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Article

On the Way to the Development of Smart Manufacturing Model in Practice

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Abstract: Digital technologies have been present in manufacturing and industry for a long time, and today they represent the basis for the application of the Industry 4.0 model in practice. The transformation marked by the Industry 4.0 model is based on the application of a large number of models of communication technologies, solutions for connecting entities (machines, parts, ...) in the factory within Internet of Things (IoT), as well as the possibility of big data analysis (BDA) throught the artificial intelligence tools (AI/ML). These technologies provide great opportunities to create more flexible and profitable manufacturing processes based on data, and using the Internet. As more and more factories and their equipment are IoT enabled, the volume of data will only grow, hence the application of digital technologies is inevitable. To truly pave the way forward to Industry 4.0 and beyond, manufacturing must evolve into cognitive manufacturing, which is the base model of smart manufacturing. This paper provides an overview of the development of the concept of digital manufacturing, from different aspects, with examples of application in real manufacturing. The goal is to create a good practice of digital manufacturing with the elements of Industry 4.0, as a basis for the development and application of the smart manufacturing (SM) model.

Keywords: digital manufacturing; Industry 4.0; smart manufacturing; ERP; MES

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1. Introduction

Rapid changes in the market and strong individualization of products create a need for great flexibility in managing manufacturing based on, such as digital manufacturing. There are several definitions of digital manufacturing, depending on the context such as is Industry 4.0 context. On the other hand, the history of digital manufacturing is longer than six decades, and it all started with the application of information technology (IT) in manufacturing, which was first stidied by E. Merchant [1–4], as one of the most famous scientists and CIRP members in the world, that deal in this field. In 1961, he defined the concept of computer application in manufacturing [1,2], and a few years later, in 1968, he defined the computer integrated manufacturing (CIM) model, with a feedback loop, where he proposed a computer model of engineering design (CAD), computer-aided manufacturing (CNC, PLC) and manufacturing management (MRP). Later, this model was elaborated in more detail in [3,4], and after two decades the concept itself was the worldwide framework for the CIM model of manufacturing, which showed how much E. Merchant was a "genius and visionary" of the application of ICT in manufacturing.

In the workshop, digitalization began with the application of programmable logic controllers (PLC) and computer numerical control (CNC, DNC) of the machine tools. In engineering-business activities, CAD, CAE, CAM, CAPP, ERP and MES systems, are used, as "islands" of automation in the organization. By integrating the physical and digital worlds (Industry 4.0), digital manufacturing enables faster transformation of the manufacturing process and higher product quality, improving business operations and driving revenue growth. Data from across the enterprise including manufacturing execution system (MES), product lifecycle management (PLM), supply chain

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management (SCM), and enterprise resource planning (ERP) — can provide insights and enable strategic decision making based on information obtained from the digital business model.

This paper has several parts: (i) analysis of the development and application of IT in manufacturing, through three stages of its development, (ii) an example of a developed and applied model of digital manufacturing, which is being developed in the direction of a digital factory, as a basis for smart manufacturing and (iii)) conclusions and future research.

The aim of this paper is to present the results of the development and implementation of the concept of digital manufacturing in the AMM Manufacturing factory, of the MIND company, Kragujevac, as an example of the best practice in Serbia. Also, this paper show how an organization should go about developing and implementing a smart manufacturing model.

2. Evolution of the Concept of Digital Manufacturing in the World - Literature Review

Digital manufacturing as a new paradigm of manufacturing systems has a history since the beginning of the sixties of the last century, so at the moment its evolution can be divided into three periods, as shown in Table 1.

Table 1. Evolution of digital manufacturing.

Period of time	Characteristics	Elements of application
Before 2010. (level 1).	Digitization of engineering / business functions. "Islands" of automation.	PLC, CNC/DNC, CAD, CAE, CAM, ERP, MRP I and ERP II, PDM/PLM.
Between 2010 and 2020. (level 2).	Part of the Industry 4.0 (AI/ML) model.	CPS, BDA, IoT, AI/ML, ERP, MES, ... (elements of Industry 4.0)
After 2020 (level 3).	Part of the Industry 5.0 (Deep ML) model.	Collaborative design, planning and management.

In the analysis that follows, a detailed analysis of all levels of development is given, from the aspect of their application in real manufacturing.

2.1. Digital Manufacturing - Model until 2010

This period refers to the period from 1960 to 2010, where three directions of development and application of IT in manufacturing can be indetified: CAx technologies (CAD, CAM, CAPP, PDM, PLM), as well as PLC, CNC/DNC machine tools, (ii) resource planning, manufacturing management, sales and supply chain management (MRP I, MRP II, ERP, CRM, SCM) and (iii) machining and manufacturing simulations (CAE (FEM), VR, simulation, ...) [5], as shown in Table 2.

Table 2. Overview and selected examples for digital manufacturing (DM) for level 1.

Ref.	Pub. year	Model DM (Digital Manufacturing)	Outputs - basic characteristics
[5]	2009	A defined model of digital manufacturing.	Digital manufacturing as a factory concept.
[6]	1999	VR in product design.	Virtual product prototype.
[7]	2000	Data integration (CAD/CAE).	Rapid product development and market entry.
[8]	2001	PLM as a feature model (10).	Integrated CAD/CAM model (via features).

[9]		STEP translator.	Integrated CAD/CAM model (via model data modification).
[10]		A model of agents for plant-level manufacturing management.	Model simulation for manufacturing management.
[11]	2002	A model of plant-level resource management agents.	Model simulation for business management.
[12]	2003	Fuzzy model for making investment decisions in the CIM concept.	Economic evaluation of strategic goals.
[13]		Rapid development of product prototypes on the web platform.	Networked system architecture.
[14]	2004	ICT as support for the mass customization (MC) model.	Defined four models for MC.
[15]	2005	Semantic model of digital factory (DF).	Factory model simulation.
[16]		ICT platform for DF.	Application to the welding process.
[17]		Validation of digital planning.	Application in the auto industry factory.
[18]		Simulation of the transport system in DF.	Optimization of technological flows.
[19]	2006	3D modeling as the basis of digital manufacturing.	Digital factory model from three angles.
[20]		Interoperability of CAD and CAI models.	EXPRESS-X model for quality management of conformity.
[21]	2007	Application of ontology for web modeling.	CAD model of the product based on semantic information.
[22]	2008	e-engineering for the digital factory.	Business simulation of a digital factory.
[23]		An open web application with knowledge sharing.	Application in advanced technological systems.
[24]	2009	OSA model for maintenance by condition.	Maintenance of mechanical and electrical systems in the factory.
[25]	2010	Digital factory.	Flexible manufacturing management model.
[26]	2011		Intelligent agents for diagnosis.
[27]	2015		Intelligent CPS system.

The approach of defining virtual manufacturing, based on VR, as a human-machine interface, using a virtual prototype, using multimedia information [6], or data integration in rapid product development [7], are two approaches to modeling and data integration. The product is defined by ten characteristics, which are monitored in operation using a PLC [8], as one of the solutions for digitizing these processes (welding). Developed and applied architecture for data exchange between CAD/CAM systems on the internet / intranet platform, using the STEP translator [9], provides the basis for competitive engineering, as the axis of interoperability of manufacturing systems. Defined and implemented the concept of agents for the simulation of models for managing manufacturing in a plant, through a defined architecture [10], and enterprise-level business planning and management (ERP) [11], are two examples of agent-based simulation. Four methods are applied for the economic selection of the most favorable CIM model for the organization [12], according to several criteria, which optimizes digitization processes. Modeling is done using the Jav-based web technique, planning manufacturing chain, and selection of collaborative manufacturer and defining manufacturing task [13], which is one of the ways to digitize business. An ICT model for mass customization (MC) was developed, which is applied to create products according to customer requirements, through four models and eight parameters [14]. The digital factory model includes: electronic product catalog, manufacturing flow with infrastructure and software support, which is the solution given in [15]. For the manufacturing of products obtained by welding its components, a digital factory (DF) model is presented, which is supported by an adequate ICT platform given in [16]. Validation of digital planning is extremely important for technological manufacturing processes in the automotive industry, which is carried out at critical points of the process [17]. For factories from the automotive industry, the optimization of manufacturing and transport flows is extremely important, and one model for a digital factory (DF) is given in [18]. The basic framework of the digital factory includes: (i) manufacturing informatics (all relevant information about the product and its manufacturing), (ii) digital manufacturing technologies (CAD / CAPP / CAM / CAI) and (iii) manufacturing intelligence (AI/ML) [19]. Conformity quality management in the manufacturing of parts in automotive industry using have been the developed and applied interoperability model [20]. The application of ontology in web modeling of semantic information for CAD models in a digital factory is presented in [21]. E-engineering is an integrated engineering environment for a digital factory on a web platform, supported by service-oriented architecture and intelligent software agents [22]. A built environment based on knowledge sharing using open web applications for a new generation of technological systems is given in [23]. Developed state-based maintenance model as an open architecture (OSA) system, supported by artificial intelligence (AI) is given in [24]. Digital enterprise technologies combined with sophisticated optimization algorithms with discrete events, as a simulation model is given in [25]. The development and application of the module of intelligent agents for the diagnosis of the condition of machine systems in the digital factory is given in [26]. CPS as a digital machine tool for optimization of machining processes for parts with free surfaces is presented in [27].

If we summarize the analysis for the first level of ICT evolution in manufacturing, we can conclude the following: (i) in manufacturing organizations, the evolution of IT application went from the automation of machine tools and robots (PLC, CNC/DNC) to the online optimization of the machining process on machine tools as CPS (cyber physical systems), (ii) through the automation of engineering design (CAD, CAE, PDM and PLC), (iii) then the planning of manufacturing and metrological processes (CAM, CAPP, CAI), (iv) to the planning and management of manufacturing (MRP I, MRP II and ERP). Thus, manufacturing organizations have become "tiger skins" or "islands of automation". The issue of the operability of data flows has become one of the main limitations of the spread of the IT concept in manufacturing. Also in the second half of the first decade of the twenty-first century, the concept of a digital factory was established as a strategic direction for the future development of manufacturing. Two dominant international projects were launched at that time and supported by the EU - Factory of the future and Manufuture, which are still ongoing.

2.2. Digital Manufacturing - Model between 2010 and 2020

From the point of view of digitization in manufacturing, the second decade of this century was marked by the emergence and maturation of the Industry 4.0 model in its application. Starting from these facts, and bearing in mind the example that will be given in the second part of this chapter, the following are analyzed from the aspect of digitalization: (i) the concept of Industry 4.0 based on digital manufacturing, (ii) advanced manufacturing systems, resulting from the development and applications of the elements of Industry 4.0, such as: digital manufacturing (DM), cloud-supported

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manufacturing (CM), smart manufacturing (SM) and intelligent manufacturing systems (IMS), (iii) Internet of Things (IoT) and Industrial Internet of Things (IIoT), (iv) big data analytics (BDA), (v) digital twins (DT), (vi) artificial intelligence and machine learning in manufacturing (AI/ML), (vii) horizontal and vertical integration and (viii) cyber physical systems (CPS) in manufacturing.

2.2.1. Digitization as the Basis of Industry 4.0 in Application

Industry 4.0 as a new concept of automation of manufacturing systems was inaugurated at CEBIT, Hanover in 2011.. At the beginning of 2012, it became an official national program for the development of German industry, so that, similar to this program, by the end of 2020., 46 other countries around the world will adopt and implement similar national programs for the development of their national industries. Serbia adopted its Industry 4.0 Program in June 2019. Thus, a new model of automation of manufacturing systems has emerged, that now represents a mature model in application. Therefore, the transformation of the industry through digitalization while exploiting the potential of new technologies is, among other things, a flexible way to individualize adaptable products. The reference architecture model for horizontal-vertical integration is RAMI 4.0 model [28]. This model is a contribution to standardization toward to building a smart factory, as shown in Table 3.

Table 3. Overview of the Industry 4.0 model with some digitalization features.

