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Editorial

Special Issue on "Application of Big Data Analysis and Advanced Analytics in Sustainable Production Process"

Sun Hur [1,*], Jae-Yoon Jung [2,3] and Josue Obregon [2]

[1] Department of Industrial and Management Engineering, Hanyang University, Ansan 15588, Korea
[2] Department of Industrial and Management Systems Engineering, Kyung Hee University, Yongin-si 17104, Korea; jyjung@khu.ac.kr (J.-Y.J.); jobregon@khu.ac.kr (J.O.)
[3] Department of Big Data Analytics, Kyung Hee University, Yongin-si 17104, Korea
* Correspondence: hursun@hanyang.ac.kr

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Citation: Hur, S.; Jung, J.-Y.; Obregon, J. Special Issue on "Application of Big Data Analysis and Advanced Analytics in Sustainable Production Process". *Processes* **2022**, *10*, 670. https://doi.org/10.3390/pr10040670

Received: 24 December 2021
Accepted: 20 March 2022
Published: 30 March 2022

Publisher's Note: MDPI stays neutral with regard to jurisdictional claims in published maps and institutional affiliations.

We live in the big data era, in which a large amount of information is continuously created, registering all kinds of events, such as those generated in the design, planning, control, and execution of manufacturing, logistics, and supply chain processes. Furthermore, a significant concern for manufacturing organizations is the environmental responsibility that has become an integral aspect of how their production processes are designed and executed. The Special Issue on "Application of Big Data Analysis and Advanced Analytics in Sustainable Production Process" received several state-of-the-art research papers related to the application of big data analysis and advanced analytics in three different areas of sustainable production processes: prognostics and health management (PHM), supply chain management (SCM), and safety policy in the workplace. A brief overview of each paper is described in the following subsections. The Special Issue is available online at: https://www.mdpi.com/journal/processes/special_issues/data_processes (accessed on 28 March 2022).

Prognostics and Health Management

PHM systems are designed to provide real-time health assessments of various types of systems based on the operation conditions of the system itself, as well as to give the estimates of the remaining useful life (RUL) until failure. The contribution of PHM systems to sustainable processes comes from the emphasis on the role of maintenance as a method for life cycle management which aims to provide the required functions while minimizing material and energy consumption [1]. PHM systems for production processes are well suited to using data collected from a plethora of sensors as an input. The Special Issue includes five research papers in the PHM area.

Fault detection for ball bearings in the manufacturing industry is studied through two different data analytic techniques. In the paper "Evaluation of One-Class Classifiers for Fault Detection: Mahalanobis Classifiers and the Mahalanobis–Taguchi System" [2], a one-class classifier for fault detection using vibration data collected from sensors is introduced by Kim, Park, and Jung. The data are first preprocessed using signal processing techniques and a classifier is built using the Mahalanobis distance combined with the Taguchi system. The results emphasize the advantage of using one-class classification methods because generating fault data is expensive and time-consuming. In the other paper, "Development of Indicator of Data Sufficiency for Feature-Based Early Time Series Classification with Applications of Bearing Fault Diagnosis" [3], a different issue of the same problem is tackled by Ahn, Lee, Park, and Hur, that is, the need of having complete time series data to obtain good results in the fault classification task. To this end, an earliness indicator based on data sufficiency is proposed, based on the cosine similarity between complete and partial sequences of the sensor data. The results using support vector machines (SVM) and artificial neural networks (ANN) show good performance using partial sequence data. The lack of labeled data are a practical problem that frequently arises when using big data for

machine learning. For this issue, a semi-supervised learning method was presented in the paper "Quality Prediction and Yield Improvement in Process Manufacturing Based on Data Analytics" by Jun, Chang, and Jun [4]. Their method adopts the label propagation and label spreading algorithm along with under- and over-sampling techniques to feed a long short-term memory (LSTM) network for predicting the quality in the plastic extrusion process. The data are composed of different sensors readings, such as temperature, screw speed, external humidity, and water temperature. On a similar subject, in the paper "A Time-Series Data Generation Method to Predict Remaining Useful Life" [5], a time series generation method, which is useful when there are not enough fault-labeled data available, is presented by Ahn, Yun, and Hur. The symbolic aggregate approximation (SAX) method is used to convert various time sequences into alphabetical representation. Those representations are reused to generate artificial sequences of alphabets, using the Markovian properties of the data generation process and transition probabilities. It is shown experimentally—using two battery capacity datasets and one bearing vibration dataset—that the samples generated by the proposed method effectively increase the performance of the prognosis model. In this case, their PHM task was to estimate the RUL of the batteries and ball bearings. Another RUL study was presented in the paper "Residual Life Prediction for Induction Furnace by Sequential Encoder with S-Convolutional LSTM" by Choi, Kwun, Kim, Lee, and Bae [6]. The data generated from the electrical system of an induction furnace are used, and a model based on a convolutional neural network (CNN) and an LSTM network, called S-convolutional LSTM, is devised in the paper. The proposed network is fed with a novel multi-channel sequential feature matrix that accurately estimates the residual life of the induction furnace with low errors.

