Guest Editorial Special Issue on Automation Analytics Beyond Industry 4.0: From Hybrid Strategy to Zero-Defect Manufacturing

MOST traditional industries or emerging countries may not be capable of directly transiting to Industry 4.0. To fill the gap between as-is Industry 3.0 and to-be Industry 4.0, some disruptive innovations from automation and industrial engineering identify best practice with adopting cost-effective semi-automated systems to manage the potential socio-economic impacts of infrastructure disruptions, while considering total resource management for sustainability. This is the so-called "hybrid strategy (HS)," or "Industry 3.5." On the other hand, the current Industry 4.0-related technologies should also emphasize quality enhancement to achieve "zero-defect manufacturing (ZDM)," also referred to as "Industry 4.1." ZDM is a systematic strategy to realize the goal of Zero Defects, which includes two phases. Phase I: accomplish Zero Defects of all the deliverables by applying efficient and economical total-quality-inspection techniques; and Phase II: further ensure Zero Defects of all the products gradually by improving the yield with big data analytics and continuous improvement. Both the challenges and opportunities from HS to ZDM have significantly expanded the scope of traditional automation science and engineering.

The goal of the Special Issue is to bring together researchers and practitioners into a forum, to show the state-of-the-art research and applications in these directions by presenting efficient scientific and engineering solutions, addressing the needs and challenges for integration of new automation technologies, and providing visions for future research and development. The central theme of the Special Issue will be bridging the gap from HS to ZDM.

The contributions in this Special Issue can be divided into the following five categories: anomaly detection and feature selection [A1]–[A5], scheduling [A6]–[A7], manufacturing analysis [A8]–[A10], advanced manufacturing [A11]–[A13], and other applications [A14]–[A15]. They are briefed as follows.

I. Anomaly Detection and Feature Selection [A1]–[A5]

The task of anomaly detection (AD) in semiconductor manufacturing process data is investigated in [A1]. Departing from the classical control chart approach and embracing modern AI methods, Maggipinto *et al.* develop a two-stage approach. First, convolutional autoencoders are built and trained with bidimensional non-image tabular data for the purpose of feature extraction. Second, various popular unsupervised AD methods are fed the output of the encoders to generate anomaly scores for each data point effectively. The improved AD is demonstrated on real plasma etch tool data obtained via optical emission spectroscopy (OES) as well as on a publicly available dataset.

In [A2], Pezze *et al.* propose a deep learning model for alarm prediction and thus support a prompt corrective maintenance of the equipment to reduce the downtime in practice. Particularly, the study proposes a loss function with multiple labels to handle the alarm frequency imbalance. The experimental analysis shows that the proposed model performs better than other existing approaches and well identifies the low-frequency alarms relevant to productivity loss.

Ye and Liu introduce a genetic monitoring and sampling algorithm to detect the mean shifts occurring in high-dimensional heterogeneous processes for quality improvement in [A3]. The proposed model integrates the Thompson sampling and quantile-based nonparametric cumulative sum control chart to build local statistics of partially observed information. The results showed that the proposed model reduces the detection delay issue and relaxes the assumption of the data distribution.

The key-variable search algorithm proposed by Ing *et al.* typically emphasizes the univariate variables which significantly affect the production yield in [A4]. However, the interaction effects between multi-variate variables are not investigated well. This study suggests a two-phase analysis which identifies key stages in the first phase and generates all paths of the key-stage devices for yield prediction. According to the yield index, the study ranks all key stages and identifies the golden path for supporting troubleshooting and driving productivity. By the way, the concept of Industry 4.1 for achieving zero-defect (ZD) manufacturing was also briefed in [A4].

In [A5], Fan *et al.* develop a data-driven framework including clustering analysis and prediction model in order to identify key features for process monitoring in semiconductor manufacturing. Particularly, the self-organizing map and

Digital Object Identifier 10.1109/TASE.2022.3180525

boosting algorithm are used to investigate the variations wafer by wafer and support the predictive monitoring. Based on the empirical study, the key status variable identifications (SVID), processing times, and the variation can be identified effectively.

II. Scheduling [A6]–[A7]

Multi-center operation and maintenance (O&M) networks are discussed in [A6]. Si *et al.* seek to lower operating costs by optimizing several interrelated decisions such as the selection of machine maintenance times, technician team grouping, and technician team routes. A formal model of transportation-oriented cross-regional opportunistic maintenance (TCOM) is developed. Due to the inherent intractability, a hybrid metaheuristic algorithm termed clustering iterated local search (CILS) algorithm is developed and tested against various existing metaheuristics. The joint consideration of these issues in long-term O&M network operations, together with efficient solution methodology, enable substantial cost savings in extensive numerical studies conducted.

In [A7], Kung and Liao consider several factors related to preventive maintenance and solve a job scheduling problem by using mixed-integer linear programming. To address the computational issue, two heuristic algorithms are developed to search for a near-optimal solution. An empirical study is conducted to validate the proposed model which effectively schedules jobs and maintenance to find a balance between yield loss and shortage loss.