Ref.	Pub. year	Model Industry 4.0	Characteristics
[28]	2017	Industry 4.0 model with its elements.	RAMI 4.0 model for H/V integration.
[29]	2017	User - server vertical transmission of information - model RAMI 4.0.	Interoperability in the RAMI 4.0 model.
[30]	2018	Product development in the Industry 4.0 model.	Increasing the competitiveness of the organization.
[31]	2018	Model 8C horizontal - vertical integration.	Improvement of ISA-95 architecture (5C), with three additional elements (3C).
[32]	2018	Application of the Industry 4.0 model at the national level - state Platform.	Example USA (IIoT) and South Korea (smart factories).
[33]	2019	Assessment of the maturity of the Industry 4.0 model in the EU.	Digital infrastructure and BDA analysis.
[34]	2020	Database architecture for the Industry 4.0 model.	Cyber Physical Manufacturing System (CPPS).
[35]	2021	Digital Transformation Maturity Model.	Roadmap for the organization to apply the Industry 4.0 model.
[36]	2021	Reference model for vertical integration in the Industry 4.0 model.	The RAMI 4.0 model is an adequate solution.
[37]	2021	Application of Industry 4.0 in SMEs.	Two examples for SMEs.

Management of information in the RAMI 4.0 model is carried out vertically between the user and the server according to the following scheme [29]. Server - information is translated into FDI and Automation ML format, creating XML files, which are then mapped into the OPC UA information model, according to the mapping rules that result in the XML definition of the address space on OPC UA. The user - the first function is to discover the appropriate server, then, the second function searches for the desired information according to the mapping rules within the server, and finally, the information is structured in FDI or Automation format by ML for the user. The digital model of the product, based on the Industry 4.0 concept, enables to the customer requests in all manufacturing stages as the signitificant competitive advantage [30]. ISA-95 is a standardized interface for vertical integration of CPS in the Industry 4.0 model. Its expansion into the 8C model enables horizontal integration, being is extremely important for the smart factories concept of [31], with example of cloud manufacturing is given. Research on the application of the Industry 4.0 concept at the national level is presented in [32]. In the USA, it is the Industrial Internet of Things (IIoT) project, and in South Korea, it is the "pilot" plants of smart factories based on the Industry 4.0 model. The evaluation of the level of maturity in the application of the Industry 4.0 model in EU countries [33] shows that two factors are the most important for the successful practical aplication: digital infrastructure and the ability to work and use the results of the BDA analysis. In [34], a database architecture model for an intelligent factory (cyber-physical manufacturing system) according to the concept of Industry 4.0 is given, with the following characteristics: flexibility, resilience, interoperability and scalability. The digital transformation maturity model is explored in [35], with the aim of creating a road map for the implementation of the Industry 4.0 model in organization. In the study [36], the reference architecture for the Industry 4.0 model is investigated, where the starting frame is the RAMI 4.0 model, and five other models are analyzed. It has been shown that the RAMI 4.0 model best meets the complex requirements of the Industry 4.0 model. Digitization of SMEs is an extremely important process on the way to their adoption of the Industry 4.0. That is why in [37] two examples for SMEs showed how this process can be successful.

It can concluded that: (i) the key to the successful implementation of the Industry 4.0 Project in the organization is the realization of the Vertical Integration, in this model, and (ii) the conducted research shows that the RAMI 4.0 model is the best support for the realization of vertical integration.

2.2.2. Advanced Manufacturing Systems for Industry 4.0

The Industry 4.0 model defines a framework for smart manufacturing (SM), where digitized smart entities (CPS) are used, focused on the customer's requirements and the quality of the product that is digitized, flexible and fully automated, and as networked with the organization and the value chain. The initial research for the development of the smart manufacturing model, that can have several modalities, began even before the Industry 4.0 model [38], as shown in Table 4.

Table 4. Overview of models of advanced manufacturing systems in the context of ICT application in manufacturing.

Ref.	Pub. year	Advanced manufacturing systems	Characteristics
[38]	2012	A networked manufacturing system.	Quick response to customer requests.
[39]	2013	Cloud manufacturing model.	Business activities (sales, procurement, planning).
[40]	2014		Engineering - manufacturing activities (CAD/CAM/ERP).
[41]		Cloud computing (CC).	Four examples in manufacturing.
[42]	2015	Additive manufacturing.	3D model of the part.
[43]		Digital eco-factory.	CPS as eco-agents.

[44]		The digital enterprise.	Reference model – open distributed processing.
[45]	2016	Smart manufacturing model for SMEs.	Example for Germany, USA and South Korea.
[46]		A collaborative robot for smart manufacturing.	Hierarchical planning method.
[47]	2017	IT architecture for the data-driven factory.	BDA analysis.
[48]		NIST model of smart manufacturing.	Information interoperability of data in products, manufacturing and business.
[49]		Smart factory model.	CPS, IoT, BDA and cloud computing.
[50]		The smart factory model – twenty-seven characteristics.	Six design principles.
[51]		Digital factory - ISA-95 model.	Three dimensions in practice (digitalization, IoT and CPS).
[52]	2018	Reference architecture for smart manufacturing (four models).	The RAMI 4.0 model has the best features.
[53]		Standardization of smart manufacturing.	Six areas of standardization.
[54]	2019	Digitization as the basis of smart manufacturing.	Resource virtualization and cloud computing are the axis of digitization.
[55]		Digital Manufacturing Platform Reference Model (I3RM).	ZDM (zero defect manufacturing) as an extension of the model.
[56]		Extended RAMI 5.0 model – smart manufacturing.	Integration of ERP/MES models via the cloud and digital twins (DT).
[57]		The new concept of CPS.	IoT different models.
[58]	2020	Machine tools as smart CPS.	BDA analysis.
[59]		Smart service manufacturing (SMS) model.	Business digital model.
[60]		Smart manufacturing model supported by digital twins (DT).	The R-CNN model is used for simulation.
[61]	2021	JWG21 meta-model (ISO TC 184 / IEC TC 65).	Digital twins.
[62]		The efficiency of smart manufacturing.	The lowest at the supply chain level.
[63]		Smart manufacturing as a model of foreign direct investment.	Positive impact on the application of the Industry 4.0 concept.
[64]		Resistance to the impacts of the COVID 19 pandemic.	Digital readiness and maturity of the organization.

[65]		A mature model of smart manufacturing.	Smart cities, as the next model.
[66]	2022	Simulation of the manufacturing process of pharmaceutical manufacturing.	The effect is 0.95, realized by digital twins (DT).
[67]		Digital eco-systems.	Digital networks of value-added products.
[68]		Hybrid digital manufacturing.	Agricultural machinery as a product.
[69]		Collaborative robotic system.	Work optimization and task reconfiguration.
[70]	2023	New consumer habits and customer demands.	Application of the Industry 4.0 model in manufacturing.
[71]		Digital manufacturing and innovation.	A key factor for the spread of the Industry 4.0 model in manufacturing.
[72]		Reference architecture for digital manufacturing.	A total of 15 different models.

The first cloud manufacturing platform was developed and presented in [39], and was more oriented towards business activities than engineering-manufacturing activities. The emphasis was on data security. The example given in [40] refers to a cloud manufacturing model that supports engineering designs (CAD/CAM) and manufacturing management (ERP), as one of the first examples. The architecture of a networked enterprise supported by the cloud computing (CC) is presented in [41], with special emphasis on interoperability, security, and standardization model and flows data. Example of additive manufacturing, with 3 D model are shown in [42], for real industrial parts, from the aerospace industry, and also the manufacturing of medical devices and parts. The digital eco-factory is simulated as a virtual factory, from eco-performance aspects, prior to the real manufacturing process [43]. Software agents are used for simulation, thus creating an e-library of machines and devices (CPS) in the digital factory. The paper discusses various aspects of the emergence and development of a digital enterprise [44], where the focus is on smart sensors and sustainable development. The reference model - open distributed processing (ODM) is proposed. The development of the smart manufacturing (SM) model at the national level, based on the Industry 4.0 model, is discussed on the examples of Germany, USA and South Korea in [45]. This model is set as a new manufacturing paradigm with the following elements: a model for SMEs, standardization of reference architecture (IoT and IIoT), real-time data flow management, and integrated performance metrics of smart manufacturing. The paper [46] presents a model of a collaborative robot in smart manufacturing, based on the application of a hierarchical planning method, with case example. The IT architecture for a data-driven factory, as a research project, is presented in [47]. The focus of the entire model is on big data analysis (BDA) from manufacturing, as a key factor for raising the quality of processes and products and reducing manufacturing costs (scrap), with example from the automotive industry. The NIST model of smart manufacturing [48] is based on the information interoperability of data in smart manufacturing about products, manufacturing and business. It is based on the integration within and between the three dimensions of the life cycle manufacturing: product, manufacturing system and business, thus observing a smart manufacturing, as a new paradigm. Smart the factory performs integration between physical and virtual technologies [49], through the three layers: physical resources, networks resources and application data, connected via CPS, IoT, BDA and cloud. An overview of definitions, models and characteristics of smart manufacturing based on Industry 4.0 is given in [50]. It defines a semantic set of twenty-seven characteristics (digital infrastructure, modularity, ..., vulnerability) and thirty-eight technologies

