Artificial Intelligence in Industry 4.0: The future that comes true: AI

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Artificial Intelligence and its Application in Manufacturing

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Abstract: *Artificial intelligence (AI) has become the most important element of the Industry 4.0 model today. It has wide application possibilities in the entire new value chain. Its history is about eight decades long, and a special area of its research and development is manufacturing, in which AI has been applied since the mid-1980s. Expert systems (ES) were the first AI tools applied in manufacturing. The goal of this paper is to perform a systematic analysis of the state of development and application of AI in manufacturing, which is originally used as an aid to the engineer, planner and designer of various engineering products. It is also used to manage processes and systems in mechanical engineering. Starting from that, the paper is structured in such a way as to provide answers to the following questions: what is AI and how did it develop, how were AI models created and how were they developed in technological systems, what are today's models and prospects for applying AI in them, as well as possible directions of future research in this area. As a special point of this paper, some results of our research in this area are presented.*

Keywords: *Artificial intelligence, Machine learning, Manufacturing systems, Manufacturing, Planning, Design, Management.*

1. Introduction

Artificial intelligence (AI) is a branch of intelligence science, which broadly encompasses two areas: natural and artificial. Natural intelligence is the science of discovering the processes and models of intelligent behavior in living systems, while artificial intelligence, or AI, is both the science and engineering of creating intelligent software systems and machines. These two areas of research are connected and have contributed to each other during the past eight decades of development.

On the other hand, AI is the basis for the development and application of smart manufacturing. What is smart manufacturing? It represents the use of advanced technologies, while performing data analysis to improve manufacturing processes, increase efficiency and optimize manufacturing [1]. Also, it integrates

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various technologies: AI, Internet of Things (IoT), Big Data Analytics (BDA), robotics and cloud computing into the manufacturing environment.

The key features of smart manufacturing are: (a) system integration - Connecting different manufacturing systems and processes through IoT and other technologies to create a cohesive and synchronized manufacturing environment, for online operation, (b) big data analytics. Here, AI is used to analyze the huge amounts of data generated during manufacturing processes. This helps identify patterns of occurrence of events, predict maintenance needs, optimize manufacturing schedules and improve overall efficiency, (c) automation and robotics - the application of robotics and automation to perform tasks, which are repeated with high precision and reliability, thus reducing human error and increases productivity, (d) IoT and networking. Using IoT devices, data is collected in real time from machines, equipment, processes and products in the factory. This data is used for monitoring, management and decision-making, (e) advanced manufacturing technologies - are additive manufacturing (3D printing), digital twins (virtual models of physical assets) and augmented reality (AR) for design, simulation and maintenance purposes, (f) supply chain integration - improving supply chain management through real-time visibility and coordination, enabling faster response to market demands and shortening delivery times, and (g) energy efficiency and sustainability - optimizing energy use and resource consumption to reduce environmental impact and improving the sustainability of manufacturing.

Smart manufacturing is a new paradigm of technological systems, and its establishment and application in manufacturing is based on AI tools and techniques, which is especially evident in the Industry 4.0 model.

Smart manufacturing has several definitions, and one of the common ones is [2,3]: " *Smart manufacturing uses cognitive computing, industrial IoT and advanced analytics to optimize manufacturing processes in ways that were not possible before." It helps organizations improve key business metrics such as productivity, delivery reliability, quality, business security and profitability, while reducing downtime and operating costs."*

Smart manufacturing technologies look deeply into the manufacturing process and business environment like never before to extract information that has tangible value for the manufacturer.

The aim of this work is to systematically analyze models of development and application of AI in manufacturing, and it contains the following units: (i) historical development of the application of AI in manufacturing, (ii) detailed analysis of today's models of application of AI, (iii) some results of our research in this areas, (iv) conclusions and future research.

2. Historical Development of the Application of AI in Manufacturing

The history of the development of the application of AI in manufacturing is more than seventy years long, and includes five stages, table 1 [3-7].

