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EFFICIENT PRACTICES OF COGNITIVE TECHNOLOGY APPLICATION FOR SMART MANUFACTURING

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Abstract:
Cognitive manufacturing (CM) provides for the merging of sensor-based information, advanced analytics, and cognitive technologies, mainly machine learning in the context of Industry 4.0. Manufacturers apply cognitive technologies to review current business metrics, solve essential business problems, generate new value in their manufacturing data and improve quality. The article investigates four powerful applications for cognitive manufacturing and their influence on a company`s maintenance. The study aims to observe kinds of cognitive technology applications for smart manufacturing, distinguish their prospective gains for manufacturers and provide successful examples of their adoption. The analysis is based on the literature and report review. Assessment of the cases of technology adoption proves that cognitive manufacturing provides both enhanced knowledge management and helps organizations improve fundamental business measurements, such as productivity, product reliability, quality, safety, and yield while reducing downtime and lowering costs.

Key words: *cognitive manufacturing, cognitive technology, Industry 4.0*

INTRODUCTION

Innovative scientific tendencies, the emergence of manufacturing 4.0 and cognitive technologies impact manufacturing procedures and effectiveness. The fundamental idea of Industry 4.0 is to adopt the Internet of Things (IoT), artificial intelligence (AI), and cyber-physical systems thus manufacturing process and business process are extremely integrated to provide flexible and efficient production [1, 2]. Manufacturing continues to change as organizations equip their factory with technologies and apply complex data analytics to improve performance, product quality, and the way perception of manufacturing information is found and responded to.

According to the 2022 manufacturing industry outlook by Deloitte, an increase in investment in artificial intelligence technologies is expected at a compound annual growth rate above 20% through 2025 [3]. A global transformation is in progress to equip manufacturing with AI. Discrete manufacturing ranks among the three industries with the highest levels of contribution in AI including quality management and automated preventive maintenance use cases [3].

In the McKinsey Global Survey "The State of AI in 2021" predictive maintenance and yield, energy, and/or throughput optimization are defined to be the most adopted AI use cases within manufacturing [4, 5]. Across manufacturing respondents, they report higher levels of cost decreases from AI adoption in more than one-and-one-half times in the fiscal year 2020 compared to the fiscal year 2019 with a dramatic increase of percentage representing a decrease of more than 20 per cent while revenue increase remains almost at the same level [4].

Considering the cognitive technology to be a part of the larger area of AI and a dramatic increase in technologies adoption, cognitive technology application for smart manufacturing is worth examining**.** Hence the article aims to investigate four applications for cognitive manufacturing, what areas of manufacturing they can refer to, what are advantages for manufacturers for embedding CT into production and give examples confirming the success of cognitive technology application.

LITERATURE REVIEW

The use of technologies in different fields under Industry 4.0, such as robotics and artificial intelligence, poses a new requirement [6]. The approach of cognitive manufacturing is consonant with such concepts as smart manufacturing [7], and Industry 4.0 [3, 8, 9]. The authors [8, 9] figure out Industry 4.0 as the most essential part of the Fourth Industrial Revolution with smart manufacturing being part of it, overlapping concepts, namely the industrial internet, the industrial internet of things and intelligent manufacturing.

Two major technologies that are pushing Industry 4.0 are IoT and analytics [10, 11]. IoT allows factories to improve their instrumented and interconnected status with the ability to provide gained relevant data together from the manufacturing environment in real-time. Moens and others [12] provide an Industrial Internet of Things (IIoT) system that includes smart maintenance solutions. They reveal the robustness and scaling of solutions as well as the availability of well-trained machine learning models in case of defect recognition. Industrial IoT establishes new features in industrial automation systems which are determined by improving system robustness and flexibility [13].

Analytics stands for determining templates in the data, a pattern of equipment approach and a forecast of possible breakdowns. It implies a variety of statistical techniques including pattern recognition, text analytics, cluster analysis, factor analysis, multivariate modelling, multiple regression, forecasting, machine learning, simulation, and neural networks [14]. The research of Rousopoulou V. and others introduce cognitive analytics, self-and autonomous-learned system bearing predictive maintenance solutions for Industry 4.0 [15, pp. 75-85]. Whereas the application of machine learning, as one of the AI-based techniques, in the manufacturing industry is deeply analysed in the article of Cioffi R. and others [16].