(Industry 4.0 elements), that support the model of smart manufacturing (intelligence, intelligent management, ..., SPC). They concluded that basic concept in design and development of the smart manufacturing considers interoperability, virtualization, decentralization, work in real time, orientation on the services and modularity. Agility, productivity and quality are complemented with different networked entities [51]. An example of a successful model from industrial practice is given, based on the ISA-95 model, observes a smart factory in three dimensions (digitalization, IoT and CPS). One of the recent trends in the development of smart manufacturing is the definition and implementation of a reference architecture. In [52] an analysis of four different models was performed : (a) RAMI 4.0 model, (b) IIRA (Industrial Internet Reference Architecture), (c) IBM Industry 4.0 model, and (d) NIST smart manufacturing model [48]. It was concluded that from the aspect of modeling and management of micro-services in the enterprise and optimization topology interaction between micro - services, smart objects and people, RAMI 4.0 model has the best characteristics. The core of the Industry 4.0 model is smart manufacturing, and the attention, as mentioned above, is focused on the development and application of the reference model. However, in the broader context of this model, many versions of the international and national standards are being developed and already implemented, especially in the field of IC technologies [53]. They relate to the following areas: (a) business operations and management standards (QMS and others), (b) manufacturing standards, (c) design standards, (d) system integration standards, (e) supporting technology standards, and (f) environmental standards. In this way, the overall model of smart manufacturing is rounded off. Today, it is considered that Industry 4.0 and smart manufacturing are the future that has arrived, based on digitization. Also, in this context, resource virtualization and cloud computing are considered to be the basis of the digitization. In [54], some models of these approaches with a focus on data security are presented. The Digital Manufacturing Platform Reference Model (I3RM) is presented in [55]. It represents a multi-dimensional eco-system, which integrates different stakeholders, including supply chains, supported by IT models. A special dimension of these studies is the integration of this model with a zero defect manufacturing (ZDM). Custom model of smart manufacturing based on RAMI 5.0 model is presented in [56]. The structure is based on the product life cycle model, and through the global cloud, it is connected to the local cloud, that manages business processes, connected by the ERP and MES model. Logistics, technological and manufacturing processes at the CPS level are defined and managed by means of digital twins. The role and functions of the CPS within the smart manufacturing concept is discussed in [57]. They defined a new CPS architecture, based on the wide range of different IoT models. The machine tool in the smart manufacturing model is defined and monitored over four levels: physical, network, server and client levels [58]. During the processing, large amounts of data are generated that are monitored online and collected through formatting, filtering, correlation, memorization, passing through intelligent algorithms and decision making. Data from different sources are used in BDA models and further used for the monitoring of the machining process, quality management, smart planning and maintenance of the machine. The study [59] considers a service-related value-added smart manufacturing model, thus developing a smart service manufacturing (SMS) model. Such SMS model includes: business digital model, service evaluation, decision management and knowledge management in the product/service life cycle. The application of the R-CNN AI model for the simulation of smart manufacturing is shown in [60]. The whole concept is based on the digital twins (DT) and includes a manufacturing cell with a robot. In the study [61], the reference model of smart manufacturing - JWG21 meta-model (ISO TC 184 / IEC TC 65) was presented, created by the work of this joint working group. In total eight models were analyzed, and a meta (joint) model of smart manufacturing was defined in two dimensions: a generic product life cycle model, and information integration based on digital twins (DT). In [62], a special dimension of smart manufacturing, its efficiency, was investigated, at the factory and/or supply chain level. The results of the study showed that the efficiency of the smart factory at the plant level is the highest, and decreases at higher country levels due to its depndence on digital infrastructure that varies across countries. Foreign direct investment has made a huge contribution to the development and application of the Industry 4.0 model in China's metal industry [63]. This created the conditions for the wide application of this concept in all industrial and economic branches. Smart manufacturing based on digitization has shown high resistance to disruptions caused by the COVID 19 pandemic [64]. This was shown by research on the digital readiness and maturity of the manufacturing industry in the developed countries of Europe, North America and the Far East. The study [65] presents a comparative analysis of smart manufacturing models in two dimensions: categories (cyber, lifetime, physical, human and architecture) and reference models (twelve models included). These studies show that the reference models for smart manufacturing have reached the appropriate maturity and that the positive experiences in their development and application should be applied to the design of smart city models, especially in the field of IoT. The study [66] shows a special aspect of smart manufacturing, which refers to the simulation of the manufacturing process, prior to the real manufacturing. They showed two examples from pharmaceutical manufacturing, where using the meta digital model of the process, an effectiveness of 0.95 was achieved between real manufacturing and the simulation model. Case example of a digital twin shows another proven advantage of smart manufacturing. Digitization has enabled the development of the new collaborative networks between organizations, thus creating added value for products within such digital ecosystems [67]. The research showed that it is necessary to work on the development and implementation of a digital platform for a collaborative network considering the following: (i) define the technology leader of the network, (ii) by establishing digital twins, the technology leaders must move to a higher level, the manufacturing and delivery of smart machines and devices, (iii) encourage members of the network to innovate, (iv) these facts are especially related to companies with added value products (cars, mobile phones, etc.), and (v) develop parallel new markets for new products from the network. Digitalization of the eco-system enables all previosly listed. In the study [68], a model of hybrid digital manufacturing is presented, that includes the following elements: (i) digitization of physical objects and processes (CPS, IoT), (ii) management of manufacturing resources (ERP/MES), (iii) relations between products and processes (PDM/PLM), and (iv) information system (CRM, CAD/CAM, SCM). This is illustrated by an example of the agricultureal product (special plows for soil cultivation). Robot-human cooperation in a smart manufacturing model with robot path optimization is presented as a research result in [69]. Additionally, the reconfiguration of the robot's manufacturing task is performed, thus generating a dynamic configuration of the entire system for the online mode of operation. During the last decade, digitization has established new rules of consumption and purchase and created new consumer habits, that has led to the manufacturing adaptation. Application of the Industry 4.0 model, with elements: CPS, IoT, additive manufacturing, BDA and AI/ML is shown in [70]. Research presented in [71], shows that innovation is a key factor for the spread of the Industry 4.0 model in manufacturing from the following aspects: (i) sustainability and digital manufacturing, (ii) development of knowledge for digital manufacturing, (iii) effects of digital manufacturing on customer's experience, (iv) apperance of digital twins, and (v) AI in digital manufacturing. Reference architecture research for digital manufacturing is presented in [72]. A total of fifteen models are presented for: (i) smart manufacturing, (ii) IoT, (iii) vertical integration, and (iv) CPS.

It can be concluded that: (i) decade of developing and applications of Industry 4.0 model, clearly defined frame and structure of smart manufacturing model, and (ii) furthermore the most important elements of that framework are determined: CPS, IoT, BDA, digital twins, AI / ML, vertical integration and cloud computing.

2.2.3. Internet of Things (IoT) and Industrial Internet of Things (IIoT)

The online connection of the entities in the smart factory is realized by means of the Internet of Things (IoT), or the Industrial Internet of Things (IIoT). The focus of this chapter is on the application of IoT and IIoT in manufacturing, within the Industry 4.0 concept or smart manufacturing model. One of the first studies in this area is given in [73], that defined IoT frameworks in manufacturing, as shown in Table 5.

Table 5. IoT for smart manufacturing.

Ref.	Pub. year	The IoT (IIoT) model in action	Characteristics
[73]	2016	Three levels of IoT.	Application for all levels of vertical integration.
[74]		IIoT for mold manufacturing.	Data-based manufacturing management.
[75]		IoT reference model.	General application.
[76]		IoT architecture.	Three types of protocols.
[77]	2017	Advanced IoT for Manufacturing.	SOA model with five layers.
[78]	2018	Platforms for IoT (nine models).	Four open source IoT.
[79]		IIoT for smart manufacturing.	Realization of SM in practice.
[80]		IoT as part of CPS.	Application examples for smart manufacturing.
[81]	2019	IoT reference architecture for business processes.	Application in services (multi-level model).
[82]	2020	IoT for manufacturing organizations.	AI/ML analysis of customer opinions about the product.
[83]	2021	IoT in manufacturing.	Advantages and limitations.
[84]		Digital manufacturing model and IoT.	Application of the BDA model.

The Internet of Things (IoT) enables the interconnection of the physical world and cyberspace, using: radio frequency identification (RFID), wireless sensor networks (WSNs), and cloud computing (CC) supported by SOA (Service Oriented Architecture). The IoT provides basic communication, with real-time feedback, through sensors, related to the the machine and associated processes, and within the vertical integration model (process, machine, workshop, factory, supply chain). In this model, IoT is used for virtulazation, including the SOA model through the collection, processing and analysis of big data on the cloud, also by using social networkin data (e.g. monitoring of products in use). With the implementation of IIoT, companies are moving to a data-based management strategy [74], and this study presents a mold manufacturing company. Their IIoT model is based on the application of OPC-UA (client/server), ZigBee (IEEE 802.15.4) interface and cloud gateway (Raspberry Pi) connection devices. The OPC-UA model uses a seven-layer data transfer model - the OSI (Open System Interconnection) model. The paper [75] presents a reference model with the characteristics and structure of a general purpose IoT. This model meets the following requirements: connectivity, communication and hardware management, data collection, analysis and activation, scalability and data security. The model architecture has five levels: device, communication, bus, event processing and analytics, and client/external communication. Protocols are important aspects of the IoT model, such as the following three models [76]: (i) semantically oriented protocols (service-oriented protocols - OPC UA (OPC unified architecture), UPnP (universal model), DPWS (device-oriented Web services), CoAP (limited application protocol), and EXI (efficient XML interface), (ii) Internet-oriented protocols (inter connection and conversion protocol based on UDP (user datagram protocol) vs. TCP with HTTP or MQTT support for IPv 4 or IPv 6), and (iii) physical layer and layer connections data with low level - communication protocols suitable for simple setup and maintenance. IoT for manufacturing commonly considers from the three-layer to the five-layer architecture supported by SOA standards [77], with specific software components installed on the hardware module according to the smart manufacturing requirements. One of the challenges is the lack of the standards related to the hardware solutions [78] and current work is focused on definitions of the technical (hardware) reference architecture. Iindustrial Internet of Things (IioT) is the basic pillar digital manufacturing, that connects all industrial entities, including machines and management systems, with information systems and business processes, toward smart manufacturing [79]. IoT can be used for continuous monitoring of the machine state in operation, for predictive maintenance, or, online monitoring of the machining process, and intelligent management. Accordingly, IIoT applications have wide potential in smart manufacturing. The study [80] analysed of the use of IoT as part of CPS in Industry 4.0 concept through the analysis of published papers related to the practice of companies in the most developed countries. It is concluded that this symbiosis is foundation for the development of smart manufacturing models. The development of an IoT reference architecture for the business processes is presented in [81]. Quality of service (QoS) is one of the basic performance indicator of the business process in service ibdustry. Using the SOA principle, a multi-level architecture for IoT for services is proposed considering: the device, network, service, service flow monitoring engine, and application. Implementation of IoT in US manufacturing organizations (239), through convergence with IT and operational technologies has been studied in [82]. Positive progress has been demonstrated for organizations that offer value-added products, and use additional analytics through social networks related to the customer expectation. AI/ML models were used for those analyses. Study of the complex model of the application in manufacturing is given in [83], where, the main drivers of the application in manufacturing are the following facts: (i) improvement of operational effectiveness and productivity, (ii) better use of equipment with lower downtime, (iii) development and improvement of business processes. Some of the main challenges in IoT application in manufacturing are related to the following: (i) interoperability and data security, (ii) lack of standardization in IoT solutions, and (iii) sustainability and energy consumption of those devices in operation. Models of digital manufacturing with IoT case studies, including big data analysis (BDA) that show flexibility and adaptability of the concept is shown in [84].

It can be concluded that (i) IoT represents very important element of the Industry 4.0 concept, including smart manufacturing and (ii) development of the reference models and standardization is current focus in model development.

2.2.4. Big Data Analysis (BDA)

Constant advances in sensor and communication technologies provide new opportunities to connect the physical manufacturing workshop and the machines into the cyber world of Internet applications. Cyber-physical system in manufacturing can manage production process through processing of advanced data and based on virtual models. The manufacturing system with sensors in which each process or piece of equipment provides data about events and status, together with market research altogether creates a big data analysis (BDA). Accordingly that can provide smart manufacturing. One of the first analysis of the BDA model for manufacturing is given in [86], as shown in Table 6.

Table 6. BDA models for manufacturing.

Ref.	Pub. year	Model BDA	Characteristics
[85]	2016	BDA for the factory.	Cloud-supported manufacturing (CM).
[86]	2018	BD – 3V (volume, shape, speed).	BDA – model and processing tools (Hadoop).
[87]	2019	Tools for BDA modeling.	A total of thirty one tools.
[88]	2020	BDA analysis in EU companies.	Manufacturing, maintenance and logistics.

[89]	2021	BDA analysis in supply chains.	Barriers to more effective implementation.
[90]		Second generation BDA.	Application of AI/ML models.
[91,92]		Application of BDA in SCM in India (Manufacturing).	Four barriers to wider implementation.
[93]		BDA in the UK manufacturing sector.	Innovations as a model for the improvement of BDA.
[94]	2023	BDA for PLM model.	Application of the ISO 14000 series.

The presented BDA model is supported by the cloud, which realizes the concept of vertical integration using the SaaS model. Big data from manufacturing and factory includes: (i) structured data by ERP/MES models (operational and time data in manufacturing and procurement data, (ii) data from sensors (on physical equipment, RFID and GPS data) obtained by IIoT, and (iii) unstructured data (from social networks, customers and marketing). Altogether it creates the BDA factory model. The term "big data" (BD) refers to a heterogeneous mass of digital data, whose characteristics (value, veracity, vision, volatility, verification, validation and variability - 7V) require specific and increasingly sophisticated computer tools for storage and analysis [86]. BDA analysis can be grouped as: (i) descriptive analytics (statistical trends), (ii) diagnostic analytics (searching for the root cause of the problem and the resulting consequences), (iii) predictive analytics (using data from the past to predict the future, using data mining techniques and AI), and (iv) prescriptive analytics (uses descriptive and predictive analytics to find the best solution). Hadoop is one of the most famous platform for BDA analysis. BDA analysis related to manufacturing is commonly - using the following tools [87]: (i) descriptive analytics (control charts, traffic lights, advanced data visualization, data mining, statistical analyses, text, video and other multimedia analytics), (ii) diagnostic analytics (cluster analytics, sequence pattern mining, modeling statistics, query tools, spreadsheets, OLAP tools, decision trees), (iii) predictive analytics (multinominal logit models, regression techniques, k-nearest neighbor (knn), bayesian model, multiple backpropagation (MBP), self-organizing map (SOM), rough sets, neural network (NN), genetic algorithm (GA), association rule, vector machine (SVM), general sequential pattern (GSP)), and (iv) prescriptive analytics (discrete modeling, linear and non-linear programming, value analysis, simulations). Analysis of 700 EU companies that have used BDA analysis showed that it was mainly used in manufacturing, maintenance and logistics [88]. This is especially shown on a large number of KPI parameters from these areas. Study of the application of BDA analysis in supply chains was presented in [89], and showed the main challenges to a more efficient application of this concept: the complexity of data integration, data security and quality, and lack of infrastructure. New models of cloud computing and second generation of BDA analysis have emerged related to engineering tasks (CAD/CAM/CAI), based on the 5G technology [90]. The second generation BDA is characterized by: high data quality and application of AI/ML models, analysis of the application of the BDA model in SCM of the Indian manufacturing industry is presented in [91,92]. Literature review has shown that the main challenges to its application are related to the following: lack of support from top management and finance, lack of skills and lack of techniques or procedures for implementation. Some case examples in innovative companies that indicate methods to apply advanced BDA are shown in [93]. Evidence shows that companies with data management culture that enable data sharing very efficiently support innovation. Also, new approaches to the application of BDA analysis are related to the management in the product life cycle (PLM), considering environmental protection [94] and 14000 series standards. The following BDA platforms are commonly used: Apache Spark, Hadoop, NoSKL, Enterprise Data Warehouses and Big Data Warehouse.