Table 1. Historical overview of the development of AI in manufacturing (supplemented according to [3-7])

<table>
<tr><th>Period of time</th><th>Characteristics</th><th>Elements of AI application in manufacturing</th></tr>
<tr><td rowspan="3">Early AI development and application (1950s - 1970s) (level 1).</td><td>1950s: The term "artificial intelligence" (AI) was defined and the fundamental concepts of AI were developed.</td><td>-</td></tr>
<tr><td>1960s: First AI research and development of models for problem solving and symbolic thinking.</td><td>Basic application of numerical control (NC) tools on control units (CDUs) of machines.</td></tr>
<tr><td>1970s: Expert systems emerge as a prominent AI application. They use knowledge-based rules to solve specific problems.</td><td>They provide decision support in manufacturing processes.</td></tr>
<tr><td rowspan="2">Robotics and automation (1980 - 1990) (level 2).</td><td>1980s: Industrial robots began to be integrated into manufacturing processes, controlled by computer systems.</td><td>Early AI algorithms for tasks such as welding, painting and assembly.</td></tr>
<tr><td>1990s: AI techniques such as machine learning began to be applied in manufacturing.</td><td>They are used for quality control, process optimization and predictive maintenance. There have also been advances in computer vision for automated inspection.</td></tr>
<tr><td>Knowledge-based systems (1990 - 2000) (level 3).</td><td>Expert systems have continued to evolve, helping to define and apply domain-specific knowledge in manufacturing contexts (knowledge engineering).</td><td>These systems provided extensive rule- and heuristic-based decision support (product design, process planning, and manufacturing management).</td></tr>
<tr><td rowspan="3">Data-driven AI (2000 to present) (level 4).</td><td colspan="2">The 2000s marked a shift towards data-driven AI models, fueled by the availability of large data sets and advances in computing power.</td></tr>
<tr><td colspan="2">Machine learning techniques such as neural networks, support vector methods, and decision trees have become increasingly popular for tasks such as predictive maintenance, anomaly detection, and optimization of manufacturing processes.</td></tr>
<tr><td colspan="2">AI-based analytics and optimization tools have begun to integrate into manufacturing operations, enabling real-time insights and continuous improvement.</td></tr>
<tr><td rowspan="3">Industry 4.0 and smart manufacturing (2010s to present) (level 5).</td><td colspan="2">The concept of Industry 4.0 emphasizes the integration of AI, IoT, cloud computing and cyber-physical systems in manufacturing.</td></tr>
<tr><td colspan="2">AI plays a key role in the development of smart factories, where machines and systems are interconnected, communicate and make decisions autonomously based on real-time data and analytics.</td></tr>
<tr><td colspan="2">The application of AI includes: design and planning of products, processes and systems, predictive analytics for maintenance, adaptive manufacturing processes, autonomous robots and supply chain management.</td></tr>
</table>

AI in manufacturing has evolved from early automation and ES, to sophisticated data-driven applications that increase productivity, quality and agility in manufacturing environments. Today's advances in AI technologies continue to shape the future of manufacturing, leading to more intelligent, efficient and adaptive manufacturing systems.

3. Overview of the Application of AI in Manufacturing - Literature Analysis

The last two decades of development and application of AI in manufacturing represent the "golden" age in this field. Thanks to the development of ICT and its application in manufacturing, they created the basis for extensive research and application of AI in manufacturing, as the following analysis shows.
This system analysis was performed according to the PRISMA methodology [7], and our questions were: Q1. What AI techniques and tools are being applied in manufacturing, and Q2. How AI improves decision-making, planning, analysis and management of manufacturing processes. The following were defined for them: time period of analysis, type of study, AI models, search methodology and assessment of study quality. The sample included 286 papers, and 35 papers met the set criteria. Broadly speaking, a systemic analysis of the application of AI in manufacturing is performed here from the following angles: (i) application of agents as an AI approach, (ii) concepts and models of application of AI in manufacturing, (iii) learning models, (iv) generative AI and its application, and (v) application of ChatGPT in manufacturing. The following analysis refers to all the mentioned areas.

3.1. Application of Agents as an AI Technique in Manufacturing

Agent-based distributed manufacturing management was a popular AI technique applied at the beginning of this century. In the traditional centralized manufacturing management systems of the time, the supervisor made decisions on manufacturing planning, scheduling and resource allocation. In contrast, in the agent model, decisions are distributed among several agents, who communicate with each other, in order to achieve optimal manufacturing results. Traditional optimization methods often consider only one domain (process planning or scheduling) and ignore the constraints of the other domain. This can lead to sub-optimal or even invalid manufacturing plans, due to the dynamic nature of real-time machine loads and plant conditions. That is why the application of AI agents is a much better solution. In this analysis, two characteristic overviews of approaches to the application of this AI technique are presented, Table 2.