The application of IoT improves manufacturing processes, as machinery and equipment become more intelligent and dynamic thanks to automation and self-optimization [17]. The more factories and appliances are applied with the IoT, the more quantity of data is. To cope with the large inflow of data and the complicatedness of analytics computing become cognitive [18, p. 4]. Therefore, to respond to the requirements of Industry 4.0 manufacturing transforms into cognitive manufacturing. Cognitive manufacturing improves businesses by using the IoT as the base and involving advanced analytics merging with cognitive technologies, as a result, it provides better indicators for quality, efficiency, and reliability characteristics.

Techniques that fulfil and augment tasks, assist in decision making, and help to meet targets that demand human intelligence are specified as cognitive technologies. Specifically, cognitive language technologies include a group of digit technologies able to analyse, understand and output human languages while interacting with machines; cognitive machine learning provides automated analysis by algorithms that avail of received data not necessarily envisaging specific programming; cognitive computer vision can extract and measure information from images even better than human vision. These technologies indicate that cognitive computing can assist manufacturers and provide information to help them decide on a system of activities.

Manufacturing companies can benefit from smart factory implementation, the adoption of the production facility that encompasses AI, robotics, analytics, big data and the IoT, with an increase in process efficiency, lower operational costs, increased safety and sustainability, and increased product quality [19]. Manufacturers adopt cognitive technologies to detail manufacturing processes and business environments aiming at obtaining information suited for further manufacturing processes digitizing and optimization. Targets for cost-effectiveness, quality, product reliability, cost, and time efficiency force organizations to search for ways how to improve their manufacturing processes.

The concept of cognitive manufacturing is relevant to the ability to deal with complex modern production systems and have a quick reaction to unforeseeable issues in production, planning and control systems. Thus, the Cognitive Factory is assumed to be flexible, adaptable, reliable, and efficient in various momentary situations [20].

METHODOLOGY

The methodology of this article was based on a three-step approach. The first step included preliminary research on the concept of cognitive manufacturing and obtaining a deeper knowledge of the research area. The second stage consisted of the examination of academic literature and report review on the applications for cognitive manufacturing leading to a restraint of the scope of a theoretical foundation. The last one covered case studies of cognitive technologies adoption to analyse their impact on the maintenance of an organization.

RESULTS OF RESEARCH

Cognitive manufacturing extracts applicable information together automatically and employs analytics to get an understanding of the manufacturing process. It robotizes reactions towards its findings and offers practical information being able to steadily deliver updated knowledge to decision-makers.

Cognitive manufacturing covers four powerful applications, which are reliability and performance management or asset performance management (APM), process and quality improvement, optimization of resources, and supply chain optimization [10, 21, 22]. These applications are presented in Table 1 encompassing the information about the categories of cognitive technologies and gains of manufacturers embedding technological solutions. It is found that applications of cognitive technologies are classified into three main categories: product, process, and insight [23] or cognitive engagement, cognitive automation, and cognitive insights [24]. Though the titles differ, their senses coincide. Therefore, product applications are adopted to a product or service to provide end-customer advantages while cognitive engagement involves cognitive technologies application to augment the end-user experience by proposing mass consumer personalisation at scale. Process applications are implemented into an organization's workflow to automate or improve operations while cognitive automation is mainly used to reproduce simplified mental processes. And insight applications use cognitive technologies to reveal insights due to operational and strategic decisions while cognitive insights can develop new patterns on the base of analysed large scale data sources in real-time and create additional-value insights. In terms of CM, we can conclude that such type of cognitive technologies as insight prevails as cognitive systems are capable of building relationships on base both structured and unstructured information, conducting analysis, and generating perceptions as regards decision-making to improve manufacturing maintenance. Process as a category cannot be minimized as manufacturing practically consists of systematically connected activities, automation of which can improve performance of an organization.

