

Innovations for Interpretability, Flexibility, and Sustainability in Intelligent Machinery and Industry 4.0

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Three levels, namely the device level, the connection level, and the systems management level, are frequently used to conceptualize intelligent machinery and Industry 4.0. Essentially, for smart manufacturing, intelligent machine tools at the device level must be able to process and transmit data during various input, output, and intermediary stages. The degree of connectivity enables intelligent information sharing and interrogation between machine tools at the connection level. Finally, the systems management level makes it possible to run and manage the entire factory, supply chain system, and value chain system with complete physical and digital synchronization among people, machines, and systems. This Special Issue (SI) provides an open call for submissions on “Innovations in Intelligent Machinery and Industry 4.0” for research and review contributions. Some scopes and topics of innovative and advanced theories and practices include, but are not limited to

- AI, machine learning, and deep learning approaches to complex decision making in smart machinery, such as intelligent control, intelligent diagnosis, and intelligent manufacturing planning;
- Managing and fully utilizing big data collected in real-time from supply chains for intelligent decision making;
- Cloud and edge computing architectures, frameworks, and practical applications for smart machinery;
- IT governance, data security and accessibility issues for complex manufacturing systems and their stakeholders;
- Real cases of innovative machinery design, intelligent machinery applications, implementations, and their impact on manufacturing and services;
- Life-cycle value chain management for smart machinery and Industry 4.0;
- Advanced and integrated digital transformation (DT) technologies and applications for Industry 4.0;
- Theoretical and empirical performance models for AI applications;
- Explainable AI, responsible AI and trustworthy AI for Industry 4.0;
- Sustainable and smart product–service systems (smart PSS) in Industry 4.0;
- Managing the risk of new technologies in Industry 4.0;
- Green and circular economy concept-centric digital transformation (DT) and innovation ecosystems in Industry 4.0;
- Business model-centric digital transformation (DT) and innovation ecosystems in Industry 4.0;
- Forecasting and industrial competitiveness analysis of emerging digital technologies in Industry 4.0, based on bibliometrics and patent analysis;
- Human factors and design of emerging manufacturing and servitization models in Industry 4.0;



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- Analyzing the functional dynamics and new models of the supply chain and the demand chain in Industry 4.0;
- Industry 4.0-based industrial innovation models, and technology policy research based on emerging digital technologies;
- Expert systems, knowledge-based systems, and clouding manufacturing systems for Industry 4.0.

The above topics and scopes are timely for the scholars and researchers who are interested in the research of intelligent machinery and Industry 4.0. Thus, this Special Issue has received quite a few submissions. After rigorous blind-review processes, eleven full articles have been accepted and published. Each of them makes significant contributions to theoretical and applied research, as well as to our understanding of advancements in intelligent machinery in terms of interpretability, flexibility, and sustainability. To provide readers with a glimpse of the eleven articles collected in this Special Issue, the main features and highlights of these papers are briefly described as follows.

Chiang et al. [1] suggested an ideal storage location planning-based consolidated picking approach to drive the smart manufacturing of wireless modules using clustering techniques. In order to develop optimal storage location planning to decrease the time that pickers take to search and retrieve components from the shelves, this research first applies warehouse data to calculate the average duration of stay (DoS) values and estimate the storage space demanded by the customer orders. Based on the macro-level optimal result, this study applied the hierarchical clustering method and the K-means clustering method to identify picking lists with a high degree of similarity. This information will be used to assist warehouse managers in developing the best picking-list consolidation strategy to reduce the distance covered and trips taken by pickers, and to increase picking efficiency. An illustration of a case study of the planning of a new storage location and a consolidated picking process was used to confirm the viability and efficacy of the suggested strategy. The findings of this study, which improved the pickers' productivity and streamlined the picking procedure, can serve as a useful guide for warehouse managers at company H and other businesses.

Yiu et al. [2] developed a digital twin-based platform for intelligent automation using virtual counterparts of flight and air traffic control operations. The authors attempted to integrate the virtual counterparts of different applications of simulation technology in aviation for collaborative decision-making training and research. Given the lack of a collaborative decision-making training platform for air traffic operations in the industry, this study used CPS to design a system architecture for pilots and ATCOs to train in collaborative decision making. It is possible to achieve and enable collaborative decision-making training and the associated intelligent automation aids. To evaluate the platform's latency and integrity, a performance analysis using flight work executed with various computational load settings was created. By suggesting such an integrated system to aid aviation training and advance human performance studies in aviation, this study makes a valuable contribution. The designed platform may be used in a collaborative exercise between pilots and ATCOs for aviation instruction. The standardized vocation educational processes can include instruction in shared situational awareness and collaborative decision making in addition to the current curriculum. This platform offers a strong basis for human-centered research, thereby supporting such research.

De Paepe et al. [3] proposed a comprehensive software stack that combines semantics and machine learning for IoT time series analysis. Then, a platform for proof-of-concept research was created. The platform includes user input, time series ingestion, long-term storage, data semantification, data-driven and semantic event detection, dynamic visualization, and event detection. The novel system architecture of this hybrid analysis platform was depicted, and an overview of the different components and their interactions are given. To show the general applicability of the presented stack for real-life monitoring beyond the presented use case, and given the current pandemic of COVID-19, we are currently researching the potential of the Dyversify stack for COVID-19 airborne transmission mon-

itoring in buildings. As such, the main contribution of this work is an experience report with challenges faced and lessons learned.

Lee et al. [4] proposed an MOS-aware (mean opinion score-aware) mobile network handover mechanism based on deep learning to determine the appropriate handover time for real-time video conference services in mobile networks. The authors constructed a wireless network topology with LTE characteristics in a Mininet-WiFi simulation. User equipment (UE) can determine the service-required MOS (mean opinion score) from the proposed deep learning-based handover mechanism with an appropriate handover time. Simulation results showed that the proposed scheme provides higher performance than the original A3 handover mechanism. This paper contributed to combining real-time video conferencing services with a deep learning-based handover mechanism by predicting MOS values to improve the quality of service for users in mobile networks.