It can be concluded that BDA model enables best effects in manufacturing, but it is also increasingly applied in smart manufacturing (the second generation of the BDA model).

2.2.5. Digital Twins (DT)

A digital twin (DT) is a (precise virtual) copy of the machine that can communicate with its physical version. Such an approach to digitalization has enabled wide possibilities within the Industry 4.0 concept, as this chapter will further analyses. That is a symbiosis of digital and physical versions of the machine that overlap each other. The study [95] presented a DT model for a smart factory considering: (i) CAD/CAE design, (ii) manufacturing (CAM/CNC), (iii) resource planning and manufacturing management (ERP/MES), and (iv) maintenance of products in operation (PLM), as shown in Table 7.

Table 7. DT models for manufacturing.

Ref.	Pub. year	Model digital twin (DT)	Characteristics
[95]	2018	DT for the smart factory.	Cloud manufacturing (CM).
[96]	2019	Reference model DT.	An example for all elements of smart manufacturing.
[97]		Maintenance in the smart factory.	Model DT.
[98]		DT for MES model.	OPC UA standard for data exchange.
[99]	2020	Six-level architecture for DT.	Robotic gripper like DT.
[100]		Maintenance models using DT.	Five models for a smart factory.
[101]		Standard for DT.	ISO 23247 (DT for manufacturing)
[102]		DT modeling.	Five basic characteristics.
[103]		CNC Machine tool as CPS.	DT is used for maintenance.
[104]	2021	DTaaS as a cloud model.	Application for SMEs.
[105]		DT for planning in the smart factory.	CAPP and ERP model.
[106]		DT for ZDM model.	Accuracy DT 99%.
[107]		DT general purpose.	Application possibilities outside of smart manufacturing.
[108]		Innovative dimensions of DT.	A total of five.
[109]	2022	DT for PLM innovation model.	Business innovations (three groups).
[110]		Data-driven DT.	Application of data mining and machine learning techniques.
[111]		More dimensions of DT (virtual).	Four dimensions of digital representation.
[112]		DT and universal interoperability.	Public and private cloud.
[113]	2023	Robotic DT model.	Smart robotic manufacturing.
[114]		DT for smart manufacturing.	Thirteen different models of protocol elements.

[115]		DT supported by the Mrakov model.	Fine timing.
[116]		DT for complex material flows.	Object-centric data mining process.
[117]		In-depth analysis of DT, on different grounds.	One Direction: CPS, Product, Enterprise.
[118]		DT - development until 2030.	Application of AI tools and techniques and deep ML models.
[119]		DT for machine care and maintenance.	"Health" model of predictive maintenance.
[120]		DT for smart manufacturing.	Integrated platform for DT.
[121]		Application of DT in real manufacturing.	Creation of multiple models (copies) of DT.
[122]		Adaptive (multiple) model DT.	Product customization.

The DT reference model is presented in [96]. Currently, the latest versions of the standards for DT in smart manufacturing are: (i) design (STEP AP 242), (ii) technology planning (STEP NC AP 238), (iii) planning inspections on CMM (DMIS 5.3), (iv) manufacturing (OPC UA CNC model and MTConnect 1.3.0), and (v) inspection on CMM (QIF Resources). The area of maintenance in a smart factory is the most suitable for the application of DT, which was shown in [97]. It should be noted that in this case the connection of CPS (machine), with BDA for condition diagnosis (in operation and failure) and predictive maintenance and DT is shown as an adaptive model of machine element degradation. In [98], a detailed analysis of the possibility of applying DT in smart manufacturing was presented focusing on the MES model (managing manufacturing in the workshop). The structure of the MES model is related relevant to the MASA reference architecture. The experiment was performed on a laboratory model, using the OPC UA standard for data exchange. A reference architecture for a six-level DT is presented in [99], considering: (i) levels 1 and 2 that consist of physical twins, (ii) level 3 is a buffer of data received from sensors and machine controllers, via the OPC UA protocol, (iii) level 4 represents the IoT gateway to the levels 5 and 6 that represent the cloud SaaS model for event simulation and emulation. They showed the case example of robotic gripper for automatic assembly where the states of correct and incorrect operation are defined as DT. The application of DT in different maintenance models (reactive maintenance (failure repairs), preventive maintenance, condition-based maintenance, predictive and prescriptive maintenance are shown in [100]. The last two models used second generation DT in smart factories maintenance. DT will be one of the most important elements of smart manufacturing [101]. However, there are still issues in about the application of this concept at SMEs. One of the proposed solutions is the development of the ISO 23247 standard (DT for manufacturing), related to the the main elements: reference architecture, digital representation and information exchange. Study [102] presents an in-depth analysis of the DT concept and different approaches in development and application: (i) DT modeling technology - from static to dynamic mappings of physical entities (from model-driven architecture (MDA) to ML-generated models, (ii) data collection and transmission technology - multiple sensor networks, broadband IoT, advanced communication protocols and interfaces, (iii) data management technology - distributed cloud server, extraction characterization and assessment of data value, identification of unstructured data, (iv) intelligent algorithms and data processing - cloud computing platforms, validation and optimization algorithms, machine learning, and (v) human-computer interaction technologies - VR/AR systems, speech recognition, collaborative platforms. An ontology application for schematic modeling of a CNC machine for DT is given in [103]. The machine tool is viewed as a

CPS and the DT is used to monitor its condition and do maintenance. DT as a service (DTaaS) is studied through the reference architecture model shown in [104], as a cloud model. This approach is especially interesting for SMEs (intelligent maintenance, real-time monitoring, remote control and monitoring of CPS functionality). The application of DT for the planning process in smart manufacturing is shown in [105], and it refers to technology (CAPP) and factory (ERP). They showed the case example of two manufacturing lines in Japan, with practically applied smart manufacturing. The realization of the smart manufacturing model according to the concept of zero defect manufacturing (ZDM), using the DT model, is shown in [106]. For the developed ZDM strategies, a simulation is performed (approximately a thousand simulations) using DT, which aiming for smart manufacturing as a practical model, with 99% accuracy of the DT model. The study [107] provides an in-depth analysis of DT from the following aspects, including for smart manufacturing: where to apply it (such as manufacturing and health system, smart cities, aerospace and shipbuilding), how to design it (e.g. reference model), and what are the most important challenges of application (e.g. flexibility, operability and modularity). DT is one of the most important elements of smart manufacturing in the Industry 4.0 model [108]. Innovative DT concept can be designed to consider performance, such as: (i) DT model oriented to product quality (it is best that DT is applied for ZDM), (ii) DT model oriented to flexibility in terms of meeting individual customer requirements), and (v) DT model based on information security and security of use for the user. Study [109] analyzed the development of a DT model for a PLM innovation model (encompassing business innovation). The elements of that business model were: (i) strategic components (strategy, resources and network), (ii) customers and market (customers, market and revenue), and (iii) value creation (manufacturing, procurement and finance). Data-driven DT for smart manufacturing is discussed in [110]. Their approach in the design of DT model used data mining techniques from manufacturing, data analysis and simulation models through machine learning. They presented a case study of drone manufacturing for which the integrated DT model was designed. Multiple virtual DT versions were analyzed in [111], with four groups of characteristics: (i) master reference data (from organization to configuration), (ii) temporal dimension (representation and synchronization), (iii) operational data (from spatial characteristics to lifetime characteristics), and (iv) physical entities models (from economic to environmental characteristics). The development of a "universal translator" for DT was analyzed in [112], since interoperability is especially important property of DT. A model of universal interoperability was proposed, based on the use of wi-fi devices, connected to six interface models (from EtherCAT to Profi BUS), and DT dashboard altogether connected to the public and private cloud. An application of DT for a robotic machining cell is shown in [113], with processing of edges on the large parts, and with process planning the process and programming the robot for that process. The entire process is also monitored via the virtual robot control unit (DT) from a distance thus creating the concept of smart robotic manufacturing. An analysis of DT in smart manufacturing was carried out in [114], aiming to determine state-of-the-art for technology applications. The following communication protocols have been considered: (i) data type (XML, JSON), (ii) application (OPC-UA, MQTT, HTTP, MTConnect), (iii) transfer (TCP/IP, UDP, ZeroMQ), (iv) physical object / data connection (Ethernet, Modbus, WLAN, WTE). An interesting approach to the application of DT, supported by the model of Markov decision processes (MDP), is shown in [115]. It enables fine timing of operations in the manufacturing process, taking into account all the uncertainties that arise in the manufacturing process. Orchestration is done in five steps (from defining the manufacturing task to online monitoring of its execution). A algorithm for the correct generation of DT, in smart manufacturing with complex material flows, especially assembly lines is shown in [116]. An object-centric data mining process is applied, and all this is illustrated with two examples. The study [117] deals with an in-depth analysis of reference models of DT for smart manufacturing, from a large number of aspects: structure, application, etc. Comprehensive analysis of the DT model in smart manufacturing is especially important considering: (i) unit level (CPS, machine tools). That level enables the optimization and monitoring of the machine processes and maintenance, at (ii) the system level (drive, organizational functions (design) that also includes several entities (from the first level forming). The essential difference is communication and coordination between DT entities, and (iii) system-system level (factory, enterprise), such as communication and coordination between CRM, CAD, SCM, ERP, or MES, as common DT models. The development of the DT model until 2030 is analyzed in [118], where Delphi method was used for predictions on representative sample of 46 units. Their conclusions indicated AI and deep ML as tools that will improve DT model applications. Research has shown that DT in smart manufacturing has mainly considered maintenance of machines and equipment. The way to apply DT in machine maintenance as CPS within the wider context of the whole company system and also including owners of those same machines outside only one company is shown in [119]. The first step in building a predictive maintenance model based on DT and cloud computing is to define the possible machine errors that can originate from networks, sensors, machine inputs, control unit and other. At the second level, sets of undefined errors (failures) are defined such as those: from the environment recognized by experts, sudden failures that were not recognized before, new funcional failures, and previously defined failures: from sensors (such as alarms), degradation of the measured parameters and parameters relating to non-compliance with safety standards. From this context, the overall "health" system of the machine is built as DT. The study [120] provides a comprehensive overview of the current application of DT in smart manufacturing. Based on the analysis performed, it can be said that DT technology is moving towards full application maturity, as it provides users with many benefits in application such as: (i) optimization of the process of manufacturing preparation, manufacturing, quality management, maintenance management (ii) product life management, (iii) management of supply chains, and (iv) management of design and construction of a new factory. All this leads to the fact that integrated platforms for DT will be developed in the near future, as a new model of planning and management of the smart factory, with the following characteristics: (i) integration with IoT and other Industry 4.0 technologies, (ii) integration with BDA, AI and deep ML, (iii) real-time optimization (manufacturing, maintenance, supply chains), and (iv) data security. The paper [121] shows the application of the DT model in a smart factory for design (of products, factories), quality control and maintenance. Current research that is focused on the development of online optimization models using DT, using ML, analysis and synthesis of quality control errors and designing and making multiple models (copies) of DT. One of the main directions of DT research is online optimization [122], toward an adaptive (multiple) DT model. Their approach is related to the customization of products, that can be produced for each individual customer with example of DT for the manufacturing of shoes, and bicycles.