Table 2. Overview of the use of agents

Area	Ref. / yr.	Method	The goal	Use
Manufacturing planning and scheduling	[8] 2006	Application of agents	Increasing the accuracy of manufacturing planning and scheduling	Management of manufacturing in the plant
Reconfigurable technological system	[9] 2009	A multi-agent system	Intelligent manufacturing management	Distributed manufacturing management

In agent-based manufacturing planning and scheduling systems, applied agent negotiation protocols require individual agents to respond to incoming bids. Therefore, in this model, it is extremely important that the knowledge base, reasoning and reasoning mechanism are developed [8]. Also, due to the autonomous and cooperative nature of the agents, planning and scheduling functions can be integrated from higher to lower levels. By applying the agent model, an innovative,agileandreconfigurable model technological system [9]. Thus, an intelligent distributed manufacturing management model was obtained. Finally, for this period of analysis, the first decade of this century, we can say that the agent model was the dominant approach to the application of AI in manufacturing.

3.2. Concepts and Models of Application of AI in Manufacturing

The second decade of this century saw a transformation of the world economy and economy, based on digitization and AI. In manufacturing, AI has produced major changes in the entire value chain, especially in: decision-making, product design, manufacturing planning and management, maintenance, quality control, while reducing downtime and manufacturing costs, increasing operational business parameters. This chapter analyzes in detail studies that have considered various aspects of the application of AI in manufacturing, at the national, regional or global level. This can help us to determine our situation, comparing it with them, and to define our policy in this area based on that. The first study [10] presented an analysis of the application of AI in 28 countries, Table 3, and the way it was defined was the GMI Summit, where dozens of Panels were held on

Table 3. Overview of studies on the application of AI(policies, national programs, good practice)

The way	Ref. / yr.	Method	The goal	Use
Global Manufacturing and Industrialization Summit (GMIS)	[10] 2020	The context of Industry 4.0	Guidelines for the application of AI	Defining the four levels of AI deployment
Foundation for autonomous manufacturing	[11] 2020	Autonomous manufacturing	Intelligent machines	In-house manufacturing and maintenance
Maturity of Industry 4.0	[12] 2020	Integration with factory functions	Model factory of the future	Wide application of deep learning models
AI as support for smart manufacturing	[13] 2020	Smart manufacturing	Improvement of the manufacturing model	National policy and strategy for the application of AI
Convergence of AI and manufacturing technologies	[14] in 2021	Modeling nonlinear AI problems with deep learning	Increase the efficiency and quality of manufacturing technologies	Application to different types of products

EU leader in the application of AI	[15] in 2021	In the Industry 4.0 model	Competitive advantage of EU manufacturing	High-tech factories
Deep learning models	[16] in 2022	CNN	Smart products	Smart manufacturing
Deep learning	[17] in 2022	CNN, RBM, RNN	Smart manufacturing	Maintenance and quality control
Analysis of ML techniques	[18] in 2023	Examples of good practice	Reduce application risks	Smart manufacturing
White paper - AI in EU manufacturing	[19] in 2023	Maturity model of AI in manufacturing	Assessment of EU companies for the application of AI	Definition of AI KPI parameters
Challenges in applying AI	[20] in 2023	Application project model	Successful application of AI	Six aspects that affect the success of an AI project in the factory
DT for the factory	[21] 2024	IDEFO model	Factory as DT	Applying AI through DT for the factory
Application of generative AI	[22] 2024	Encouraging producers	Policy of application of generative AI	Application in manufacturing

