ISSN: 0974-5823 Vol. 7 (Special Issue 4, 2022)

International Journal of Mechanical Engineering

Towards Intelligent Manufacturing Systems for Industrial Revolution 4.0: An Overview

Syahrul N. Junaini

Universiti Malaysia Sarawak, 94300 Kota Samarahan, Sarawak, Malaysia.

Mohd Saleh Abbas

INTI International University, Nilai, Negeri Sembilan, Malaysia

Zakaria Amir

Azman Hashim International Business School, Universiti Teknologi Malaysia

Sarina Mail

Universiti Teknologi Malaysia, Malaysia

Farah Zeehan

Department of academic Excellence, Teacher Education Institute Temenggong Ibrahim Campus, Johor, Malaysia

Muhaimin Haziq Mihat

Institute of Nano Optoelecteonics Research and Technology (INOR), Universiti Sains Malaysia, Pulau Pinang, Malaysia

Abstract - Throughout the previous decade, the fourth industrial revolution has created many chances to enhance manufacturing and production processes. These innovations aim to bridge the divide between physical and digital technology in order to create a more intelligent and efficient manufacturing system. To completely grasp the relationship between intelligent manufacturing and IR4.0, first, we begin with reviewing eight advantages of intelligent manufacturing in relation to IR 4.0. Second, while deploying an intelligent manufacturing system inspired by AI has several benefits, it also introduces several complications. Finally, we see Cyber Physical Systems (CPS) as an innovative option for researching and developing intelligent manufacturing processes.

Index Terms - Industrial Research, Intelligent Manufacturing, Internet of Things, Manufacture

INTRODUCTION

Over the last few years, the fourth industrial revolution, (referred to as Industry 4.0) has created various enhancements to manufacturing and production processes. These innovations aim to combine physical and digital technology to create a more intelligent manufacturing system that is more efficient [1]. The aim of this paper is to provide an overview of the literature on intelligent manufacturing systems, with a focus on the industrial revolution 4.0.

This paper is organized as follows: Next, we present benefits of implementing intelligent manufacturing for IR4.0. After that, we discuss challenges in AI-inspired intelligent manufacturing systems (IMS). After that, we present a brief idea of how Cyber Physical Systems (CPS) could be an innovative option for and developing intelligent manufacturing processes.

BENEFITS OF IMPLEMENTING INTELLIGENT MANUFACTURING FOR IR 4.0

The first benefit is that intelligent manufacturing exploits developments in wireless networking, the Internet of things, and big data [2]. These technologies are convergent in the sense that they help organizations to boost their efficiency and minimize their expenses. The purpose of an intelligent manufacturing system is to enable a corporation to minimize costs and boost efficiency [3]. By building a platform for innovation support capacity it promotes collaboration across departments and production lines [4].

Second, as conventionally, the typical manufacturing process is sequential—on the other hand, intelligent manufacturing permits the use of many machines to do the same task at various locations, controlled by computers. For instance, by utilizing intelligent manufacturing techniques, a machine may produce more and more components concurrently. We refer these operations to as concurrent engineering. Intelligent manufacturing systems accomplish these goals through the use of several technologies, including sophisticated analytics tools [5].

Third, intelligent manufacturing technologies boost the machinery capability and return on investment, while also shortening the time required and increasing efficiency. This is true with the advent of machine learning. It is a branch of artificial intelligence that focuses on computers' ability to learn from, understand, and forecast data. In the smart factory setting, they used it for predictive maintenance [6]. They may also use it with imaging and sensor technologies to monitor the functioning of systems [7].

In addition, machine learning may predict the ideal production output and differentiate it from nonconforming products [8]. The intelligent manufacturing system can then adjust to ensure the product meets specified quality criteria.

Fourth, intelligent manufacturing processes can improve the long-term efficiency of a machinery or plant based on the criteria of mutual information [9]. In a production line, it is possible for each product to be created on many lines rather than one. For instance, if a product must be created in three separate colours, three distinct lines might be used. The intelligent manufacturing system will recognize this and will then pick the optimal mix of machines to finish the work. Beyond job sequencing, intelligent manufacturing automation can determine the optimal combination of equipment and workers, resulting in a more fluid manufacturing process towards [10].

