this work delve into the implementation framework of data-driven process monitoring methods, conduct a comprehensive review of state-of-the-art techniques, and examine the challenges encountered in practical industrial applications while proposing potential solutions to mitigate them.

(2) Rute Souza de Abreu et al. explore the application of spiking neural networks (SNNs) in predicting system faults in industrial processes, aiming to improve productivity, reduce costs, and enhance safety [15]. Traditional methods often struggle with the complexity of this task. The proposed approach leverages the Generalized Stochastic Petri Net (GSPN) model and the inherent capacity of SNNs to process temporal and

check for updates

Citation: Ji, C.; Sun, W. Special Issue on "Process Monitoring and Fault Diagnosis". *Processes* **2024**, *12*, 1432. https://doi.org/10.3390/pr12071432

Received: 24 June 2024
Accepted: 5 July 2024
Published: 9 July 2024

Copyright: © 2024 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https://creativecommons.org/licenses/by/4.0/).

spatial aspects of data, positioning them as a powerful tool for fault anticipation. A comparative analysis with Long Short-Term Memory (LSTM) networks indicates that SNNs offer comparable robustness and performance, which demonstrates their potential in addressing the challenges of fault prediction in syntactical time series.

(3) Qu et al. propose a fault diagnosis method for bearing vibration signals utilizing the wavelet packet energy spectrum and an enhanced deep confidence network [16]. The method decomposes the signal into frequency bands using wavelet packet transform, extracts fault features through energy spectrum analysis, and optimizes the deep belief network's hyperparameters with the sparrow search algorithm to enhance diagnostic accuracy. The experimental results using Case Western Reserve University's rolling bearing data demonstrate that the method achieves high diagnostic rates of 100% and 99.34%, demonstrating its effectiveness and stability.

(4) Hao et al. introduce a novel remaining useful life (RUL) prediction model for rolling bearings using a bi-channel hierarchical vision transformer [17]. By employing hierarchical vision transformer networks with varying patch sizes, the model extracts deeper features that capture degradation process information. A dual-channel fusion method is then integrated into a classic RUL prediction network, enhancing prediction accuracy. Compared to standard methods, the proposed approach achieved up to 9.43% and 43.10% greater prediction accuracy in two validation experiments using PHM 2012 datasets, which demonstrates its suitability for rolling bearing RUL prediction.

(5) Éva Kenyeres and János Abonyi present a study on the application of Particle Filtering (PF) for tracking and fault diagnosis in complex process systems with nonlinear models and non-Gaussian noise [18]. The authors present a sensor placement strategy, a tuning method for PF parameters, and a comparative analysis of classical and intelligent PF algorithms. By examining bias and impact sensor faults, the study demonstrates the effectiveness and efficiency of particle filtering for state estimation and fault detection in wastewater treatment systems.

(6) Zhang and Sun present an improved probabilistic neural network (PNN) with particle swarm optimization (PSO) for transformer fault diagnosis [19]. The model leverages dissolved gas ratios in transformer oil to enhance accuracy and efficiency, minimizing human intervention. The PSO-optimized PNN achieves higher diagnostic accuracy than the BPNN and traditional PNN, while maintaining solution speed, enabling real-time applications. A case study was used to validate its feasibility and effectiveness.

(7) Shan and Zhu introduce an enhanced gas pipeline leakage detection method that incorporates an Improved Uniform-Phase Local Characteristic Scale Decomposition (IUPLCD) and a Grid Search-optimized Twin-Bounded Support Vector Machine (GS-TBSVM) [20]. The method first decomposes signals into Intrinsic Scale Components (ISCs) using IUPLCD and then optimizes signal reconstruction by selecting the most significant ISC components based on their energy and amplitude standard deviation. The denoised signal is fed into a GS-TBSVM model and optimized through a grid search algorithm to accurately identify the real-time working conditions of the gas pipeline. The experimental results demonstrate that this approach effectively filters signal noise and achieves a maximum identification accuracy of 98.4% for gas pipeline leakages.