various aspects of AI not only applied in manufacturing. She also defined a multi-level model for the application of AI in manufacturing: (i) AI champions, completed digital transformation with a clear strategy for further application of AI, (ii) AI innovators, a clear digital transformation strategy, including AI, implemented in stages. The project enters full implementation, (iii) AI and digital companions, are organizations that have horizontal digital integration (sales, procurement, engineering, manufacturing), but not vertical integration (CAD, CAPP, CAM, MES, ERP). The same applies to elements of AI in application, and (iv) AI and digital first-timers are those organizations that have not yet entered the transformation project. Management has no strategy for this Project, their survival in the market is questionable. The document [11] of the Foundation for Autonomous Manufacturing starts from the premise that machines in manufacturing should be made intelligent for decision-making in relation to all issues of manufacturing and maintenance. This means that the Industry 4.0 model was established and applied, and supported by AI models, this manufacturing model is characterized as follows: (i) continuous optimization of the manufacturing process, with its online diagnostics, (ii) quick reaction to changes in manufacturing quality parameters, (iii)) close coordination of machines in the process, (iv) human interventions that can be a source of errors, remove, for example reprogramming, (v) improve the machine self-diagnosis process, and (vi) apply tighter control tolerance limits. AI represents the maturity of the application of Industry 4.0 in practice [12]. This paradigm is based on the following facts: (i) predictive maintenance. By applying deep machine learning (DML) and big data analysis (BDA) models, large savings are achieved and downtime is reduced, (ii) quality assurance and inspection. Using computer vision and the DML model, the analysis and recognition of errors on products is performed, after manufacturing operations and on the assembly line, (iii) optimization of supply chains. AI models can be effectively used here for inventory management, demand forecasting and delivery scheduling, (iv) application of generative AI in engineering activities. Rapid prototyping and product improvement, (v) digital twins and simulation. AI models in this area reduce maintenance costs, predict failures and optimize energy consumption, and (vi) AI models for information security. Far Eastern countries (Japan, South Korea, China, Taiwan and India) adopted national programs for AI at the end of the last decade, which included its application in manufacturing [13]. These Programs defined the Smart Manufacturing model, as a framework for the AI-based factory model. At the moment, the application of AI in manufacturing covers a wide range of machine learning models, where the key to success is pattern recognition for highly nonlinear data, analysis of unstructured data, robustness of repetitive tasks, and high interoperability [14]. To illustrate the aforementioned facts, the following examples are given: autonomous vehicle control, assembly robot in the automotive industry, predictive maintenance of wind generators, manufacturing quality management in a steel plant, and semiconductor manufacturing quality management. All the above examples speak of the high potential of convergence of AI and various manufacturing problems that can be solved. The analyzes presented in [15] show that the EU applies more AI in manufacturing than the industrialized countries of the Far East, as well as North America, on average about 30%. These facts speak of the importance of the symbiosis of research, development and application of AI in manufacturing through the Industry 4.0 model, which as a model was "born" in the EU. Further analysis shows that AI in the EU is mostly applied in intelligent maintenance (MES), quality control and inspection (MES) and manufacturing planning and management (ERP). The study [16], discusses the challenges and possibilities of applying deep learning models in smart manufacturing. The analysis shows that CNN is the best model, and the challenges are: data quality, data security, and learning model reliability. All these analyzes were performed for the application of AI in maintenance, quality control, collaborative robots and supply chains.An in-depth analysis of the application of deep learning models (DML) in smart manufacturing is presented in the study [17]. The latest research shows that in smart manufacturing models, only 2% of the data generated is relevant for use and decision-making, so these approaches are also called data-driven systems based on AI, supported by deep learning (CNN, RBM, RNN). All this is illustrated with examples from maintenance and quality control. The study [18] provides a detailed overview of the application of machine learning techniques with application in smart manufacturing. However, examples of good practice also have major challenges in application, which should be taken into account: data collection and management, human resources (ML experts), infrastructure (hardware, software), information security risks and supplier business models. A maturity model of AI application in EU companies is presented in [19]. KPI parameters are defined for it, at the process, CPS, factory level, which is connected to the

RAMI model of horizontal and vertical integration. The maturity model evaluates the process, CPS and factory in five dimensions: productivity, time to market, worker role, resilience, society and environment. In the study [20], various aspects of the application of AI in smart manufacturing were analyzed, and some of the most important challenges are: data quality for deep learning models, integration of AI models into factory functions and systems, application costs, readiness of the factory environment for the application of AI models, legal and ethical rules and restrictions, and employee resistance to change. All this means that Project AI in the factory should be handled very carefully. A particular challenge for implementing AI in the factory is to do it using the intelligent DT factory model [21]. The factory was modeled as a hieraphic system through the IDEFO model, and then a virtual counterpart was developed for all components. The entire system was tested in the laboratory on one example. A study [22] discusses the application of generative AI in manufacturing in the US, by the US Society of Manufacturing Engineers. Namely, it is considered that generative AI is the immediate future of the application of AI in manufacturing, so a policy and strategy should be established at the national level to encourage its application, which is detailed in the study.

Therefore, concluding the analysis of this chapter, we can state the following: (i) industrially developed countries have their own national and regional strategies and programs for the application of AI in manufacturing, (ii) the Industry 4.0 model is the best base and framework for the application of AI in manufacturing, and especially the model of smart manufacturing, which is developed from this concept, and (iii) everything said says that Serbia should also seriously address these trends and approaches, all with the aim of developing and building a new industry.