APM (Table 1) improves the accuracy and maintenance of equipment and assets. Intelligent assets and equipment employ interconnected sensors, analytics, and cognitive capabilities to sense, communicate and self-diagnose any type of failures that can arise [25, p. 57].

Cognitive manufacturing applies advanced analytics and data mining techniques to decrease unnecessary downtime, and maintenance costs and enhance productivity. Cognitive APM can not only foresee a potential issue, but it can also gain information about similar cases, and relevant data on how such issues have been fixed before and based on such information it gives recommendations on how to solve the impending failure. In the report, it is stated that cognitive APM application has allowed an automotive manufacturer to reduce equipment downtime by 34 per cent and decrease equipment maintenance costs by 10 per cent [10]. Other examples are the successful cases of the AI predictive maintenance platform adopted by Nissan and smart sensor and advanced machine learning analytics applied by Deutsche Bahn [26, 27]. The company claims an unplanned downtime reduction of 50% and a payback period of fewer than 3 months. Deutsche Bahn uses smart sensors and advanced machine learning analytics to reduce maintenance costs and avoid infrastructure failure. These technologies have allowed the rail network company to achieve a cost reduction of 25 per cent. Leading global manufacturer of industrial pumps, seals, and valves and service provider of comprehensive flow control systems has achieved a decrease in the maintenance costs and improvement of asset availability for users by up to 10 per cent; detected events or predicted failures become possible in 5-6 days in advance – instead of hours with an advisory application for predictive maintenance, supported by machine learning and augmented by natural language processing [14].

Process and quality improvement (Table 1) optimize the yield and productivity of manufacturing operations. Cognitive processes and operations involve the assessment of a huge variety of information from workflows, context, process and environment to quality controls, improving operations and decision-making [25, p.57]. Cognitive manufacturing tools help manufacturers to observe and understand operational quality features more precisely and figure out even slight problems. Manufacturers can gain an edge from adopting cognitive applications that will result in increased revenues, reduced quality control labour costs and savings from lower repair and warranty costs. There are two cases listed in the report that confirm the impressive benefits of technology adoption: a European automobile manufacturer reached a 25% improvement in productivity by using predictive models while an electronics manufacturer expects a decrease in quality control labour costs by 5 to 20% [26]. Automated optical inspection systems are used by Bosch to capture images of parts to be checked and a task-specific software for automatically detecting defects on those products [26]. Implementation of such an optical inspector has made it possible to reduce total test time reduction up to 45%.

Table 1

Cognitive Manufacturing Applications Specification

Application for CM	Brief description	Prevailing application type of CT	Potentially achieved benefits
APM	Cognitive APM uses the available scope of information to offer possible solutions to alleviate upcoming issues	Insight	Improved reliability, performance of equipment and assets, reduced costs, reduced downtime
Process and quality improvement	Process and quality improvement involves CM process and quality instruments to observe operational properties to ascertain quality regulations, provide the ability to determine the possible quality concerns earlier and more certainly than other techniques	Insight	Increased yield; improved uptime, productivity, revenues; reduced costs
Resource optimization	CT enable manufactures to use resources in more efficient way	Process, insight	Enhanced safety, reduced costs
Worker safety	CT embody data from the sensors that workers are equipped with to determine situations when employees` health threat appears in real time	Process	Improved worker safety and operations
Energy resource optimization	Applications of cognitive and other techniques allow identifying energy inefficiencies	Insight	Reduced energy consumption and costs
Optimizing factory floor planning and scheduling	CT are used to adapt operations according to the carried out what-if analyses	Process, insight	Optimized planning and scheduling
Supply chain optimization	Advantages can be achieved while adopting cognitive technologies techniques gathering information from structured and unstructured data roots	Process, insight	Fewer out-of-stock events, improved on-time delivery, reduced inventory costs

Smarter resources optimization (Table 1) includes combining a great variety of data from different individuals, locations, usage and expertise with cognitive insight to optimize and improve the use of resources such as labour, workforce, and energy [25, p. 59]. Reduced worker downtime and optimised work environment, improved worker health and productivity are the consequences achieved by a technology application. Cognitive technologies (CT) that enable worker fatigue alerts and proximity monitoring used by one industrial product manufacturer improved the company's associated safety compliance metrics by 10% [10]. Cognitive manufacturing applications can help companies to monitor and predict their energy usage and energy consumption behaviour. Reduction in energy consumption due to optimization of company's processes can reach the rate of 10 per cent [10].