Fifth, intelligent manufacturing makes production processes more adaptive and efficient, thus fostering rapid company growth [11]. Intelligent manufacturing offers a more seamless and enhanced production process that is easier to monitor. Apart from these advantages, intelligent manufacturing systems can dramatically reduce waste and disposal, for example using digital twin [12]. This would ultimately result in a more productive and sustainable production.

Sixth, intelligent manufacturing processes have the potential to have a broad variety of consequences for businesses' interests. For example, it may be utilized to create new business models and boost the performance of small and medium-sized enterprises (SMEs) [13]. Here, intelligent manufacturing processes can help reduce costs [14], improve health and safety standards [15], expand production capacity and monitoring [16], as well as efficient inspection to adapt to ambiguity in industry demand [17]. Indeed, intelligent manufacturing may boost small SME’s innovation and competition edge.

Seventh, artificial intelligence (AI) and deep learning is expected to fuel the next generation of industrial systems. Artificial intelligence may help organizations reduce mistakes, boost productivity, and operational performance to cater the ever-changing landscape of Industry 4.0 [18]. The influence of artificial intelligence on manufacturing will be concentrated on the systems themselves, as well as the added value they bring to their users. While artificial intelligence may be used to a wide variety of industrial processes, AI will help to automate, optimize, and control manufacturing processes [19]. Artificial intelligence is rapidly being integrated into production processes and has the potential to handle a range of manufacturing-related concerns.

Finally, intelligent manufacturing processes can help firms and governments boost their openness in managing manufacturing data. For instance, using intelligent manufacturing processes may increase a process's visibility to stakeholders, allowing for more effective monitoring and governance [20]. As a result, intelligent manufacturing processes have the potential to significantly reduce costs, increase productivity, and increase profitability [20].

CHALLENGES IN AI-INSPIRED INTELLIGENT MANUFACTURING SYSTEMS (IMS)

While deploying AI-inspired intelligent manufacturing system has several advantages, it also poses a few challenges. This issue demands investment in technology. To do so, corporations and governments must finance the technology, software, and staff.

The first challenge is that intelligent manufacturing system requires a comprehensive, integrated system to be considered from top to bottom, from management systems to worker capabilities. For example, production engineering, and process control may be influenced by intelligent manufacturing systems. Along with an increased importance on the Internet of Things (IoT) in recent years, there has been an increased emphasis on the development of IMS [21].

IMS systems provide a full and integrated solution for product and process development, as well as production processes [22]. For example, IoT facilitates machinery connectivity, allowing for the collecting of data from sensors and its application to decision-making [23]. It also enables real-time data-driven monitoring of manufacturing processes [24]. Globally, the IoT technology is expanding at a great pace. Indeed, IoT enables the future of production by making systems smarter and more connected. It has the potential to have a significant impact on not just industry, but also on society [25]. We expect ioT to completely reengineer manufacturing processes, resulting in significant cost savings.

The second challenge is, we often view IMS as a time-consuming and difficult technology to deploy in industrial organizations. This is because IMS includes a broad range of technologies, from sophisticated big data analytics [5], [18] to innovative manufacturing methods. Additionally, the inherent complexity of industrial operations complicates integrating various technologies effectively. Designing and deploying an IMS requires close collaboration across a range of stakeholders, including managers, engineers, and employees [26]. While various barriers exist, the potential effect of IMS makes it an appealing study issue.

Third, although artificial intelligence has been a subject of study for decades, it was not primarily concerned with factory and machinery control engineering. Control engineering is concerned with the design of systems to regulate one or more variables. However, recently, interest in fusing artificial intelligence with control engineering to produce intelligent controllers has soared. One of these methods is distributed artificial intelligence (DAI) [27]. It may construct systems capable of independently changing their behavior in response to changing operational situations or uncertainties encountered. An intelligent manufacturing system utilizes humans, cyber systems, and physical systems to fulfill defined production objectives.

CYBER-PHYSICAL SYSTEMS (CPS) FOR IMS

Cyber Physical System (CPS) is a cutting-edge research and development field devoted to the study and development of intelligent industrial processes. Introducing the CPS concept and the growth of smart manufacturing has increased the competitiveness of the manufacturing industry [28].

In the meantime, CPS has earned a reputation for automating machines to create more efficient manufacturing processes. Real-time sensor data analysis is crucial for optimizing production flow and reducing downtime. CPS is based on integrating various layers of information technology into manufacturing machinery, and it can change manufacturing processes, product structure, and manufacturing system [29]. Many sensors and actuators, the use of embedded computers to gather data from sensors and operate actuators, the use of standard protocols to improve the efficiency of production lines, and so on.