3.3. Analysis of Learning Models Applied in Manufacturing

The essence of today's application of AI in manufacturing is the application of various learning models, especially those related to deep learning, to solve various engineering, business and managerial problems. That is why this area is separated as a unit, and examples of the application of these models are given in Table 4.

Supervised (deep learning) and unsupervised learning are previously widely used learning models for the application of AI in manufacturing. One example of the application of these models is given in [23], and it refers to the prediction of the quality of the technological process in a steel rolling mill. In order to model the rolling process online, the following are monitored: rolling force, speed and temperature of the process, and all these parameters are monitored via six characteristics.

Table 4. Overview of the application of AI learning models in manufacturing

The way	Ref. / yr.	Method	The goal	Use
Three process parameters	[23] 2013	4 Learning models	Better quality of rolled steel	Process quality management
45 process parameters	[24] 2013	Method of support vectors	The same quality of every product	Quality monitoring of 4 technological processes
Paradigms of intelligent manufacturing	[25] 2017	Deep learning	Intelligent manufacturing	Model-driven collaborative manufacturing
Development of the application of ML in smart manufacturing	[26] 2018	ANN/CNN	State of ML Application in US Industry	Digital manufacturing
Deep learning model development	[27] 2018	Extreme Gradient Boost (XG Boost)	Improvement of manufacturing quality	Smart manufacturing at Bosch
Application of elements of Industry 4.0	[28] 2018	CNN, support vector method, random forest model, recurrent NN and Bayesian classifiers	Intelligent decision making	Smart manufacturing
Industrial intelligent model	[29] 2018	"ABCDE" model	Building an AI platform for smart manufacturing	Intelligent CPS (Machine Tool)
Application in the MES model	[30] 2019	CNN	Development of intelligent manufacturing	Intelligent plant management (MES)
Detection of assembly errors	[31] 2019	XG Boost, random forest model and support vector method	Error detection	Volkswagen assembly line
Predictive maintenance	[32] 2019	Online status monitoring	A new maintenance model	Machine care

The following learning techniques were used: deep learning - Bayesian classifiers, decision tree, K nearest neighbor and support vector method, and learning - K means. The sample for defining learning included 470 examples of measurement, and the results in application were excellent, which was demonstrated. In the study [24], a cluster model is described for the improvement of product quality through all its stages of manufacturing (casting, processing by plastic deformation, processing by cutting and thermal treatments). As a deep learning model, the support vector method was used, where the learning sample included 45 parameters with 360 samples. Thus, a model was established for online monitoring of product quality through the specified stages of manufacturing. The AI-supported intelligent manufacturing model is based on four paradigms [25]: (i) model-driven intelligent collaborative manufacturing, (ii) knowledge-based enterprise cloud service, (iii) human-machine-material cooperative cloud workshop, and (iv) autonomous intelligent manufacturing units (CPS). So, for example, the first paradigm means that cloud is a model of all kinds of manufacturing resources/capacity, and then intelligent cloud technologyshould be used to automatically match product requests and resource/service requests. Based on this, define an intelligent infrastructure for the product - support. Also, those operational centers of intelligent manufacturing platforms in the cloud must support model-driven collaborative activities of the total product life cycle: research and development, manufacturing, manufacturing management, logistics and support services. All the above elements are supported by various AI learning models. The study, presented in [26] included the analysis of over 4000 references from the field of advanced manufacturing, from the aspect of application and possibility of applying machine learning models. Recommendations are given for the faster application of these models in advanced manufacturing, namely: management support in application and their greater use for decision-making, establishment and use of a digital knowledge base, application to the product life cycle and the basis from which to start for the successful application of ML is digital manufacturing. In manufacturing, an abundance of data is generated, from different sources and in different forms, so they should be organized and prepared for use in learning models [27]. Therefore, the construction of a learning model for smart manufacturing consists of four steps: (i) collection of raw data, (ii) their processing and editing, (iii) development and testing of the learning model (70% is used for the development of the learning model, and 30% for its testing (verification)), and (iv) application of the model in practice, through its validation. It (validation) includes the following steps: accuracy, sensitivity, precision and F-measure. All this is illustrated with an example of a deep learning model from Bosch smart manufacturing. The study [28] provides an overview of the application of deep learning models in manufacturing. The elements of Industry 4.0, such as the Internet of Things (IoT), big data (BDA), digital twins (DT) and cloud computing (CC), form an ideal framework for the application of deep learning models, such as: CNN, the method of support vectors, random forest model, recurrent NN and Bayesian classifiers, in smart manufacturing. These deep learning approaches in this study are illustrated with examples from: quality control and inspection, predictive maintenance, and condition diagnostics. One approach to the development of industrial AI models is defined as the "ABCDE" model, and is presented in [29]. The meaning of the labels in the model is: A - technology analytics, forms the core of the AI eco manufacturing system model (data, software/hardware platform, CPS, B - big data technology (BDA), C - cloud and cyber technology, D - knowledge domain, E - evidence Big data technology and cloud are essential elements of the data source that make up the AI platform Domain knowledge and evidence are key elements due to: (i) understanding the problem and focusing the power of AI on solving it, (ii) disseminating the system and collecting real data, (iii) understanding the physical meanings of the parameters and their relationship in the model, and (iv) communicating the change of these parameters from one CPS to another The development and application of the Industry 4.0 model is focused on the intelligent development of the MES model, and forits application it is necessary to use the deep learning model, especially the CNN model shown in [31]. It is a Volkswagen assembly line, where the sample included 18148 units of products with 29 characteristics. The developed model enabled the