(8) Wang et al. propose a Distributed Robust Dictionary Pair Learning (DRDPL) method that effectively utilizes high-dimensional process data for refined monitoring in modern industrial systems [21]. The method partitions the global system into sub-blocks based on prior knowledge, employs a robust dictionary pair learning approach to build local models with sparse and low-rank constraints, and integrates local monitoring information using Bayesian inference for global anomaly detection and isolation. The method is validated through numerical simulations, benchmark tests, and successful application in an aluminum electrolysis process.

(9) Donggyun Im and Jongpil Jeong propose a large-scale Object-Defect Inspection System (RODIS) leveraging Regional Convolutional Neural Network (R-CNN) and Artificial

Intelligence technology to automate the quality inspection of vehicle side-outers, which are large, have numerous inspection points, and require high quality [22]. RODIS addresses challenges in industrial vision systems and the lack of automated inspection references. The study authors introduce the framework, hardware, and inspection method, focusing on on-site dataset creation. Field experiments and model comparisons revealed that the Mask R-CNN with the ResNet-50-FPN backbone achieves superior performance, demonstrating an AP of 71.63 for object detection and 86.21 for object segmentation.

(10) Manarshhjot Singh et al. propose a novel fault detection method based on Energy Activity (EA) that can detect minor faults in systems with high component uncertainty, which overcomes the limitations of traditional model-based approaches that rely on precise parameter values [23]. Various EA forms are developed and simulated on a two-tank system with different fault types. Compared to traditional model-based fault detection using Analytical Redundancy Relations (ARRs), the integral form of EA was found to be the most effective. Further testing on a real two-tank system considering model and measurement uncertainties validates the robustness of the proposed EA-based fault detection method.

The articles featured in the following Special Issue serve as a compelling testament to the rapid growth and remarkable potential of the field of process monitoring and fault diagnosis in the process industry. As its applications broaden across numerous domains, research in this area requires proficiency in process engineering, control engineering, data analysis, pattern recognition, and machine learning, among other disciplines. We firmly believe that this Special Issue will serve as a bridge between these communities, emphasizing the benefits of collaboration across interdisciplinary domains.

We express our sincere gratitude to the authors, reviewers, and editorial staff who have contributed immensely to the realization of this Special Issue. Their enthusiasm and expertise have enabled us to showcase the latest advancements in process monitoring and fault diagnosis, and we hope that it will inspire further innovation and exploration in this exciting field.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Isermann, R.; Ballé, P. Trends in the application of model-based fault detection and diagnosis of technical processes. *Control Eng. Pract.* **1997**, *5*, 709–719. [CrossRef]
2. Venkatasubramanian, V.; Rengaswamy, R.; Yin, K.; Kavuri, S.N. A review of process fault detection and diagnosis Part I: Quantitative model-based methods. *Comput. Chem. Eng.* **2003**, *27*, 293–311. [CrossRef]
3. Ge, Z. Review on data-driven modeling and monitoring for plant-wide industrial processes. *Chemom. Intell. Lab. Syst.* **2017**, *171*, 16–25. [CrossRef]
4. Qin, S.J. Survey on data-driven industrial process monitoring and diagnosis. *Annu. Rev. Control* **2012**, *36*, 220–234. [CrossRef]
5. Quiñones-Grueiro, M.; Prieto-Moreno, A.; Verde, C.; Llanes-Santiago, O. Data-driven monitoring of multimode continuous processes: A review. *Chemom. Intell. Lab. Syst.* **2019**, *189*, 56–71. [CrossRef]
6. Qin, S.J.; Dong, Y.; Zhu, Q.; Wang, J.; Liu, Q. Bridging systems theory and data science: A unifying review of dynamic latent variable analytics and process monitoring. *Annu. Rev. Control* **2020**, *50*, 29–48. [CrossRef]
7. Ji, C.; Ma, F.; Wang, J.; Sun, W. Orthogonal projection based statistical feature extraction for continuous process monitoring. *Comput. Chem. Eng.* **2024**, *183*, 108600. [CrossRef]
8. Ji, C.; Ma, F.; Wang, J.; Sun, W. Profitability related industrial-scale batch processes monitoring via deep learning based soft sensor development. *Comput. Chem. Eng.* **2023**, *170*, 108125. [CrossRef]
9. Kong, X.; Ge, Z. Deep Learning of Latent Variable Models for Industrial Process Monitoring. *IEEE Trans. Ind. Inf.* **2021**, *18*, 6778–6788. [CrossRef]
10. Arunthavanathan, R.; Khan, F.; Ahmed, S.; Imtiaz, S. A deep learning model for process fault prognosis. *Process Saf. Environ. Prot.* **2021**, *154*, 467–479. [CrossRef]
11. Jia, M.; Hu, J.; Liu, Y.; Gao, Z.; Yao, Y. Topology-Guided Graph Learning for Process Fault Diagnosis. *Ind. Eng. Chem. Res.* **2023**, *62*, 3238–3248. [CrossRef]
12. Liu, L.; Zhao, H.; Hu, Z. Graph dynamic autoencoder for fault detection. *Chem. Eng. Sci.* **2022**, *254*, 117637. [CrossRef]