Supply chain optimization approaches (Table 1) enhance clarity and insights of gained information from structured and unstructured data sources to investigate the predictive capability of a global production chain to minimize supply chain costs, disruptions and risks.

For example, one company managed to reduce its global supply chain costs by about 10% by cognitive technologies embedded in an automotive Original Equipment Manufacturer (OEM) to resolve the suitable flow of a product through the supply chain, transportation, production, and storage [10]. Cognitive supply chains can ensure a decrease in inventories. There are two other examples when an automotive OEM and an industrial products manufacturer each reduced their service parts and spare parts inventories, respectively, by more than 20% [10]. To give another example of supply chain optimization, Continental has created software to predict the optimal points for tire changes on its fleet [26]. These predictive systems allow Continental to reduce its stock of tires as well as improve safety on the road.

CONCLUSIONS

The article reveals applications for cognitive manufacturing, how technologies influence manufacturing processes and what their implementations result in. The theoretical foundations have been developed for this purpose [28, 29]. Today it is possible to cope with a great variety and amount of data because the level of technological development that assists IoT and advanced analytics is high with a possibility to scale. The technologies make it achievable for companies to profit from the rapidly generated data with the help of IoT applications covering the data collected by sensors or unstructured data contained in other sources. Cognitive technologies similar to the human brain can get a sense of data. The modern manufacturing era intensifies targets of competitiveness, cost efficiency, flexibility, innovation, and responsiveness, therefore it raises the significance of the level technologies can understand data.

Manufacturers use cognitive technologies setting different goals. Thus, the application of technology solutions makes it possible not only to solve the business problem they challenge but also to enhance overall maintenance dramatically and gain benefits. Technologies can based on the description of the issue analyse it and provide the manufacturer with a set of options even specifying per cent of the success of each option. As the result, the technique improves the time rate needed to accomplish the task, which influences productivity and cost level. Cognitive technologies acutely consider manufacturing processes and business environments to extract information important for a manufacturer. The procedure implies new data sources and unstructured data and employs advanced analytics to find out important relations. Cognitive visual inspection systems can carry out product checks based on images of manufactured products to single out defects. Such technologies allow manufacturers to enhance fabric processes, and maintenance and diminish costs. The quality of the product is one of the crucial characteristics manufacturers express concerns about relying on a minimum rate of defects and a high rate of production accuracy as essential performance measurement. Cognitive manufacturing assists organizations in obtaining data on product quality from design through manufacturing. What is more, technologies also enable companies to receive information about product quality through warranty and support programs after distribution. Such procedures boost output, reduce warranty costs and support to ascertain that a customer experience is positive. In addition, cognitive manufacturing prevails in using data obtained from different sources. After the information is analysed, there is a basis for knowledgeable system creation with the possibility of constant updating and learning. The main advantage of such an approach is that the system can make recommendations due to the understanding of the manufacturing process and overall manufacturing conditions.

REFERENCES

[1] B.E.L.R. Flaih, D. Yuvaraj, S.K.A. Jayanthiladevi and T.S. Kumar, "Use Case of Artificial Intelligence in Machine Learning Manufacturing 4.0," *International Conference on Computational Intelligence and Knowledge Economy (ICCIKE)*, 2019, pp. 656-659, doi: 10.1109/ICCIKE47802.2019.9004327.

[2] S. Wang, J. Wan, D. Li, and C. Zhang, "Implementing Smart Factory of Industrie 4.0: An Outlook," *International Journal of Distributed Sensor Networks*, vol. 12, no. 1, p. 3159805, Jan. 2016, doi: 10.1155/2016/3159805.