detection of assembly errors with an accuracy of 98.25%, which was satisfactory. The study [32] shows the application of a deep learning model for predictive maintenance (online monitoring of machine condition and intervention as needed). The paper showed that convolutional neural networks (CNN) and recurrent neural networks (RNN) are mostly used for state monitoring (machine care), deep learning models. It is expected that research in this area will develop in the following directions: (i) for large open-source data sets, CNN models up to 150 layers, with 10 hidden layers each, will be developed, (ii) greater use of the knowledge domain (not only process knowledge), (iii) visualization of learning data, (iv) deep learning knowledge transfer, (v) balancing knowledge classes about the state (health) of machines.
At the end of the analysis of learning models applied in manufacturing, we can draw the following conclusions: (i) deep learning models are widely applied today, especially in maintenance and quality control, and (ii) the wider application of Industry 4.0 elements is expected to encourage further development and application of deep learning models in manufacturing.

3.4. Generative AI and its Application in Manufacturing

Generative AI (GenAI) models typically use machine learning algorithms to analyze patterns and relationships in existing data and then generate new content that is often difficult or impossible for humans to create, an approach that also applies to manufacturing. Thus, generative AI models are being researched and developed today for: product design and design for additive manufacturing (AM), materials science, optimization of business and technological processes, robotics and automation, predictive maintenance, quality control and supply chain management. Limitations in the application of these AI models can be: data quality, interoperability, scalability and cyber security. An overview of selected examples of generative AI applications is given in Table 5.

Table 5. Overview of the application of generative AI (GenAI) models in manufacturing

The way	Ref. / yr.	Method	The goal	Use
Business and technological processes	[33] 2023	GenAI analytics	Process transformation	In the Industry 4.0 model
A three-level model	[34] 2023	Integration	Autonomous system	Factories of the future
GenAI model	[35] 2024	CAD model	A new design model	Product design
GenAI model architecture	[36] 2024	Four levels	Business Improvement	Smart factory
GenAI as a support for Industry 4.0	[37] 2024	Integration	Application of the GenAI concept	Factory with the Industry 4.0 model
Identification of 10 areas of innovation management	[38] 2024	A new model of innovation management	Faster implementation of innovations in practice	Innovation management

GenAI has been applied to several elements of Industry 4.0, namely: forecasting demand and marketing strategy, designing new products, optimizing the workforce and their skills, improving quality control and predictive maintenance [33]. GenAI enables managers to transform manufacturing by optimizing processes, improving product design, improvingqualityproducts, thus raising the application of innovations in manufacturing. At the same time, GenAI technologies facilitate predictive analytics for demand forecasting as well as improvementmarketing strategies and identifying market trends. All of the above is illustrated with several examples. A particularly interesting analysis was presented in the study [34], which referred to the place and role of GenAI in the factories of the future. A three-level model is proposed: assistance, recommendation and autonomous systems. Assistance means that GenAI should generate the program code for the machine tool, and the engineer only reviews it, while recommendation means that GenAI guides the maintenance technician to select the necessary maintenance instructions in a predictive model, step by step, including spare parts. And finally, autonomous systems in the factory of the future supported by GenAI, are those that will have self-regulating capabilities and adapting to unknown situations. For the factory of the future, AI will be the cornerstone of its business, and the key model will be GenAI [35]. Here's how the new approach - GenAI looks at product design. GenAI brings revolutionary changes in product design, bringing a unique blend of creativity and efficiency. More specifically, generative text-to-image tools help designers bridge the gap between concepts and manufacturing-ready models.