It can be concluded that the most applied element of the Industry 4.0 is DT that is starting to develop toward mature technology. Our paper will show in next chapter (3.2) application of this concept in our research.

2.2.6. Artificial Intelligence and Machine Learning (AI/ML)

Research related to the AI and ML in manufacturing systems began in the eighth decade of the last century. First studies in this area at the Faculty of Mechanical Engineering in Belgrade, also started at that time when prof. V. Milačić was the head and the fourth author, at the first International Conference "Intelligent Manufacturing Systems" in Dubrovnik, in 1985, with this topic. Today, evolution of these technologies has occurred and review of their development and applications in manufacturing systems is given in [123], and as shown in Table 8.

Table 8. AI/ML in manufacturing systems.

Ref.	Pub. year	AI/ML model	Characteristics
[123]	2004	AI/ML for technology systems.	Inductive learning.
[124]	2015	ML reference architecture for smart manufacturing.	Generic appointment management platform.
[125]	2017	KBS for the digital factory.	Support for the designer's cognitive activities.

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[126]	2020	AI in manufacturing.	Three application examples.
[127]		Optimization of electricity consumption.	Part of the MES model, supported by ANN.
[128]	2021	Application of AI/ML models in manufacturing.	The five most important areas.
[129]			Digital skills, company size and intensity of R&D activities.
[130]	2023	AI trends in manufacturing.	Intelligent manufacturing.
[131]		AI in manufacturing (process, machine, system).	Application examples.
[132]		AI support for project selection.	The most important criterion - finances.
[133]		Application of generative AI in manufacturing.	Application in marketing, sales, research and development and procurement.
[134]		KBS for ML in smart manufacturing.	Care and maintenance of CPS.
[135]		ML models.	Decision making, monitoring, management and collaboration.

The paper [124] presents a reference architecture for ML, that is used for scheduling in the smart manufacturing of parts for the automotive industry. Designing a factory as a digital model is presented in [125], with a knowledge-based system (KBS) is used as a design tool, that helps the designer's cognitive activities. In the study [126], a broad overview of the application of AI tools and techniques in manufacturing, including smart manufacturing, is presented, where three examples are given: (i) maintenance of machines for the manufacturing of composite materials, in order to prevent sudden failure, (ii) ZF factory for manufacturing transmission - predictive maintenance of the gear manufacturing machine and improvement of its OEE parameters, and (iii) smart inspection of the gears at the end of the manufacturing line at ZF. A hybrid control system, supported by the BDA and machine learning, is used to optimize energy consumption in real time, as presented in [127]. This model is part of the MES system, which is supported by the cloud model, and the model is managed by ANN. The research presented in [128] shows that about 60% of smart manufacturing models use AI and ML in practice, in the following areas: quality control and scrap detection, equipment maintenance and failure prediction, predictive machine maintenance, DT and supply chain management. The study [129] deals with defining the influence of manufacturing, organizational and environmental factors, as a prerequisite for the successful application of AI technologies in manufacturing. An analysis of 700 companies worldwide was carried out, and it was concluded for example that digital skills, company size and R&D intensity are the most important influential factors for the wider application of AI in manufacturing. An analysis of AI trends with application in manufacturing during the last decade is presented in the study [130]. It has been shown that developed industrial countries have the most research in these areas: generative AI, ANN, ACO, ML, deep ML, ML algorithms, with application in various areas of smart manufacturing (such as design, planning and management). A study [131] analyzed the application of AI in smart manufacturing, from the three aspects: (i) process (quality control, wear of parts, DT, ACO (optimization), (ii) machine (predictive maintenance, robot task planning and motion management, collaborative robots, CPS as an intelligent machine), and (iii) system (ERP, MES, SCM). Selection and evaluation of the development projects in manufacturing, with applied AI models is shown in [132], using data mining models at strategic, tactical and operational levels, where the attention is focused on the application of solutions and the effects they bring. Generative AI based on the new models of neural networks - GAN and VAE, enabled deep learning models [133]. The latest research has shown that this type of AI is mostly used as intelligent support in marketing, sales, R&D and procurement Today, data-driven learning models for smart manufacturing are increasingly being studied and developed, since sensors with very good characteristics have been developed and applied. In [134], a knowledge-based system (KBS) model for machine learning was applied in smart manufacturing for the monitoring and maintenance of machine tools as a CPS. In smart manufacturing, [135] the following learning models are applied: (i) supervised learning (decision trees, vector machines and neural networks), (ii) reinforcement learning (neural networks), and (iii) unsupervised learning (neural networks, generative NN and cluster algorithms). All of them are used for different purposes in smart manufacturing, such as decision making, monitoring, management and collaboration.

It can be concluded that AI/ML are becoming models increasingly applied in smart manufacturing with high future potential, including some of these aspects in our research.

2.2.7. Horizontal and Vertical Integration

The infrastructure of a smart enterprise consists of vertical and horizontal data integration related to processes, machines and systems. There is also a third model, and it is related to the product, and data integration is related to the product life cycle (PLM) and strongly encouraged by the Industry 4.0 model. One of the important technologies for the integration is RFID, as shown in [136], where a reactive model for tracking and converting a large amount of data, "unlabeled" elements (business processes, indicators) and "labeled" low-level elements (persons, objects) is given in Table 9.

Table 9. Horizontal and vertical integration in smart manufacturing.

Ref.	Pub. year	Integration model	Characteristics
[136]	2011	RFID - application in smart manufacturing.	Reactive model.
[137]	2013	PLM - Interoperable Semantic Model.	KBS with knowledge sharing.
[138]	2015	Intelligent ERP model.	Agent-based KBA.
[139]	2016	RAMI 4.0 – RDF model.	Semantic Sensor Network (SSN).
[140]		IS companies - horizontal integration.	Four components of development and application.
[141]		MES model for smart manufacturing.	Based on the standard MESA model.
[142]		Product-driven IS architecture.	Model-driven interoperability.
[143]	2017	Digital Supply Chain (DSC).	Horizontal integration.
[144]	2018	Integration of smart manufacturing and SCM.	Integration with social networks.
[145]	2019	Maturity of the Industry 4.0 model in application.	Vertical and horizontal elements.
[146]	2020	Node-RED platform, smart assembly line.	H/V integration and IoT.
[147]		MBCoT – manufacturing blockchain of things.	Significant advancement of IoT.
[148]	2021	CPS with UJ open source.	RAMI 4.0 with OPC UA protocol.
[149]		The fifth level model of V integration.	Success factors of V integration.
[150]	2022	Additive manufacturing - QA and QM model.	Blockchain technology V integration.

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[151]		Digital shadow (DS) for the MES model in the grinding plant.	Manufacturing scheduling, capacity planning, execution of work orders and capacity management.
[152]		MES model for injection molding drive.	An open source model.
[153]		V integration – ontological interoperability.	Packaging in the beverage industry.
[154]		MES model for digital manufacturing.	SaaS, MTA and OPC-UA support.
[155]	2023	A blockchain model for smart manufacturing.	Three levels of models.
[156]		QM model for digital manufacturing.	Vertical integration.

An example of the interoperable manufacturing system, driven by data, and supported by a semantic model in the PLM concept is presented in [137]. This model is supported by the Knowledge Sharing System (KBS), and has been applied in aircraft manufacturing through the concept of vertical integration. An advanced planning system based on the ISA 95 model, as an intelligent agent system for ERP, is presented in [138]. A knowledge base of agents is being formed, which are related to real manufacturing tasks, which has been shown by several examples. The connection between the RAMI 4.0 model and the concept of resource description (RDF), using semantics, is presented in [139]. Thus, a knowledge base and ontological units (OM) were created, based on the semantic network of sensors (SSN) is organized, for the realization of the concept of vertical integration in the Industry 4.0 model. Horizontal integration through the model of the company's information system is considered in the paper [140]. The following components of this model have been identified, that should be constantly improved in the Industry 4.0 model: (i) managing the data value chain, (ii) always considering of the context, (iii) taking care of the usability, interaction and visualization of the information system, and (iv) competencies and continuous training of employees as one of the key factors for the success of IS in practice. In order to realize the smart manufacturing model, it must first be first applied in the plant, making MES (work order management in the plant) a smart software. The study [141] defines the framework of the MES model for smart manufacturing, starting from the conventional version of this concept, which is then standardized. The key technologies for realizing this concept in practice are: CPS, IoT, BDA, cloud computing and AI/ML, as is shown by several examples. Digitization has changed the paradigm of manufacturing information systems, where their interoperability has been in focus [142]. Industry 4.0 has made it possible to integrate business, engineering and manufacturing processes, building a model-driven (product) information system architecture, while also creating model-driven interoperability. Digital supply chain (DSC) is a horizontal model of integration in the concept of Industry 4.0 [143], and its basic components are: digitalization, SCM (supply management) and supporting technologies of Industry 4.0 (IoT, DT and cloud computing). The integration of smart manufacturing and supply chains (SCM) is presented in [144]. There, special emphasis is given to the development of a platform that will integrate the business requirements of procurement, as well as social networks related to the customer opinions and requirements, which are directly or indirectly related to SCM. In [145], a model for assessing the maturity of the Industry 4.0 model in the organization is presented, where the overall model is divided into vertical elements (people, organization, equipment, processes and products) and horizontal elements (habits, planning, management and sales). The model was tested through the six examples. Connecting elements by using IoT, using vertical and horizontal integration, to build a CPS is presented in [146]. In that way, using the Node-RED platform, a smart assembly system was formed. The application of blockchain technology in smart manufacturing is a novelty, which improves the performance of IoT systems [147], by building the architecture of the manufacturing blockchain of things (MBCoT). It is secure, traceable and decentralized, which makes it more challenging for the digital security as illustrated by the case studies. The essential properties of the Industry 4.0 are H/V integration of the factory, decentralization of computing resources and continuous digital engineering in the product life cycle [148]. RAMI 4.0 is the reference architecture for this concept, and they presented the developed and implemented open source model for the CPS control unit. The OPC UA model was used as a protocolas shown by several case studies. In the Industry 4.0 model, vertical integration is realized by the following chain: (i) CPS (data source), (ii) data collection (SCADA), (iii) MES (manufacturing management in the plant), (iv) resource planning (ERP) and (c) product lifecycle management (PLM) [149]. They studies, the interrelationships of this concept through, on several case examples and considering the following aspects: technology, organization and environment. Managers are shown how to manage these influences to make the V integration model as good as possible in practice. Quality management of additive manufacturing (AM), through a vertical integration model, with the assistance of blockchain technology is presented in [150]. They concluded that the security of traceable data related to quality has been raised to the highest level, because it was necessary. In practice, the QA and QM models were realized and applied. The DT is a virtual representation of the machine, and the digital shadow (DS) contains aggregated traces of data, that can be in a form of records and metadata [151]. Records consist of master data and transaction data, and metadata describes master and transaction data by adding additional information to the data record, such as timestamp and origin. Data traces originate from different IT systems and are integrated into DS. Therefore, DS is applied for planning and management of injection molding manufacturing, in such a way that for CPS systems where manufacturing is realized, it generates a knowledge base of data and meta data, based on which DS is built for manufacturing scheduling, capacity planning, realization of work orders and capacity management. The next example [152], refers to grinding and digitalization of manufacturing in SMEs. The open source MES model was developed using IoT, intelligent planning, DT and cloud computing. Study [153] analyzed the ontological interoperable model of Manumata vertical integration, with four modules: (i) requirements (information and constraints from the real process), (ii) reference ontology as the first level of modeling knowledge and information about materials, products, machines and processes, (iii) applied ontology, as a model of the inference machine, from the previous level, and (iv) smart manufacturing, as a framework where all of the previous is applied. The whole concept has been applied to packaging the in the beverage industry. The study [154] presented a solution for the application of the MES model in digital manufacturing, as an improved SaaS solution, supported by the MTA (multi-layer architecture) model. OPC-UA is used as a protocol model. IoT and NN models are used for BDA analyses. One model of smart manufacturing, supported by blockchain technology, is presented in [155]. It consists of three levels: (i) connection network (CPS entities), (ii) cyber network (cloud computing (notification, interface, storage and data processing), (distributed processing (BDA, AI, DT, ...), and (iii) management network (in distributed intelligent decision-making systems (self-optimization, self-adjustment and self-configuration) for: ERP, MES, SCM and CRM modules. Vertical integration model for QM in digital manufacturing is presented in [156], with a real industrial example one Serbian company.