13. Shen, S.; Lu, H.; Sadoughi, M.; Hu, C.; Nemani, V.; Thelen, A.; Webster, K.; Darr, M.; Sidon, J.; Kenny, S. A physics-informed deep learning approach for bearing fault detection. *Eng. Appl. Artif. Intell.* **2021**, *103*, 104295. [CrossRef]
14. Ji, C.; Sun, W. A Review on Data-Driven Process Monitoring Methods: Characterization and Mining of Industrial Data. *Processes* **2022**, *10*, 335. [CrossRef]
15. Souza de Abreu, R.; Silva, I.; Nunes, Y.T.; Moioli, R.C.; Guedes, L.A. Advancing Fault Prediction: A Comparative Study between LSTM and Spiking Neural Networks. *Processes* **2023**, *11*, 2772. [CrossRef]
16. Qu, J.; Cheng, X.; Liang, P.; Zheng, L.; Ma, X. Fault Diagnosis of Bearings Using Wavelet Packet Energy Spectrum and SSA-DBN. *Processes* **2023**, *11*, 1875. [CrossRef]
17. Hao, W.; Li, Z.; Qin, G.; Ding, K.; Lai, X.; Zhang, K. A Novel Prediction Method Based on Bi-Channel Hierarchical Vision Transformer for Rolling Bearings' Remaining Useful Life. *Processes* **2023**, *11*, 1153. [CrossRef]
18. Kenyeres, É.; Abonyi, J. Goal-Oriented Tuning of Particle Filters for the Fault Diagnostics of Process Systems. *Processes* **2023**, *11*, 823. [CrossRef]
19. Zhang, X.; Sun, Z. Application of Improved PNN in Transformer Fault Diagnosis. *Processes* **2023**, *11*, 474. [CrossRef]
20. Shan, H.; Zhu, Y. Gas Pipeline Leakage Detection Method Based on IUPLCD and GS-TBSVM. *Processes* **2023**, *11*, 278. [CrossRef]
21. Wang, J.; Chen, X.; Deng, Z.; Zhang, H.; Zeng, J. Distributed Robust Dictionary Pair Learning and Its Application to Aluminum Electrolysis Industrial Process. *Processes* **2022**, *10*, 1850. [CrossRef]
22. Im, D.; Jeong, J. R-CNN-Based Large-Scale Object-Defect Inspection System for Laser Cutting in the Automotive Industry. *Processes* **2021**, *9*, 2043. [CrossRef]
23. Singh, M.; Gehin, A.-L.; Ould-Boaumama, B. Robust Detection of Minute Faults in Uncertain Systems Using Energy Activity. *Processes* **2021**, *9*, 1801. [CrossRef]

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.