CONCLUSION

In summary, the fourth industrial revolution has improved manufacturing processes in several ways. We have discussed eight benefits of improving intelligent manufacturing for IR 4.0. While implementing an intelligent manufacturing system inspired by AI provides a lot of advantages, it also presents several problems. We also introduced Cyber Physical Systems (CPS) as a cutting-edge branch of research and development dedicated to the study and development of intelligent industrial processes.

REFERENCES

[1] A. Jamwal, R. Agrawal, M. Sharma, and A. Giallanza, “Industry 4.0 technologies for manufacturing sustainability: A systematic review and future research directions,” *Appl. Sci. Switz.*, vol. 11, no. 12, 2021, doi: 10.3390/app11125725.

[2] L. D. Gitelman and M. V. Kozhevnikov, “Electrification in industrial revolution 4.0,” *Int. J. Energy Prod. Manag.*, vol. 5, no. 4, pp. 367–379, Nov. 2020, doi: 10.2495/EQ-V5-N4-367-379.

[3] Y. Xiao and Z. Zeng, “A Construction Method of Intelligent Manufacturing System under Industry 4.0 Model,” *Sci. Program.*, vol. 2021, 2021, doi: 10.1155/2021/4775237.

[4] X. Zhang, “Economic benefit evaluation modelling of intelligent manufacturing enterprises based on entropy value method,” *Int. J. Manuf. Technol. Manag.*, vol. 35, no. 3, pp. 271–285, 2021, doi: 10.1504/IJMTM.2021.118807.

[5] J. Wang, C. Xu, J. Zhang, and R. Zhong, “Big data analytics for intelligent manufacturing systems: A review,” *J. Manuf. Syst.*, 2021, doi: 10.1016/j.jmsy.2021.03.005.

[6] S. Ayvaz and K. Alpay, “Predictive maintenance system for production lines in manufacturing: A machine learning approach using IoT data in real-time,” *Expert Syst. Appl.*, vol. 173, 2021, doi: 10.1016/j.eswa.2021.114598.

[7] M. Syafrudin, G. Alfian, N. L. Fitriyani, and J. Rhee, “Performance analysis of IoT-based sensor, big data processing, and machine learning model for real-time monitoring system in automotive manufacturing,” *Sens. Switz.*, vol. 18, no. 9, 2018, doi: 10.3390/s18092946.

[8] S. M. Acosta and A. M. Oliveira Sant’Anna, “Machine learning-based control charts for monitoring fraction nonconforming product in smart manufacturing,” *Int. J. Qual. Reliab. Manag.*, 2022, doi: 10.1108/IJQRM-07-2021-0210.

[9] M. Xu, J. Sheng, B. An, and N. Kang, “Intelligent manufacturing resource allocation efficiency based on mutual information criterion,” *Jisuanji Jicheng Zhizao XitongComputer Integr. Manuf. Syst. CIMS*, vol. 23, no. 9, pp. 1842–1852, 2017, doi: 10.13196/j.cims.2017.09.002.

[10] H. Quinones and Y. Yong, “Intelligent manufacturing automation,” 2017. [Online]. Available: https://www.scopus.com/inward/record.uri?eid=2-s2.0-85015720454&partnerID=40&md5=efe97228a882d8f28225cb484deccb6b

[11] C.-F. Chien and C.-C. Chen, “Adaptive parametric yield enhancement via collinear multivariate analytics for semiconductor intelligent manufacturing,” *Appl. Soft Comput.*, vol. 108, 2021, doi: 10.1016/j.asoc.2021.107385.

[12] B. He and K.-J. Bai, “Digital twin-based sustainable intelligent manufacturing: a review,” *Adv. Manuf.*, vol. 9, no. 1, 2021, doi: 10.1007/s40436-020-00302-5.

[13] T. Geng and Y. Du, “The business model of intelligent manufacturing with Internet of Things and machine learning,” *Enterp. Inf. Syst.*, vol. 16, no. 2, pp. 307–325, 2022, doi: 10.1080/17517575.2020.1722253.

[14] Z. Wang, W. Zhang, X. Jin, Y. Huang, and C. Lu, “An optimal edge server placement approach for cost reduction and load balancing in intelligent manufacturing,” *J. Supercomput.*, vol. 78, no. 3, pp. 4032–4056, 2022, doi: 10.1007/s11227-021-04017-7.