III. Manufacturing Analysis [A8]–[A10]

Batch-discrete manufacturing systems refer to production lines with mixed batch (i.e., multiple parts being manufactured simultaneously on a batch machine) and discrete part operations. Many industries, such as aircraft, automotive, battery, medical device, and defense industries, include such kinds of production lines. In view of this, in [A8], Liu *et al.* present a novel methodology for accurate modeling and performance evaluation of batch-discrete systems. The heating (batch) and trimming (discrete) operations in composite panel production lines are presented to illustrate how to apply the model and analysis in practice. Such work provides a quantitative tool for production engineers and managers to design, analyze, and improve batch-discrete manufacturing systems.

Deep drawing is a metalworking procedure that aims to get a cold metal sheet plastically deformed in accordance with a pre-defined mold. In-process control approaches can be performed to reduce defects of workpieces. A process control architecture based on model predictive control (MPC) is created by Cavone *et al* in [A9]. It considers a multi-variable system model, i.e., the deep drawing process is represented by a single-input multiple-output Hammerstein–Wiener model that relates the blank holder force with the draw-in of n different critical points around the die. A real-world case study is conducted to demonstrate the effectiveness of the proposed process controller in a digital twin framework.

Tresca *et al.* address the problem of automating the definition of feasible pallets configurations in [A10]. It is crucial for the competitiveness of logistics companies. Its solution requires the fast solution of a 3-D bin packing problem (3D-BPP) with additional constraints important for many real-world applications. A metaheuristic is designed to provide pallets configurations for a given set of items. The computed configurations satisfy practical requirements of items' grouping by logistic features, load bearing, stability, height homogeneity, overhang, as well as weight limits, and robotized layer picking. Computational experiments are performed which demonstrate that the proposed method is able to compute high-quality solutions.

IV. Advanced Manufacturing [A11]–[A13]

Digital Twin (DT) has become the key technology and tool for manufacturing industries to realize intelligent cyber-physical integration and digital transformation in the era of Industry 4.0 and beyond. However, developing DT systems to realize intelligent manufacturing is challenging. Hung *et al.* establish a novel implementation framework of digital twins for intelligent manufacturing, denoted as IF-DTiM in [A11], which fully utilizes new-generation container technologies and cloud manufacturing services to gain distinct merits to distinguish itself from other works. IF-DTiM contains Product DT for products, Equipment DT for equipment, and Process DT for production lines, which can generically fulfill the demands and scenarios to achieve intelligent manufacturing for various manufacturing industries. Also, an example DTiM system for CNC machining based on IF-DTiM is presented to facilitate the practitioners to adopt the designs and niches in IF-DTiM to build their desired DTiM systems.

In [A12], An *et al.* introduce the concept of deep reinforcement learning-based detection for addressing the attack strategy against dynamic power grids. The long-short term memory network is used to extract the key features over time and find the system which is attacked. The study considers the continuous attack and discontinuous attack, respectively, and suggests simulation to demonstrate the proposed detection scheme.

In [A13], the process control strategies are proposed by Liu *et al.* to improve the continuous flow of biomass to the reactor in a biorefinery. The stochastic programming technique is formulated to optimize the infeed rate of biomass to the system, processing speed of equipment, and the inventory level under a stochastic carbohydrate content. The sample average approximation is used to approximate the proposed model, and the results showed that sequencing bales based on moisture level and carbohydrate content can improve processing time and processing rate of the reactor.

V. Other Applications [A14]–[A15]

In [A14], compositional optimization is recently proposed by Hagebring *et al.* for the optimization of discrete-event systems. It is based on the idea that a modular optimization model allows to divide the optimization into separate subproblems to mitigate the state space explosion problem. The modular optimization learner (MOL) is proposed in this article. It is a method that interacts with a simulation of a system to automatically learn these modular optimization models.

MOL uses modular learning that takes a hypothesis structure of the system as the input, and uses the provided structural information to split the acquired learning into a set of modules, as well as to prune parts of the search space. Computational experiments prove that modular learning can reduce the state space to a large extent compared to monolithic learning. Hence, it enables the learning of much larger systems.

Manufacturing processes often contain multiple machining operations in sequential order. A complex data-driven model that blindly throws all given data in a single predictive model might not be optimal in such a setting. In [A15], Chung *et al.* suggest a multi-stage inference approach that decomposes a data-driven model into several more manageable sub-problems using the prior knowledge of the operational sequence and then introduces an inference procedure to quantify and propagate uncertainty across operational stages. A case study on additive manufacturing with comprehensive simulations illustrates that the proposed framework provides well-quantified uncertainties and superior predictive accuracy compared to a single-stage predictive approach.

The Guest Editors would like to thank all the authors and reviewers for their outstanding work. The Guest Editors would also like to thank the Editors-in-Chief Michael Wang and Yu Sun, the Editorial Assistant Rebecca Hytowitz, and many others for their efforts devoted to this Special Issue.

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APPENDIX: RELATED ARTICLES

[A1] M. Maggipinto, A. Beghi, and G. A. Susto, “A deep convolutional autoencoder-based approach for anomaly detection with industrial, non-images, 2-dimensional data: A semiconductor manufacturing case study,” *IEEE Trans. Autom. Sci. Eng.*, early access, Jan. 17, 2022, doi: 10.1109/TASE.2022.3141186.

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