Finally, in the paper "Real-World Failure Prevention Framework for Manufacturing Facilities Using Text Data" by Park, Choi, and Choi [7], the use of text data is explored for proposing a framework for failure prevention in the manufacturing industry. The method initially takes raw facility failure logs combined with additional data, such as facility location, season, the person in charge, and failure intervals, as input. After that, the data are preprocessed using text data analysis techniques and the FP-growth algorithm is used to extract pre-failure rules of different operators that are formed from explainable antecedents—location, cumulative failures, did the operator have lunch?—and failure consequents—aging, part damage, etc.—as well as support and confidence values for failure prevention in intelligent factories.

Supply Chain Management

SCM is also closely related to sustainability. For that reason, there is even a term called sustainable supply chain management (SSCM), which integrates the environmental and social considerations to the activities of traditional SCM [8]. In this regard, in the paper "Integrating FMEA and the Kano Model to Improve the Service Quality of Logistics Centers" by Tang, Chen, and Lin [9], service quality in the logistics center of a large organic retail store in Taiwan is focused on. The study was carried out using the answers of questionnaires from logistic experts from the company as well as 220 employees from the store. Later, two advanced analytics methods—the failure model and effect analysis (FMEA) technique combined with the Kano model—are adopted to iden-tify the most important items that would help to avoid failures in the logistic center. The results provide the customer perspective and the internal staff perspective on failures to implement a continuous improvement plan in the logistic center. On a different topic, in the paper "Integrating Machine Learning, Radio Frequency Identification, and Consignment Policy for Reducing Unreliability in Smart Supply Chain Management" by Sardar, Sarkar, and Kim [10], radio frequency identification (RFID) technology and machine learning are combined for demand forecasting. A change in the traditional SCM method based on consignment policy is presented, in which the manufacturer becomes the leader by forecasting the demand and installing the RFID technology for their products and the retailer acts as a follower. LSTM networks forecast the demand, and the total profit equations are solved based by the Stackelberg game approach. The ML-RFID model has a 43% higher profit compared to

the traditional model. Moreover, the environmental measure for the ML-RFID model is lower compared to that of the traditional method. These studies show that it is possible to integrate advanced analytics and big data in order to integrate environmental protection measures into SCM activities.

Safety Policy in the Workplace

Finally, in the paper "Research on the Correlation between Work Accidents and Safety Policies in China" by Wang, Wei, He, Zhang, and Wang [11], the data of 8143 safety policies, accident-related deaths, and the gross domestic product (GDP) in China from 2000 to 2020 were collected from China's Work Safety Yearbooks. Their study begins by finding the turning points in the trend of the number of safety policies and creating a set of dummy variables that are then combined with the number of accidental deaths each year and fed into a linear regression, solved using the ordinary least squares (OLS) method. After that, several statistical tests are carried out to analyze the results, and it is concluded that "the strict safety policy has a long-term negative impact on mortality" because "increasing the number and implementation of safety policies can significantly im prove the situation of production safety".

Final Remarks

The above papers show that there is a big opportunity for big data, advanced analytic, and predictive methods—such as machine learning and deep learning—to contribute to the sustainable development of various types of processes in the different domains, especially the manufacturing industry. We thank all the contributors and the Section Managing Editor, Mr. Stevan Wang, for their enthusiastic support for this Special Issue. We also appreciate the help of the editorial staff of *Processes* for their efforts.

Funding: This work was supported by the National Research Foundation of Korea (NRF), grants funded by the Korean government (MSIT) (Nos. 2017H1D8A2031138, 2019R1F1A1064125, and 2019R1A2C1088255).

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

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