[15] A. Gu, Z. Yin, C. Fan, and F. Xu, “Safety Framework Based on Blockchain for Intelligent Manufacturing Cyber Physical System,” in *Int. Conf. Ind. Artif. Intell., IAI*, 2019, vol. 2019-January. doi: 10.1109/IAI47267.2019.9085328.

[16] W. Chen, “Intelligent manufacturing production line data monitoring system for industrial internet of things,” *Comput. Commun.*, vol. 151, pp. 31–41, 2020, doi: 10.1016/j.comcom.2019.12.035.

[17]C. Xu and G. Zhu, “Intelligent manufacturing Lie Group Machine Learning: real-time and efficient inspection system based on fog computing,” *J. Intell. Manuf.*, vol. 32, no. 1, pp. 237–249, 2021, doi: 10.1007/s10845-020-01570-5.

[18] R. Dubey *et al.*, “Big data analytics and artificial intelligence pathway to operational performance under the effects of entrepreneurial orientation and environmental dynamism: A study of manufacturing organisations,” *Int. J. Prod. Econ.*, vol. 226, 2020, doi: 10.1016/j.ijpe.2019.107599.

[19] A. T. Rizvi, A. Haleem, S. Bahl, and M. Javaid, *Artificial Intelligence (AI) and Its Applications in Indian Manufacturing: A Review*, vol. 52. Springer Science and Business Media Deutschland GmbH, 2021, p. 835. doi: 10.1007/978-981-33-4795-3_76.

[20] F. Lampathaki, C. Agostinho, Y. Glikman, and M. Sesana, “Moving from ‘black box’ to ‘glass box’ artificial intelligence in manufacturing with XMANAI,” 2021. doi: 10.1109/ICE/ITMC52061.2021.9570236.

[21] P. Trakadas *et al.*, “An artificial intelligence-based collaboration approach in industrial iot manufacturing: Key concepts, architectural extensions and potential applications,” *Sens. Switz.*, vol. 20, no. 19, pp. 1–20, 2020, doi: 10.3390/s20195480.

[22] C. Liu, R. Luosang, X. Yao, and L. Su, “An integrated intelligent manufacturing model based on scheduling and reinforced learning algorithms,” *Comput. Ind. Eng.*, vol. 155, 2021, doi: 10.1016/j.cie.2021.107193.

[23] L. Shan, Z. Wang, and C. Jiang, “Key technologies of real-time visualization system for intelligent manufacturing equipment operating state under IIOT environment,” *J. Internet Technol.*, vol. 21, no. 5, pp. 1479–14789, 2020, doi: 10.3966/160792642020092105021.

[24] L. Zhang, Y. Hu, Q. Tang, J. Li, and Z. Li, “Data-driven dispatching rules mining and real-time decision-making methodology in intelligent manufacturing shop floor with uncertainty,” *Sensors*, vol. 21, no. 14, 2021, doi: 10.3390/s21144836.

[25] H. B. Mahajan, A. Badarla, and A. A. Junnarkar, “CL-IoT: cross-layer Internet of Things protocol for intelligent manufacturing of smart farming,” *J. Ambient Intell. Humaniz. Comput.*, vol. 12, no. 7, pp. 7777–7791, 2021, doi: 10.1007/s12652-020-02502-0.

[26] M. Zhang, L. Shi, X. Zhuo, and Y. Liu, “Research on collaborative efficiency evaluation of complex supplier network under the background of intelligent manufacturing,” *Processes*, vol. 9, no. 12, 2021, doi: 10.3390/pr9122158.

[27] R. Klamma *et al.*, *Scaling mentoring support with distributed artificial intelligence*, vol. 12149 LNCS. Springer, 2020, p. 44. doi: 10.1007/978-3-030-49663-0_6.

[28] Y. Cui, S. Kara, and K. C. Chan, “Manufacturing big data ecosystem: A systematic literature review,” *Robot. Comput.-Integr. Manuf.*, vol. 62, p. 101861, 2020.

[29] X. Zhou *et al.*, “Intelligent Small Object Detection Based on Digital Twinning for Smart Manufacturing in Industrial CPS,” *IEEE Trans. Ind. Inform.*, 2021, doi: 10.1109/TII.2021.3061419.