[3] Deloitte, "2022 manufacturing industry outlook," 2021. Accessed: Feb. 18, 2022. [Online]. Available: https://www2.deloitte.com/content/dam/Deloitte/us/Documents/energy-resources/us-2022-manufacturing-industry-outlook.pdf.

[4] McKinsey & Company, "Global survey: The state of AI in 2021|McKinsey," *www.mckinsey.com*, Dec. 08, 2021. https://www.mckinsey.com/business-functions/mckinsey-analytics/our-insights/global-survey-the-state-of-ai-in-2021 (accessed Feb. 18, 2022).

[5] A. Kwilinski and A. Kuzior. "Cognitive technologies in the management and formation of directions of the priority development of industrial enterprises", *Management Systems in Production Engineering*, 2020, 28(2), pp. 133-138.

[6] P. Fobel and A. Kuzior, "The future (Industry 4.0) is closer than we think. Will it also be ethical?," *Proceedings of the International Conference of Computational Methods in Sciences and Engineering 2019 (ICCMSE-2019)*, 2019, doi: 10.1063/1.5137987.

[7] S. Phuyal, D. Bista, and R. Bista, "Challenges, Opportunities and Future Directions of Smart Manufacturing: A State of Art Review," *Sustainable Futures*, vol. 2, p. 100023, 2020, doi: 10.1016/j.sftr.2020.100023.

[8] P. Grefen, I. Vanderfeesten, K. Traganos, Z. Domagala-Schmidt, and J. van der Vleuten, "Advancing Smart Manufacturing in Europe: Experiences from Two Decades of Research and Innovation Projects," *Machines*, vol. 10, no. 1, p. 45, Jan. 2022, doi: 10.3390/machines10010045.

[9] K.-D. Thoben, S. Wiesner, and T. Wuest, "'Industrie 4.0' and Smart Manufacturing – A Review of Research Issues and Application Examples," *International Journal of Automation Technology*, vol. 11, no. 1, pp. 4-16, Jan. 2017, doi: 10.20965/ijat.2017.p0004.

[10] "Cognitive Manufacturing: An Overview and Four Applications that are Transforming Manufacturing Today," 2018. [Online]. Available: https://www.ibm.com/downloads/cas/VDNKMWM6.

[11] I. B. M. Contributor, "IBM BrandVoice: How Cognitive Computing And The IoT Can Transform Manufacturing To Please Customers," *Forbes*, Aug. 11, 2016. https://www.forbes.com/sites/ibm/2016/08/11/how-cognitive-computing-and-the-iot-can-transform-manufacturing-to-please-customers/?sh=2dc93097272f (accessed Feb. 19, 2022).

[12] P. Moens *et al.*, "Scalable Fleet Monitoring and Visualization for Smart Machine Maintenance and Industrial IoT Applications," *Sensors*, vol. 20, no. 15, p. 4308, Aug. 2020, doi: 10.3390/s20154308.

[13] S. Iarovyi, J.L.M. Lastra, R. Haber, and R. del Toro, "From artificial cognitive systems and open architectures to cognitive manufacturing systems," *2015 IEEE 13th International Conference on Industrial Informatics (INDIN)*, vol. pp. 1225-1232, Jul. 2015, doi: 10.1109/indin.2015.7281910.

[14] Deloitte, "Exponential technologies in manufacturing," 2018. Accessed: Feb. 19, 2022. [Online]. Available: https://www.compete.org/storage/reports/exponential_technologies_2018_study.pdf.

[15] Kiritsis, D., Hodkiewicz, M., Lazaro, O., Lee, J., Ni, J., eds. "Data-Driven Cognitive Manufacturing – Applications in Predictive Maintenance and Zero Defect Manufacturing". Lausanne: Frontiers Media SA. 2021, doi: 10.3389/978-2-88966-583-9

[16] R. Cioffi, M. Travaglioni, G. Piscitelli, A. Petrillo, and F. De Felice, "Artificial Intelligence and Machine Learning Applications in Smart Production: Progress, Trends, and Directions," *Sustainability*, vol. 12, no. 2, p. 492, Jan. 2020, doi: 10.3390/su12020492.

