Editorial

Semantic artificial intelligence for smart manufacturing automation

Smart manufacturing is arriving [1]. It promises a future of highly responsive manufacturing operations with advanced sensing, reasoning, and decision-making capabilities towards mass personalization [2]. Statistical AI, e.g., machine learning technologies, has shown great potential in making manufacturing smart [3]. However, Statistical AI's approximative, agnostic, and context- and task-specific nature has limited its implementation in real-world manufacturing contexts, which demand guaranteed product quality, robust system performance, and ubiquitous transparency. Semantic AI – the combination of Statistical AI and Symbolic AI technologies, could be the answer to the in-depth adoption of AI technologies in industry. Semantic AI enables interpretable manufacturing decisions with augmented intelligence via integrating the merits of statistical learning and semantic reasoning. This timely special issue contains ten articles demonstrating state-of-the-art achievements on Semantic AI, focusing on a variety of technologies, i.e., knowledge graph, semantic web, knowledge discovery, meta-heuristic algorithms, reinforcement learning, and deep learning, with novel applications in machining process automation, assembly troubleshooting, system simulation, production scheduling, 4D printing and robot automation.

In the paper titled *"An automatic method for constructing machining process knowledge base from knowledge graph"*, Guo et al. developed an automatic knowledge construction framework and integrated algorithms for extracting, representing and fusing machining knowledge from textual sources in the field of machining. Apart from their developed algorithms, they also provided a feasible approach to structuralizing, cleaning and processing unstructured machining knowledge cues.

In a slightly different application scenario – assembly root cause analysis and troubleshooting, Ning et al., in *"Knowledge discovery using an enhanced latent Dirichlet allocation-based clustering method for solving on-site assembly problems"*, developed a knowledge discovery approach to mining assembly problems, causes and solutions from historical troubleshooting records. Their general methods of topic modeling, clustering and pattern association provided insights on mining empirical rules from a textual corpus.

In the paper titled *"Transformation of semantic knowledge into simulation-based decision support"*, Jurasky et al. coined an ontological approach to developing a digital replica for simulation. This enables fast and profound model-based decisions, particularly beneficial in a dynamic and uncertain environment. Their work consists of three components: (1) the Simulation Ontology, a semantic model for the basic building blocks and interrelationships of a simulation, (2) Mapping Rules that support the transfer of knowledge from an existing domain ontology into instances of the Simulation Ontology and thereby present a novel approach for model conceptualization, as well as (3) a Parser, which automatically generates an executable simulation model from the instantiated Simulation Ontology. Their framework was validated in an order fulfillment simulation application.

In the paper titled *"Semantic coupling of path planning and a primitive action of a task plan for the simulation of manipulation tasks in a virtual 3D environment"*, Zhao et al. proposed an ontology-based approach that uses semantic task-level information to generate paths for a primitive action of a task plan. Results demonstrated better path planning control via task-related information, leading to lower computational time and more relevant trajectories for primitive actions.

In the paper titled *"A semantic-level component-based scheduling method for customized manufacturing"*, Li and Tang developed a semantic-enriched information model to obtain shopfloor status via semantic reasoning, together with a computation model to abstract the stochastic scheduling process of production. They then integrated the semantic model with the computation model for dynamically assigning production tasks to manufacturing resources.

When knowledge is difficult to be obtained from existing data sources, implicit knowledge could be derived from exploring the solution space in a dynamic system. Heuristic and meta-heuristic methods are prominent examples of such methods. In *"Network-based dynamic dispatching rule generation mechanism for real-time production scheduling problems with dynamic job arrivals"*, Zhuang et al. developed a network-based dynamic task dispatching rule generation mechanism to achieve real-time production scheduling in smart factories, when heterogenous manufacturing jobs arrive dynamically.

Advanced meta-heuristic algorithms can also be used for co-optimizing production schedules in distributed factories. In the paper titled *"Production scheduling for blocking flowshop in distributed environment using effective heuristics and iterated greedy algorithm"*, Chen et al. presented a list of meta-heuristic algorithms and an iterated greedy algorithm for solving the blocking flowshop problem in a distributed production network.

Reinforcement learning is another algorithm for learning knowledge from environment interaction. Focusing on high-mix-low-volume dynamic production, Zhou et al. in *"Multi-agent reinforcement learning for online scheduling in smart factories"* developed a distributed multi-agent learning scheme for scheduling production jobs between heterogeneous manufacturing units. The authors developed an AI scheduler with neural networks for each manufacturing unit. These AI schedulers make scheduling policies independently and can collaborate to handle unexpected events such as urgent work orders and machine failures.

In a relatively new application domain – 4D printing, Ji et al., in *"Optimal shape morphing control of 4D printed shape memory polymer based on reinforcement learning"*, developed a reinforcement learning-based closed-loop control scheme for Shape Memory Polymer actuation. Precise and prompt shape morphing is achieved compared with a PI controller. The training efforts of reinforcement learning are further reduced by simplifying the optimal control policy using the structural property of the prior trained results.

The last article – *"Error compensation of industrial robot based on deep belief network and error similarity"*, established a mapping model between a robot's theoretical pose coordinates and its actual pos errors, based on deep belief networks and error similarity. This model is then used for pose error prediction. The proposed scheme can enhance a deep belief network's learning capability and interpretability by adding the extracted error similarity information between samples.

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[1] Y. Lu, X. Xu, and L. Wang, 'Smart manufacturing process and system automation – A critical review of the standards and envisioned scenarios', *Journal of Manufacturing Systems*, vol. 56, no. July, pp. 312–325, Jul. 2020.

[2] Y. Lu, C. Liu, K. I.-K. Wang, H. Huang, and X. Xu, 'Digital Twin-driven smart manufacturing: Connotation, reference model, applications and research issues', *Robotics and Computer-Integrated Manufacturing*, vol. 61, p. 101837, Feb. 2020.

[3] J. Wang, Y. Ma, L. Zhang, R. X. Gao, and D. Wu, 'Deep learning for smart manufacturing: Methods and applications', *Journal of Manufacturing Systems*, vol. 48, pp. 144–156, Jul. 2018.

Yuqian Lu (Lead editor)
The University of Auckland, Department of Mechanical and Mechatronics Engineering, 20 Symonds Street, Auckland, 1010, New Zealand
Email: yuqian.lu@auckland.ac.nz

Lihui Wang
KTH Royal Institute of Technology, Department of Production Engineering, Brinellvagen 68, 114 28, Stockholm, Sweden
Email: lihuiw@kth.se

Jinsong Bao
Donghua University, College of Mechanical Engineering, Renming North Road 2999, Shanghai 201620, China
Email: bao@dhu.edu.cn

Jose Martinez Lastra
Tampere University, Faculty of Engineering and Natural Science, P.O. Box 600 FI-334100, Tampere, Finland
Email: jose.martinezlastra@tuni.fi

Farhad Ameri
Texas State University, Department of Engineering Technology, 601 University Dr. San Marcos, TX 78666 USA
Email: ameri@txstate.edu