The job of a product design engineer is to define specific design goals, taking into account design metrics, such as: sustainability goals, manufacturing costs, product compliance with customer (market) requirements and manufacturing conditions. GenAI systems generate different design options based on these predefined parameters. In the study [36], the architecture of the GenAI model is shown, which includes four levels: (i) hardware infrastructure, (ii) work on the IoT (Industrial Internet of Things) platform PTC ThingWorx that manages business (sales, procurement), engineering (CAD, CAM, PLM) and manufacturing information system (ERP, MES), (iii) machine learning models for GenAI - Azure OpenAI Service, and (iv) application development for specific problems of the organization. The study [37] talks about how the Industry 4.0 model can be the basis for the application of the GenAI concept. In this sense, it is suggested that each organization, which starts this way, must define a special integration project. The study [38] describes future research opportunities related to the application of GenAI in innovation management, where ten areas of application of this model in innovation are identified.

Concluding this analysis, we can conclude the following: (i) GenAI is a new model of applying AI in manufacturing, whose possibilities and application examples are still being explored, and (ii) it can be said that the first experiences about it indicate that this approach is more user-oriented than other deep learning models, which represents a good basis for its faster penetration into manufacturing.

3.5. Application of ChatGPT in Manufacturing

ChatGPT is a powerful AI language model, which can be applied in various industries to automate tasks, improve efficiency and improve user experience. So for example in a smart factory, this AI tool can be useful for us to: (i) help MES by generating reports, provide real-time feedback and enable remote monitoring and control of manufacturing processes, (ii) help ERP systems by generating reports, by providing personalized customer support and optimizing supply chain logistics, (iii) assisting QMS by analyzing data from quality control processes to identify defects and causes of errors, and (iv) assisting PLM by generating digital twins of products or systems, enabling tracking and real-time simulation of manufacturing and maintenance. An overview of the application of this AI model is shown in Table 6.

Table 6. Overview of the application of the ChatGTP model in manufacturing

The way	Ref. / yr.	Method	The goal	Use
Collection and analysis of knowledge	[39] 2023	Searching for knowledge	Defining knowledge of terms (26)	Knowledge about Industry 5.0
IoT	[40] 2023	Analysis of information from manufacturing	Report generation	Manufacturing
Flag presentation	[41] 2023	Answers to the questions	Engineer training	Help the engineer
Platform of business and technological knowledge	[42] 2023	Online management	Support for smart manufacturing	Industry 4.0 model

Therefore, we can state that the application of AI in manufacturing is increasingly moving from algorithmic to linguistic intelligence, where interactive activities between humans and machines play an active and important role online in real time. ChatGPT has proven its effectiveness in providing comprehensive information and knowledge about Industry 5.0 [39]. For the defined 26 keywords (AI for advanced automation, metaverse learning and optimization,...), satisfactory answers were given from the large knowledge base that was used. The study [40] talks about the challenges of applying this AI model in different areas, but the context of applying IoT in manufacturing is interesting for us. More precisely, how the information coming from the manufacturing can be used for the application of this tool, which was already stated in the introduction of this chapter. Manufacturing includes a large number of complex tasks, which require extensive knowledge and experience to perform. With the rapid development of AI, especially with the emergence of language models such as ChatGPT, new opportunities for knowledge assurance are opening upthrough the conversation [41]. In this study, it was shown that ChatGTP k ao generative model, provides promising creations on the comprehensive, creative, and objective manner, thereby demonstrating its potential to support works of summarization, synthesis, and creation. The study also presented a three-layer model developed for the needs of manufacturing and training of engineers. In the concept of Industry 4.0, ChatGTP will be a business and technological knowledge platform that will be of great help to engineers and managers to manage smart manufacturing online [42].

Concluding the analysis of this chapter, we can state that this model (ChatGTP) is in its infancy, so new experiences about its application in manufacturing are still expected.
At the end of this detailed analysis, we can conclude that AI in manufacturingenters a new phase of development and application, listed in Table 1 as level 5, which refers to smart manufacturing, and the basis of that application is the GenAI model.