[17] T. Kalsoom *et al.*, "Impact of IoT on Manufacturing Industry 4.0: A New Triangular Systematic Review," *Sustainability*, vol. 13, no. 22, p. 12506, Nov. 2021, doi: 10.3390/su132212506.

[18] S. Bonnaud, C. Didier, and A. Kohler, "Industry 4.0 and Cognitive Manufacturing Architecture Patterns, Use Cases and IBM Solutions," Sep. 2019. [Online]. Available: https://www.ibm.com/downloads/cas/M8J5BA6R.

[19] D.R. Sjödin, V. Parida, M. Leksell, and A. Petrovic, "Smart Factory Implementation and Process Innovation," Research-Technology Management, vol. 61, no. 5, pp. 22-31, Sep. 2018, doi: 10.1080/08956308.2018.1471277.

[20] M.F. Zaeh *et al.*, "The Cognitive Factory," *Springer Series in Advanced Manufacturing*, pp. 355-371, doi: 10.1007/978-1-84882-067-8_20.

[21] M.S. Sheikh, "Cognitive Manufacturing in Perspective of Future Manufacturing Industries," *International Journal for Research in Applied Science and Engineering Technology*, vol. 8, no. 10, pp. 862-866, Oct. 2020, doi: 10.22214/ijraset.2020.32041.

[22] A.V. Carvalho, A. Chouchene, T.M. Lima, and F. Charrua-Santos, "Cognitive Manufacturing in Industry 4.0 toward Cognitive Load Reduction: A Conceptual Framework," *Applied System Innovation*, vol. 3, no. 4, p. 55, Dec. 2020, doi: 10.3390/asi3040055.

[23] D. Schatsky, C. Muraskin, and M. Wagner, "Complimentary article reprint Cognitive technologies The real opportunities for business," 2015. Accessed: Apr. 11, 2022. [Online]. Available: https://www2.deloitte.com/tr/en/pages/technology-media-and-telecommunications/articles/cognitive-technologies.html

[24] M. Lester and A. Htet, "What are cognitive technologies and how are they classified? – Intelligent Automation Blog|Deloitte Australia," *Deloitte*, 2019. https://www2.deloitte.com/au/en/blog/intelligent-automation-blog/2019/what-are-cognitive-technologies-how-they-classified.html (accessed Apr. 11, 2022).

[25] J. Soldatos, O. Lazaro, and F. Cavadini, "The Digital Shopfloor: Industrial Automation in the Industry 4.0 Era," *The Digital Shopfloor: Industrial Automation in the Industry 4.0 Era*, vol. pp. 3-46, pp. 1-496, Apr. 2019, doi: 10.13052/rp-9788770220408.

[26] P. Baruchelli, F. Botto, and A. Cimatti (FBK), "End-to-end digitized production test beds Overview on maturity of AI innovations in manufacturing," Dec. 2020. [Online]. Available: https://eit.europa.eu/sites/default/files/overview_on_maturity_of_ai_innovations_in_manufacturing_20529-d11.pdf.

[27] A. Kuzior and M. Staszek. Energy management in the railway industry: a case study of rail freight carrier in Poland. Energies, 2021, 14 iss. 21 pp. 1-21 (art. no. 6875) https://doi.org/10.3390/en14216875

[28] A. Kuzior, A. Kwilinski and V. Tkachenko. Sustainable development of organizations based on the combinatorial model of artificial intelligence. *Entrepreneurship and Sustainability*, 2019, 7(2), 1353-1376. http://doi.org/10.9770/jesi.2019.7.2(39)

[29] V. Tkachenko, A. Kuzior and A. Kwilinski. Introduction of artificial intelligence tools into the training methods of entrepreneurship activities. *Journal of Entrepreneurship Education*, 2019, 22(6), pp. 1-10. Retrieved from https://www.abacademies.org/articles/Introduction-of-artificialintelligence-tools-1528-2651-22-6-477.pdf

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