Based on all previously presented, it can be concluded that: (i) data integration is one of the pillars of Industry 4.0, that will gain even more importance in the future, and (ii) our example presented in this paper refers to the vertical information integration.

2.2.8. Cyber Physical Systems (CPS)

A cyber-physical system (CPS) is an intelligent system monitored and controlled by a computer, consisting of two parts: a machine, as a physical device, and a virtual part, as its online representation. It is one of the basic elements of the Industry 4.0, with architecture defined through the five levels [157]: (i) smart connectivity (sensor network that collects data for ERP, MES and SCM, using the most common MTConnect protocols), (ii) information conversion and processing (algorithms and models for monitoring the state of the machine and its components, smart data analytics), (iii) cyber level (DT and ST), (iv) cognition level (reasoning and inference), and (v) configuration level (self-optimization, tuning and configuration), as shown in Table 10.

Table 10. CPS in Industry 4.0.

Ref.	Pub. year	CPS model	Characteristics
[157]	2015	Five-level model for Industry 4.0.	Self-optimization, tuning and configuration.
[158]	2017	CPS predictive analytics for manufacturing.	Using the PMML language.
[159]		NIST reference model for CPS.	Application in manufacturing.
[160]	2018	Smart CPS.	Cognitive agent (IoT, DT).
[161]		OPC-UA levels for CPS.	Machine tools like CPS.
[162]	2019	New CPS architecture – three levels.	OPC-UA communication protocol.
[163]	2021	Connecting IIoT and CPS.	Integration of IIRA and RAMI 4.0.
[164]	2023	Three-tier CPS architecture for smart manufacturing.	Application in maintenance, scheduling and quality control.
[165]		Application of AR in smart manufacturing.	Application in maintenance.
[166]		Integration of DS and RFID for CPS.	Increasing schematic interoperability.

Predictive analytics is the basic model for monitoring the state of machines as a CPS system, and an open-source solution is presented in [158]. It uses Predictive Modeling Language (PMML), and the software is open source. The model has five modules: a description of the machine and its structure, as a CPS, specific meta models, a diagnostic module and a prediction module, and module for the presentation of the state of the machine. ANNs are used in this model. The first set of studies on CPS systems was done by NIST [159], considering different aspects: structure, purpose, interoperability, etc. A four-level reference model is proposed and an example is given for CPS in manufacturing. Smart CPS is presented as a model in [160]. It adapts to changes in manufacturing (reconfigurable model), has cognitive abilities (perception, reasoning, learning and cooperation), and acts as a cognitive agent that is connected to IoT and creates DT in smart manufacturing. One of the important aspects in CPS application is the definition of the OPC-UA level for smart manufacturing. The model diagram for this protocol has four levels [161]: (i) CPS level (IoT and powerlink), (ii) communication level (OPC UA server and interface), (iii) information level (AutomatiomML language), (iv) and factory level, which is connected to the OPC UA server. The paper [162] proposes a new CPS reference architecture, which has three levels: (i) human component (learning techniques and holistic component), there are also interfaces with other two levels (user, cyber component, and machine interface. The protocols used here are OPC-UA, Ethernet and Powerlnk), (ii) the machine as a physical entity (Industrial Internet, M2M communication), and (iii) cyber component (DT). The last two components are connected to the interface for data collection and process management. It is considered that IoT and CPS will play a major role in the future development and application of the Industry 4.0 model in manufacturing. The goal is to develop IIoT systems and CPS structures, which will enable the connection of network devices and the virtualization of company assets and their connections. One approach to realize it through the connection between IIRA (CPS) and RAMI 4.0 (Industry 4.0) reference architectures is shown in [163]. CPS architecture for smart manufacturing is presented in [164]. The architecture has three levels: (i) base level (machine tools, robots, AGV, RFID entities, sensors, measuring devices, interfaces), (ii) middle level (CPS node (machine tool), CPS unit (machine tool with robot), and CPS System (Drive), at this level these CPS elements are supported by systems for condition monitoring, performance forecasting, scheduling and quality management, and (iii) a computing level (data collection, integration, processing and presentation), with results analysis and intelligent decision-making. Support for a more effective application of CPS in smart manufacturing are VR maintenance systems [165]. The whole concept has been applied to: condition monitoring, failure diagnosis, technology maintenance management and predictive maintenance

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model development. Development of a new CPS concept based on the integration of DT and RFID concepts is shown in [166]. RFID is used for the development and generation of DS (digital shadow), thereby increasing the semantic interoperability that is very significant for its application in condition maintenance and predictive maintenance.

It can be concluded that: (i) CPS represents a basic element of Industry 4.0 in smart manufacturing with increasing importance resulting in development of different concepts and (ii) our research the OPC-UA protocol is used for our CPS application, based on previous methods.

2.2. Digital Manufacturing - A Model after 2020

Recent Covid19 pandemic made huge disruptive changes, where Industry 4.0 concept offered profound possibilities to overcome such challenges, especially related to the manufacturing through remote work. In 2020, the EU adopted the Industry 5.0 document, and defined possible future development directions, with special emphasis on Industry 4.0 as its foundation. One of the first studies in cognitive management related to the smart manufacturing concept was published in [167]. It shows an adaptive system with feedback, and two levels: cognitive and executive, with case studies in micro-milling and drilling machining that has online control of the process, as given in, Table 11.

Table 11. Digital manufacturing, model after 2020.

Ref.	Pub. year	Digital manufacturing model	Characteristics
[167]	2015	A cognitive machine tool	Micro milling and drilling.
[168]	2018	Deep Learning BDA (DCNN) for CAD and PLM models.	3D models (recognition).
[169]	2019	Deep learning (DCNN) for the diagnosis of machine systems.	Condition monitoring and failure diagnosis.
[170]		Swedish industry - BDA analyses.	Application of deep ML.
[171]		Blockchain for AM.	DT for aircraft parts.
[172]		Digital platforms for smart manufacturing.	IoT, MES, SCI.
[173]	2020	BoT (blockchain of things) for smart manufacturing.	Application for ERP and MES model.
[174]		KBS for Semantic Interoperability.	Ontological approach.
[175]		ERP and MES in real time.	Predictive manufacturing planning and maintenance.
[176]		Industry 5.0.	Strategic directions of EU industry development.
[177]	2021	Adaptive management of the processing process.	Deep ML.
[178]		Decision-making in textile manufacturing.	Deep ML (DQ network).
[179]		Cognitive DT.	Intelligent agents.
[180]		MES model supported by blockchain technology.	CPS reference architecture.

[181]	2022	Socio-CPS (SCPS).	Meta-product services in the cloud.
[182]		CAPP model powered by deep learning.	Optimization of processing with the highest quality of processed parts.
[183]		ANFIS model for cutting mode optimization.	At the same time, tool wear is monitored.
[184]		Cognitive DT for maintenance.	Improved features.
[185]		Manufacturing supported by the cloud with the application of blockchain technology.	TaaS private cloud.
[186]		AR powered by deep learning.	Maintenance in smart manufacturing.
[187]		Adaptive milling.	Variable structure of ANN.
[188]		Universal smart manufacturing.	Supported by the cloud.
[189]	2023	DT and application development.	All areas of smart manufacturing.
[190]		Metaverse for manufacturing.	Integration of the physical, cyber and social worlds.
[191]		DT for maintenance optimization.	CPS - offshore oil and gas extraction platforms.
[192]		Safety of smart manufacturing.	Semantic reasoning.
[193]		Smart assembly.	DT and deep learning.
[194]		DT for process industry.	ML for managing critical processes.
[195]		Validation of DT.	Congruence between a physical system and its digital model.

In [168], a model of object recognition in different formats, using deep learning techniques (Deep Convolutional Neural Network - DCNN) is presented. This approach was used for CAD and PLM models, in manufacturing of parts from the automotive industry. The most common application of deep learning techniques is the diagnosis and maintenance of CPS in smart manufacturing [169]. In this reference, an analysis of the application of the DCNN model was performed. The study [170] shows an analysis of the level of digitization of the Swedish industry, where Industry 4.0 model has been accepted by the industry as a framework for the development of smart industry. In that study, BDA analysis using deep ML have been used as the next steps in concept development. Blockchain technology will be one of the leading technologies in the application of the Industry 4.0 model [171]. They used AM in the manufacturing of aircraft parts to support data security within the DT model. The development and application of digital platforms for IoT, MES, SCM, and digital ecosystem has been important for the smart manufacturing [172]. All these models represent a good approach for the easier development and application of smart manufacturing models in industry. The development of a BoT (blockchain of things) model for application in smart manufacturing, a knowledge-driven concept for a DT manufacturing cell is presented in [173]. By applying this approach, a safe, traceable and decentralized model of smart manufacturing was created, which was demonstrated in several examples. Knowledge-based systems (KBS) are increasingly being applied in the smart manufacturing model [174]. They used the concept of ontology-based interoperability semantics and showed several case studies. In [175], a model of BDA analysis with the application of deep learning for ERP and MES model is presented, where this approach is used to perform predictive manufacturing planning, as well as predictive maintenance of CPS, in real time. The study [176] is an official document of the EU on the development strategy of the industry for the green agenda, with key elements being: human-centric with human-machine collaboration, bio-inspired technologies and smart materials, real-time DT, BDA and cyber security, AI/deep ML and energy efficient technologies. Adaptive management of the machining process with CPS and application of ML, including, quality monitoring of the machined surface and monitoring of the tool wear, is shown in [177]. The foundation of that model was data collection and processing by different learning models of ANN. Manufacturing and dyeing of textiles is a complex technological and chemical process. They can be effectively managed, especially the processes of chemical textile manufacturing, by applying the analysis of hierarchical processes (AHP), Markov decision processes (MDP) and deep ML (DQ network) [178]. Cognitive DT is a new approach with additional characteristics of communication, analytics and intelligence, at three levels [179]: approach, analytics and cognition. The access allows online communication with the machine to update the status of the twins. Additional analyzis is obtained through learning, and cognition enables new conclusions from the global knowledge base, thus creating intelligent agents. Management of manufacturing in the facility, according to the MES model for Industry 4.0, using blockchain technology, is presented in [180]. For CPS (CNC machine tool), a reference architecture was developed based on the RAMI 4.0 model, and the OPC-UA model is used as a communication protocol. An open, reliable and cure CPS architecture was obtained for operation in the MES environment. In the Industry 5.0 model, socio-CPS (SCPS) has emerged, that is built on the new economic, environmental and social challenges [181]. The new SCPS model should achieve high resource utilization and provide products and services to meet individual needs based on experience through meta-product services in the cloud, on the way to smart, resilient, sustainable, human-centered solutions. Projecting Prismatic Parts Manufacturing Technology (CAPP, CAM) model, supported by deep ML techniques is presented in [182]. The knowledge base about the machine, part, tool, processing conditions and cutting modes is formed using the ontology, and the whole model is tested on several prismatic parts. The optimization of the milling cutting mode using a learning model based on fuzzy sets (ANFIS) is presented in [183], with two-input, four-level, one-output ANN model. During this process, tool wear is also monitored online. A cognitive DT for maintaining CPS in smart manufacturing is presented in [184]. Its additional feature is semantic support for the new DT model using ontology. Thus, a hybrid DT is obtained, which has improved characteristics compared to the classic DT. Manufacturing supported by cloud and blockchain technologies, as a new model of smart manufacturing, is presented in [185]. A "blocktrust" model has been developed that protects data in a unique way using a TaaS private cloud, as shown by several examples. New augmented reality (AR) models, supported by deep ML techniques, are presented in [186]. It is used for various recognitions, and as far as smart manufacturing is concerned, it is the maintenance and recognition of parts during robotic manipulation. An online milling control model, with optimization of quality parameters and tool wear monitoring, using deep ML (MPAN - multi-pyramidal ANN) methods, is presented in [187]. A special feature of this model is to precisely monitor tool wear and monitor the interoperability of the AN network structure with online generation, monitoring and processing of milling process characteristics. Digitization in manufacturing is based on online processing of real industrial data with new dimensions appearing [188], based on characteristics, such as flexibility, quantity and type of manufacturing, global optimization, and according to different criteria of all manufacturing subsystems. It is proposed to develop a platform for a universal digital model of smart manufacturing supported by the cloud. DT as a 3D digital replica of an entity in smart manufacturing is gaining more and more importance [189]. It has mostly proven its application advantages in R&D activities, for innovative products where costs have been drastically reduced. The key technologies for the further development and wider application of DT are: IoT, cloud computing, AI and AR (augmented reality). The application of DT in manufacturing planning and management brings the following benefits: (i) reduction of manufacturing costs of new products, (ii) reduction of the new product time-to-market, (iii) improvement of product traceability, and (iv) optimization of energy consumption. Metaverse is a term recently used in the field of smart manufacturing related to the symbiosis of avatars (people), portals (sensors, AR) and virtual world (parallel universe) [190]. According to the concepts of Industry 4.0 and Industry 5.0, it includes physical, cyber and social entities, through the exchange of data, information, knowledge and models. The paper [191] presents a model for making decisions about predictive maintenance of CPS, as complex plants, using DT for optimization of maintenance technology. Linear programming supported by metaheuristics is used, and everything has been applied to offshore oil and gas extraction platforms. In [192], ontological mapping of DT and real states of CPS in the plant has been analyzed aiming to increase the safety of manufacturing within man - machine – environment triangle. The model is supported by a semantic reasoning, one of the AI tools. The application of VR in the smart assembly model is presented in [193]. Using DT and a deep active learning model (based on human movement modeling), a smart assembly system was developed. The paper [194] presents the DT model for the process industry, where it offers unprecedented opportunities for predicting and managing parameters of critical processes, by using ML, as shown by case examples they presented.. Rapid validation of DT is extremely important in smart manufacturing [195]. It represents the alignment of physical and virtual models, at different levels of detail. Congruence between a physical system and its digital model is measured by comparing the data as a sequence, and measuring their level of similarity to the digitally produced data, using an appropriate comparison technique.