Varna et al. [5] proposed a real-time integrated SMD component detection and classification system using a camera and a CNN deep learning model. The suggested system can identify and count surface-mounted devices (SMDs) that are moving along a conveyor. It is also a low-cost system that can instantly identify surface-mounted components on a conveyor belt, thanks to an embedded microcomputer. Additionally, a system-based performance comparison of various CNN deep learning models was offered. The mean average precision and inference time were used to compare the effectiveness of the algorithms under investigation. A low-cost integrated system for a conveyor to detect packed and unpacked moving SMD components is demonstrated using the proposed hardware setup. With all restrictions, the system satisfies the need for real-time detection in an industrial setting. A dataset including 7061 images of 8198 capacitors, 10,467 resistors, 8543 diodes, and 1328 transistors produced the experimental results. The average precision ratings for capacitor and resistor detection were 97.3% and 97.7% on four different surface-mounted components, respectively. The findings suggest that the system with the implemented YOLOv4 tiny algorithm on the Jetson Nano 4 GB microcomputer achieves a mean average precision score of 88.03% with an inference time of 56.4 ms, and 87.98% mean average precision with a 11.2 ms inference time on the Tesla P100 16 GB platform.

Yang et al. [6] designed and implemented an explainable bidirectional long short-term memory (Bi-LSTM) model, based on a transition system approach, for cooperative AI workers. In this study, the manufacturing process time was predicted using log data. The data preprocessing was carried out using the transition system. The Bi-LSTM model was used for learning, though LSTM has the drawback of tending to converge based on the previous pattern. A Bi-LSTM with an added reverse LSTM has been created to improve the LSTM's performance. In this paper, the manufacturing execution time was predicted. Through several experiments, the research demonstrated that bidirectional learning produces better results than prediction based solely on historical manufacturing execution data. An AI model was created and the results of the experiments were compared and analyzed to demonstrate the viability of the approach. In addition, a qualitative analysis using explainable AI (XAI) approach was made possible through a visual graph. The findings of the experiments presented in this paper indicate that it is possible to convert the manufacturing process prediction model trained using the transition system into an explanatory AI model.

Customer demand changes frequently in the roofing manufacturing industry. Standard dispatch rules for assigning manufacturing resources are not efficient. Ren et al. [7] proposed a combinatorial dispatch rule with the three basic dispatch rules: earliest due date (EDD), first in first out (FIFO), and shortest processing time (SPT). The new scheduling algorithm was able to reduce material changing lead time by over 40%.

Hinojosa-Meza et al. [8] proposed a cost-effective and portable instrumentation to enable accurate pH measurements for Industry 4.0-based vertical farming applications. By performing a well-designed sensor calibration, near Nernstian response was demonstrated. The instrumentation was shown to be precise in determining the pH of substances in the 2–14 range when compared to a laboratory gold standard that is ten times more expensive

to implement. With an average absolute deviation of 0.06 pH units and a standard deviation of 0.03 pH units, the instrument was proven to yield accurate pH results.

Trappey et al. [9] utilized machine learning language models to generate innovative knowledge graphs for an advanced patent mining interface. This study focuses on automatically generating knowledge graphs of utility patents with novel (chemical) processes. The research methods are split in two parts: (1) the visualization of chemical processes in a chemical patent's most relevant paragraphs, and (2) a knowledge graph of any domain-specific collection of patents. The language modeling algorithms applied in this research, include sentence-BERT for sentence classification, keyBERT for keyword extraction, and ALBERT for text vectorization. The results demonstrate that the average retention rate of the knowledge summary graphs for the case study exceeds 80%. This study shows that using a graphical approach to represent patent knowledge is a big step forward from basic text-based summarization during patent mining.

In semiconductor manufacturing, predicting the wafer material removal rate (MRR) is crucial for overall quality control. In order to predict the MRR, Liu et al. [10] proposed a fusion network deep learning model which consists of deep features created by non-linear transformations and shallow features encoded from domain knowledge. The proposed method was tested on a dataset from the 2016 Prognostics and Health Management Data Challenge, and demonstrated superior performance against three other ensemble learning techniques.

Service design is difficult due to our inability to characterize disadvantaged flows. Zhonghang et al. [11] proposed a new approach, targeting the causes of the service process problem to find an optimum solution. The method visualizes service process problems using a model with service touchpoints. Process-trimming rules are then applied to trim disadvantaged flows. Dominance rules can then be used to rank the program for optimization. The service design method has been illustrated with an application for successfully designing medical and health services.

This Special Issue covers a broad range of industries and use cases in Industry 4.0. These include warehouse pickup optimization in electronics manufacturing [1], digital twin intelligence platforms in aviation [2], public health social experimentation projects in the public sector [3], video service conference upgrade applications in network telecommunications [4], AI-based product inspection in electronics manufacturing [5], manufacturing time prediction using Bi-LSTM and XAI approaches [6], an algorithm for more efficient production planning and scheduling in roofing manufacturing [7], portable and intelligent pH measurement for agriculture [8], graphical representation of patent knowledge for patent analysis [9], more accurate wafer material removal prediction for the semiconductor industry [10], and reduction of the problems associated with service process flow design in the health service industry [11]. The guest editors thank all the authors for their contributions to this Special Issue. This Special Issue is intended to be a modest but significant step towards the research frontiers of intelligent machinery/manufacturing and Industry 4.0. We sincerely hope these papers will pique researchers' interests in and enthusiasm for the aforementioned research scopes and topics.

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

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