4. Some Research Results of the Faculty of Mechanical Engineering in Belgrade

This analysis refers only to the first-named author's research results in this area. Namely, we can state with pleasure that in the mid-eighties of the last century, under the leadership of prof. Dr. Vladimir Milačić, at the Faculty of Mechanical Engineering in Belgrade, the research program - Intelligent Manufacturing Systems began to be implemented, where the first-named author had a significant place and role. As a young researcher, I completed and defended myPhD thesis in 1988, in the field of development of an Expert system for maintenance of machine tools (EXMAS), which was also verified by the most important references of that time [43 - 45]. Research in the field of ES continued in the field of inspection on CMM [46], with the development of a model for inspection of box parts on CMM (EXINS), also verified by the most important reference at that time. Later, these researches were continued, so that at the end of the second decade of this century, this author developed an original model of virtual manufacturing metrology (CPM^3 - Cyber Physiacl manufacturug metrology model), also verified in a large number of references of the most important international journals, and in Mongrafia [47], which was published by Springer, and it received the Award of the City of Belgrade for Science, 2019, as the highest national recognition for science.

This brief overview tells us that at the Faculty of Mechanical Engineering in Belgrade, at the Department of Manufacturing Engineering, there is an enviable history of the development and application of AI in the aforementioned field.

5. AI in Manufacturing – What's next?

The future of manufacturing is smart manufacturing, or otherwise, the full application of the Industry 4.0 model in manufacturing. In such a sequence of events, the role of AI will be large and significant, which means that it will apply to [19,20,34]: (i) digital manufacturing, which will be based on AI, where it will create digital versions of physical products, enabling virtual prototyping, simulation and testing, before real manufacturing, (ii) design for manufacturing, AI will help to create products suitable for manufacturing, which will meet all the requirements of the customer, ecology while saving resources, (iii) optimization of the manufacturing process, AI can analyze manufacturing data to optimize manufacturing processes, reducing energy consumption, waste and costs, (iv) intelligent manufacturing planning, based on AI can optimize manufacturing resources, based on demand forecasting, supply chain constraints and manufacturing capacity, (v) optimization supply chain, using AI to optimize inventory, logistics and delivery routes, reducing costs and shortening delivery times, as well as risk management, (vi) automation and collaborative robots, use AI algorithms to optimize assembly, welding and inspection tasks. Cobots with AI increase productivity and reduce labor costs, (vii) augmented reality (AR) and digital twins (DT) supported by AI are used to simulate processes, machines and systems, and for their maintenance, (viii) condition monitoring and predictive maintenance, use machine learning algorithms to analyze equipment performance data, predicting when maintenance is needed and proactively schedule maintenance, reducing downtime and increasing overall equipment efficiency, (ix) quality control and assurance, AI is used to analyze product quality data in real time, detecting defects and errors, while enabling rapid corrective actions to improve product quality, (x) AI-based data analytics will analyze large amounts of manufacturing data (BDA) to identify trends, behavioral patterns and correlations, enabling data-driven decision making, and (xi) cyber - AI-powered security systems can detect threats and respond to them in real-time, protecting against cyber-attacks.

These are some directions of the future application areas of AI in smart manufacturing, and as AI technology (GenAI, ChatRTG) continues to develop, we can expect even more innovative applications to emerge in the future.

6. Conclusion

Since the basic context of this work is AI in manufacturing, in conclusion we can point to trends in the future development of AI, which will have a direct impact on its application in smart manufacturing. A few basic AI development trends are: (i) general AI (GAI), refers to hypothetical AI systems, which will possess human-like AI, capable of reasoning, learning and applying knowledge to a wide range of tasks. In that case, GAI could surpass human intelligence in many areas, (ii) edge AI, refers to the use of AI and machine learning in frontier areas, where data is generated and processed in real time, without the need for centralized processing, (iii) transfer learning, is a technique in which AI models can learn from one task or domain and apply that knowledge to another related task or domain, without the need for relearning, and (iv) quantum AI, similar to quantum computing, which has the potential to advance AI, providing new methods for machine learning, optimization and simulation, which could lead to breakthroughs in areas such as smart manufacturing, medicine, finance and climate modelling.

All the mentioned facts speak of the great perspective of the development and application of AI in smart manufacturing as well.

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