It can be concluded that development of smart manufacturing has begun, where deep ML, blockchain technology, digital platforms, KBS models and cognitive DT will be increasingly used in future.

3. Research and Case Example of the Digital Manufacturing Model in AMM Manufacturing Company

The manufacturing of components and body parts of rail vehicles (passenger program) as well as accompanying tools and jigs is the key business of AMM Manufacturing. It supplies products to large companies in the railway industry (Siemens, Alstom, Hitachi, Stadler, Škoda, etc.), and it has been implementing the digitalization project since its foundation in 2018, simultaneously introducing the elements of Industry 4.0, aiming for the full smart manufacturing factory. The basic structure on the digital model in the organization is shown in Figure 1.

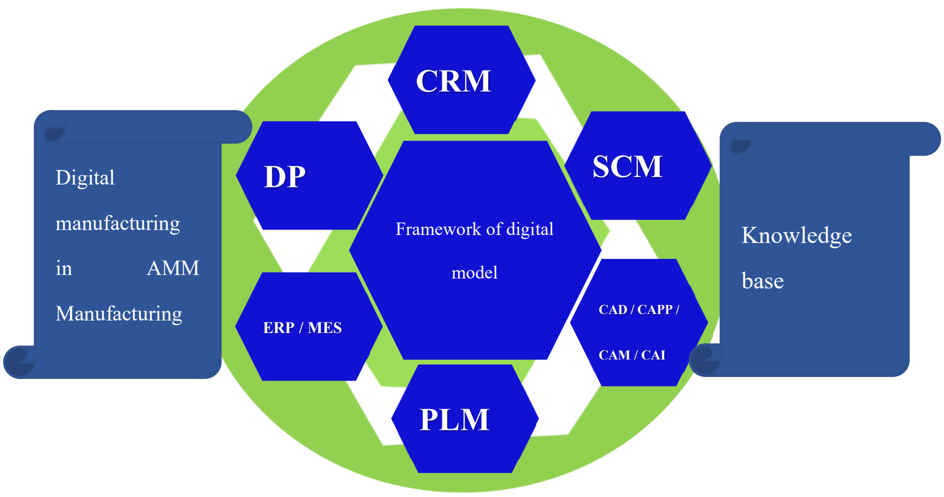

Figure 1. Digital model of AMM Manufacturing company.

"Islands" of automation, business and engineering-development activities were created, that are now being integrated according to the Industry 4.0 concept into the cloud model of digital manufacturing [196,197]. The digital manufacturing model, that is being developed in this company, has an integrated knowledge database on the cloud and dedicated main server supporting all company units, updated on a daily basis - with the latest (current) versions of products and recording the history of changes. Additionally, the Quality 4.0 model is an integral part of the company digital model, considering all system elements, from the definition and adoption of the customer requirements (CRM), to product delivery (DP) shown in advance.

3.1. Digital Manufacturing - Manufacturing and Technological Resources

AMM Manufacturing company has modern machining centers, CNC machines and different welding tools, machines and robotic systems, as well as modern shot blasting and painting chambers with integrated HVAC systems, as shown in Figure 2.

Machines	Traverse paths mm			Pcs.
	X	Y	Z	
HAAS VF4	1.200	600	600	2
HAAS VF8	1.600	1.000	800	1
HAAS VF10	3.050	820	750	1
HAAS ST 30	2.400	700	800	1
ZIMMERMANN FZ30	5.000	2.860	1.250	1
ZIMMERMANN FZ30	5.000	3.360	1.500	1
SAHOS Power Turbo	25.000	2.500	1.050	1
Fooke ENDURA 1003	61.600	4.500	1.500	1
matec-30 L	3.000	600	700	1
Fooke ENDURA 1006 LINEAR	20.000	4.500	1.600	1
SHW	8.000	2.100	1.300	1

Figure 2. Part of the machinery and equipment at AMM Manufacturing company.

Business planning and management in this company takes place through the ERP model, by using "Microsoft Dynamics NAV", while the following were selected for application in other technical-manufacturing processes: Dassault Catia V5, Autodesk Inventor, Autodesk AutoCAD. Work is now underway to build a CPS system for the machining parts. Example of load simulation of the tool is shown in Figure 3.

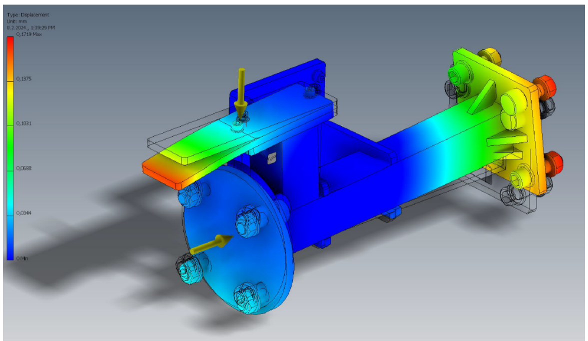

Figure 3. Example of the load simulation of the tool.

Technology development in manufacturing of railway systems comprises development of different tools by using digital simulation, as shown in Figure 3, where example of method of load evaluation for the correct dimensions in assembled elements and associated welds.

3.2. Digital quality management model

Within the digitalization process, exceptionally high attention is paid to the quality control of processes, parts and systems, due to the stringent requirements for the safety and quality of all systems in the railway industry. Accordingly, all necessary certificates are obtained for the quality of the process (primarily QMS and other models). Different quality control methods are is shown in Figure 4.

Dimensional quality control

Non-destructive quality control

Figure 4. Product and process quality control.

Depending on the requirements and quality characteristics, the following quality methods are applied: VT (Visual Test) - Visual quality control, MT (Magnetic Test) - Testing with magnetic particles, UT (Ultrasound Test) - Ultrasonic testing, PT (Penetrant Test) - Testing with liquid penetrants, RT (Radiographic Test) - Radiographic examination, LT (Leak Test) - Examination of welded joints. All tests are supported by the accredited laboratory methods according to the ISO/IEC 17025:2017 standard.

Cooperation with the IMW Institute, as an integral part of the MIND park, provides an additional advantage for the testing of welded joints and materials (mechanical-metallographic and chemical testing), where the highest level of precision and sensivity testing is achieved through the application of digital technologies.

Digital radiography enables online monitoring of material quality characteristics and instantaneous practical data acquisition.

Figure 5. Digital radiography.

Digital technologies have proved their benefits in quality control for products and materials and welded joints testing.

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Figure 6. Optical microscopy tests at micro scale.

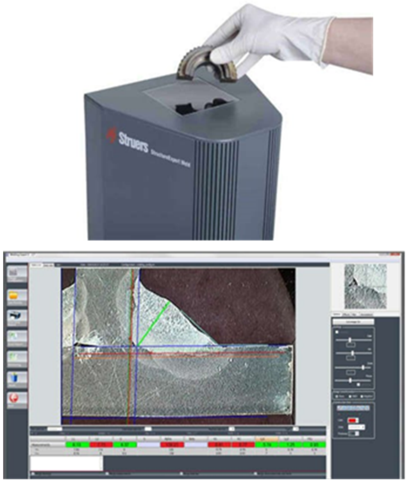

Figure 7. Optical microscopy tests at macro scale.

Company forms, control sheets and protocols, based on the established procedures, manufacturing procedures and/or control plan, have been setup in the company to ensure digital traceability throughout the entire product life cycle, and related to the control of the materials, raw materials, dimensions or welds at individual positions or assemblies. Different analysis can be realized from the quality aspects, by using DT and BDA analyses, such as suppliers, type of materials, time and other.

3.3. CAD/CAM Systems in Digital Manufacturing Modeling

The development of parts and components of railway vehicles also includes the development of associated tools and jigs that ensure the gradual assembly of individual positions and semi-finished products into a complex welded assembly such as the roof, end or side wall, floor or even the entire wagon.

The development of the tools and jigs must incorporate static analysis of mechanical parts, to ensure relevant rigidity of the structure, since dimensional tolerances of the large welded assemblies are up to 0.1 mm. During the manufacturing of such an assembly, the jig is gradually loaded by adding individual positions, while the jig itself is rotated on the manipulators in order to provide the welders with the technologically and ergonomically best possible position and access to the components.

These activities would not be possible without modern software solutions in manufacturing planning and modeling, as well as professional design and manufacturing team.

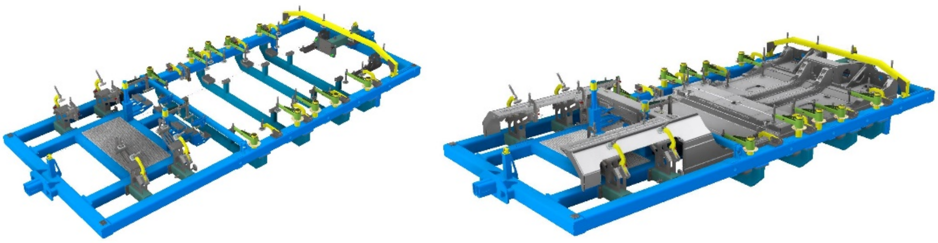

Figure 8. Design of the for the manufacturing of a welded assembly CAD model.

Separate elements and parts are machined at CNC machines or machining centers, before their assembly and welding in the jig. The process of machining planning (CAPP model), and CNC coding, is by CAM software (Figure 9). Digital design (CAD) and manufacturing (CAPP/CAM) of auxiliary clamping tools is used to ensure the correct and stable positioning of the workpieces with length up to 21000 mm.

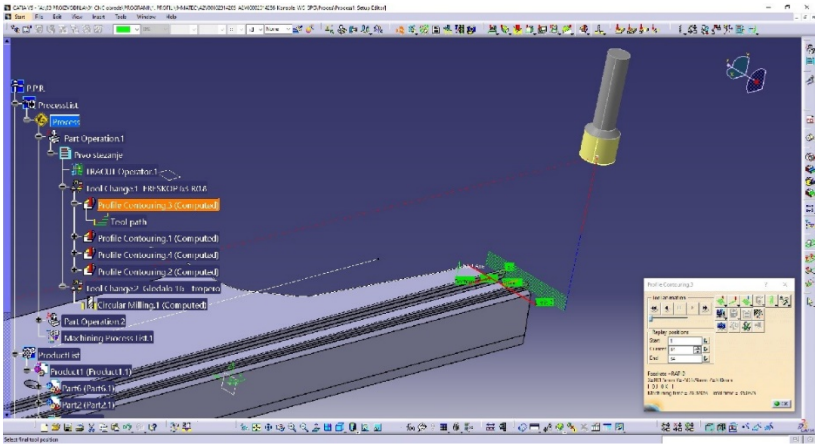

Figure 9. Example of CAM software used for simulation and coding in realization of the machining process.

3.4. Warehouse Management System (WMS)

Planning and management of the technological and manufacturing resources, using a WMS system (as an "add-on" in ERP software) includes an overview of digital data warehouse as well as system checking of all logistics activities, as shown in Figure 10.

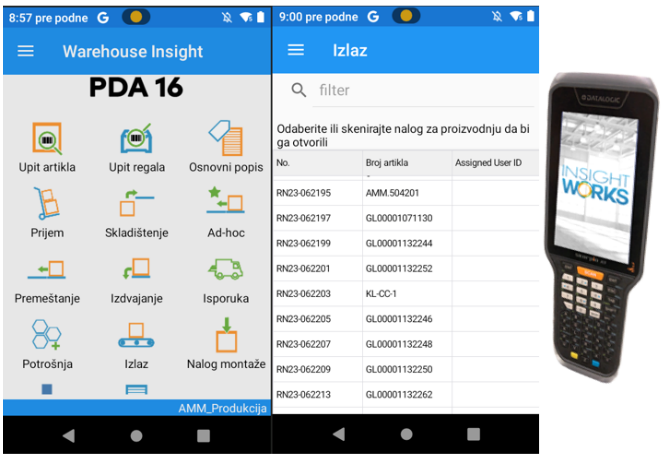

Figure 10. Warehouse Management System (WMS).

Transfer of materials from one warehouse to another or material spending is documented by the WMS software when logistics workers scan barcodes on the materials and warehouse locations, by using hand-held devices equipped with WMS software.

The batch label of the material and quantity are entered in the software at the initial receipt of the material and further automatically transferred to all work orders related to that material, thus ensuring digital traceability of the material throughout the entire product life cycle.

Logistics workers can enter new work order or select from the existing ones in the drop down menu during the scanning of the barcode, related to the specific material and further enter material quantity to be transferred.

3.5. Advanced Planning and Scheduling (APS)

Dynamic manufacturing planning contains three levels, in permanent connection with ERP sofware with online data exchanges by using : OMPX, OPSX and OSR modules.

The first level, OMPX – Ortems Manufacturing Planner Express, has a planning period from 3 months to 2 years, Figure 11. It enables definition of medium-term manufacturing plans and accordingly business plans. Accordingly management and the commercial department are provided with online monitoring of the plans realization and can act if needed.

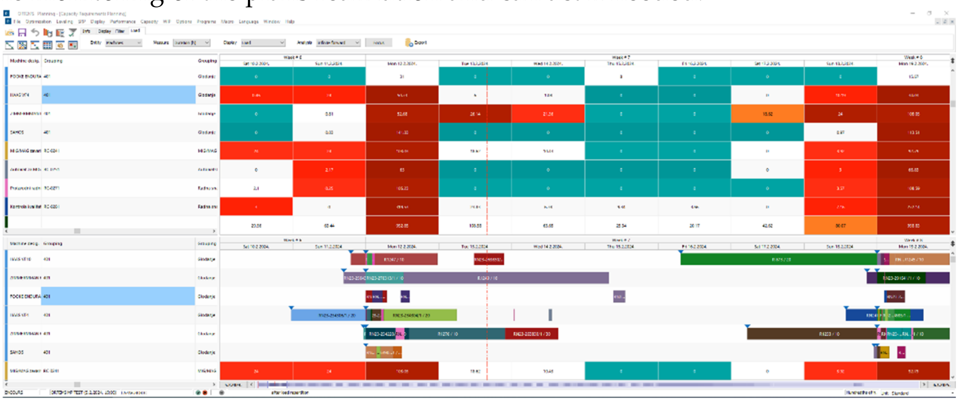

Figure 11. Report within the OMPX module.

OMPX module enables display of all purchase orders in a long time periods (more than three years), generated by the ERP software. According to the real practice, three years period is quite enough for the adequate management and planning of the production process.

Different process simulations are enabled, based on the possibility to see projects during the longer time, with different "what if" scenarios, especially useful for capacities and availability of materials. It is possible to simulate new business and define priorities accordingly.

The second level, OPSX - Ortems Production Scheduler Express, has a planning period from 3 months to 1 day, and represents micro-planning, as shown in Figure 12.

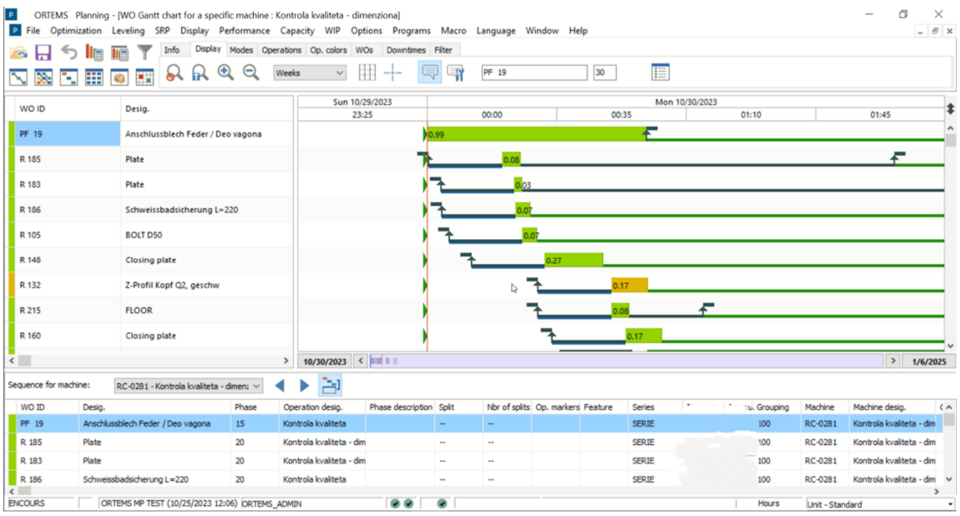

Figure 12. Report within the OPSX module.

OPSX module enables management to create detailed plans and micro plans for the machines and work centers, up to the desired level of accuracy and related to the moment of starting the manufacturing operation (just in time).

OPSX module provides insight into the capacity use and shows "bottlenecks" in manufacturing, based on of which jobs can be redistributed. Also, the connection of work orders for several components from one assembly, as well as all restrictions, if any, can be easily monitored.

Finally, the third level, OSR - Ortems Synchronized Requirements Planner, integrates the MRP and ERP model, as shown in Figure 13.

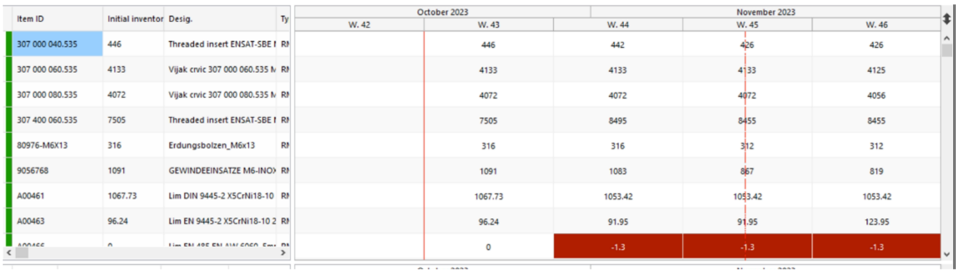

Figure 13. Report within the OSR module.

OSR module provides an insight into the availability of materials on daily bases according to the planned capacities, and defined supplier conditions (procurement time and minimum quantity order) beside other data from the ERP sofware, based on which the Procurement department can initiate procurement in a timely manner. In that way, the synchronization of the work order execution in the plant with other business processes is performed and monitored on a daily/hourly level.

3.6. MES System in Digital Manufacturing

Up-to-date manufacturing status and registration of the accompanying activities is provided by "add-on" module in ERP sofware, as shown in Figure 14.

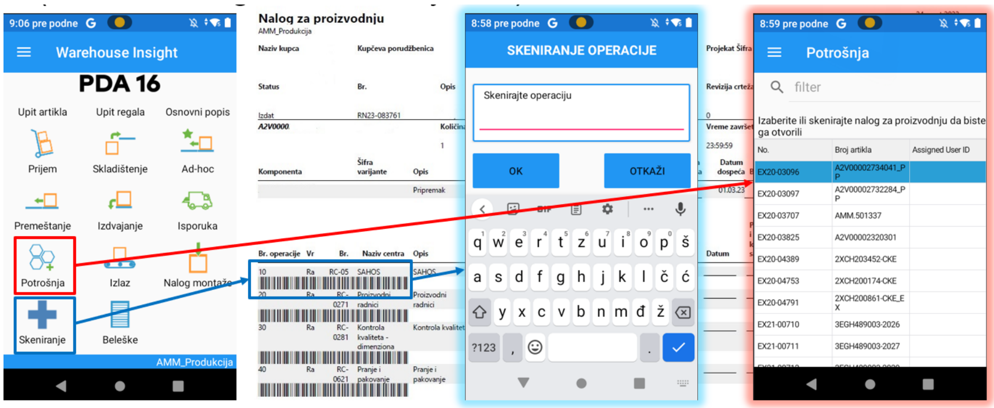

Figure 14. MES model.

It is possible to quickly and easily mark the start/end of the manufacturing operation, as well as the spending of materials, by scanning a unique bar code for each manufacturing operation from the work order.

These tasks can be also done by entering the work order number to the bar code scanning device or selecting the task from the drop down menu.

3.7. Other Digital Manufacturing Model Services

AMM Manufacturing company is also developing a manufacturing concept supported by cloud computing, using SaaS, PaaS and IaaS models. At this moment, the following SaaS models have been implemented: Microsoft Dynamics NAV, Microsoft 365 and Smartsheet, that can ensure the collaboration of several company departments. That collaboration model can be applied to day-to-day tasks, or to the development process and project management.

Cyber security for this aspect of manufacturing is extremely important, and the following security models are used: Antivirus, Firewall, IPS and WEB filtering, and VPN system.

Data security is the most important element of the digitalization. The exchange of data and documentation, internally and externally, is under constant surveillance of the security software that monitors and filters network traffic, blocks potential intrusions and provides a secure virtual network to enable remote work.

Additional data security is provided by the "backup" servers, and physical data storage units.

4. Conclusion and Future Research

Digital manufacturing is the foundation of the Industry 4.0 model, as well as the Smart Manufacturing (SM) model. Smart Manufacturing is the objective of the future development of AMM Manufacturing company and will be a further subject of research and development. Further evaluation and setup of the CPS model in manufacturing will be studied, especially from aspects of the processing center (MC) for the manufacturing of railway systems and deep application of IoT, BDA, AI/ML models as cloud manufacturing, also considering adequate infrastructure for the full application of the concept of horizontal and vertical integration.

New results in the development and application of our concept of smart manufacturing (SM) can be soon expected.

It can be concluded that the development of the smart manufacturing concept has marked a new era with strong increase of application of deep ML, blockchain technology, digital platforms, KBS and cognitive models of digital manufacturing, as the new research challenges.

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