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5-Dimensional Definition for a Manufacturing Digital Twin

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Abstract

The Digital Twin is a recently developed innovative technology in Industry 4.0. The cyber-physical system (CPS) is a concept closely connected with Industry 4.0 that can form a basis for creating a Digital Twin. In this paper, a comprehensive model of a Digital Twin approach for a manufacturing environment and related production processes is proposed. The presented model is based on combining a 5-Dimensional definition for the Digital Twin and cloud-based CPS (C2PS) architecture. The model consists of five layers to replicate the physical object as a virtual object and to collect and convert data. Analysis of the virtual model for prediction of future development, decision-making, re-configuration, what-if analysis, and understanding of the effect of changes in the real time process is performed in the fourth layer. The user interface layer is the connection between the virtual and physical model. Use of a Digital Twin in manufacturing enables improvement in the effectiveness of Lean Manufacturing, leading to savings in resources such as cost and time. Uncertainties inherent in manufacturing processes mean that the Digital Twin approach is a more suitable method for optimization of the overall process and the sub-processes than pure simulation. An accurate Digital Twin model can improve safety, save costs, speed up manufacturing of new products and implementation of new processes, and provide global optimization results. In practice, however, provision of data is a challenge to use of the Digital Twin approach because modern manufacturing uses a variety of data in different formats with different owners. Access to all required data and information and obtaining permission for its use in creation of a Digital Twin is a topic for future research.

Keywords: Digital Twin; Cyber-Physical System; Smart Manufacturing; C2PC Architecture; Data Ownership.

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1. Introduction

Digitalization in manufacturing opens new doors to significant improvements in productivity and effectiveness in complex systems [1]. Integration of cutting-edge technologies like the Internet of Things (IoT), machine learning, fuzzy analysis, data mining and Big Data enable smart manufacturing, which is at the heart of Industry 4.0 [2]. The important difference between current manufacturing and smart manufacturing is the interaction between the cyber-system and physical system [2,3]. The cyber- physical system (CPS) is a core concept of Industry 4.0. The CPS consists of a set of physical devices and products that interact with virtual cyberspace through a communication network [4]. The Digital Twin, a virtual replica of a physical object, is another part of Industry 4.0. Technology related to Industry 4.0 has developed rapidly and Industry 4.0 has been heralded as starting a new age of manufacturing and leading to complete transformation of current production systems and their management. Industry 4.0 merges technologies that break the boundaries between the physical and digital areas, and it enables people around the world to access knowledge through mobile devices [5]. Each physical object is represented by a cyber-part as a digital prototype that subtends data, information and knowledge of the physical object. Therefore, both parts, i.e. the physical entity and the virtual model, act as a Digital Twin, that is: "The Digital Twin can monitor and control the physical entity, while the physical entity can send data to update its virtual model" [4]. Real-time reflection of the physical space, interaction and convergence in physical and virtual spaces, and self- evolution are key properties of a Digital Twin [6]. Clearly, construction of a Digital Twin is a non-trivial task, and researchers are trying to generate the Digital Twin blocks of additive manufacturing using a many different approaches, for example, heat and material flow simulation, simulation of solidification, grain structure and texture evolution, modeling of microstructure and properties, and calculation of residual stresses and distortion [7,8]. Mold simulation software and Internet of Things have been integrated to build a Digital Twin model for every stage of design of an injection mold in [9]. Although 3D simulation and database construction form the basis of the Digital Twin model, another important issue is communication between the parts in the physical and virtual environments. A number of different methods have been investigated, for example, manufacturing standards have been used to represent and exchange data for modelling the communication between the parts via a Tweeting machine [1]. In the work, a Digital Twin model of a cutting tool was made by integrating the 3D model and the properties of the tool via ToolMaker. Use of Ethernet/IP is another method to add low-level communication between physical devices and virtual models [10]. In [11], a Digital Twin model was created to improve the performance of a hollow glass production line. The model integrated a simulation platform, information channel and calculation system to optimize the production line.

In this article, existent knowledge, technology and methods are gathered to create a comprehensive, accurate and extensive virtual model suitable for a variety of fields of manufacturing and production. Other research has presented a Digital Twin for one specific machine operating in particular conditions; the aim of this study is to contribute knowledge that will assist in generalization of the Digital Twin approach for all manufacturing processes and transformation to future smart industrial production.

2. Research problems

Much research describes the Digital Twin on the basis of its three components: the physical model, the collected data and information, and the virtual model. Gabor et al. [12] proposed a simple definition of a Digital Twin as the simulation of a physical model in order to predict the future. The concept has been extended over time to more precisely reflect the role of and results from the virtual space. Thus, in [13], the Digital Twin is defined as the virtual replacement of a physical object with communication ability that acts like a smart object through the Internet of Things. The definition adopted in [14] for digital twinning of aircraft is: “An integrated multi-physics, multi-scale, probabilistic simulation of a vehicle or system that uses the best available physical models, sensor updates, fleet history, etc., to mirror the life of its flying twin. The Digital Twin is ultra-realistic and may consider one or more important and interdependent vehicle systems.”

This work advances the concept of the Digital Twin by integrating real-time information communication and artificial intelligence. The Digital Twin model integrates all information, multi-physics and possible environments that influence the final product to imitate the behavior of the physical space in order to predict, make decisions and optimize a manufacturing process or production line.

Massive data flow is a fundamental feature of modern production lines. In addition to the volume of data, the many different data communication protocols and formats complicate information conversion and transfer between different phases of the manufacturing process [1]. The main difference between the model used in this work and previous works is found in the approach of collecting and storing the entire data and then mapping the data to the 3D model. The data transfer is in real-time and data is updated between the physical and virtual model. All the parts of the system are expressed with relations, actions and communication between them; therefore, by changing one part or parameter, other related objects are changed automatically by artificial intelligent methods.

Data ownership is a complicated issue because of the considerable resources expended on data creation, data management and data usage. In effect, the problem is a data control issue about the flow and value of information. In the context of this study, the issue of value is particularly pertinent when the data has more than one owner. In such cases, therefore, the degree of ownership needs to be determined to ascertain the value gained from usage of the data for each creator. Information privacy determines how it is possible to use data or information, how information moves from one source to another, and responsibility for control of the information and information flow.

Cost is crucial in business and manufacturing, and considerable efforts are invested to reduce costs throughout the product lifecycle from design to maintenance. In Internet 4.0, design costs are reduced by simulating the performance of the specific manufacturing system using the virtual model and computer analysis, and consequently, the amount of required prototyping, testing and experimental work is reduced [15]. Using a Digital Twin, the need for expensive physical mock-ups is eliminated, giving cost savings and reductions in the length of the design phase of the product. In addition, use of a Digital Twin can reduce product manufacturing time. For instance, if the application of the product is changed, requiring changes to the product, it is possible to modify existing models and update manufacturing parameters and procedures on the basis of the Digital Twin. It is also possible to collect data during manufacturing operations and include it as part of the Digital Twin. This information can then be used to update the model for real or altered operation conditions. A further benefit of the approach is that the Digital Twin enables use of real data as verification input to improve the simulation model [16].

Based on above discussion, the main research questions in this study are: What is the meaning of the Digital Twin concept for future manufacturing and how does it differ simulation? The sub questions are: What are the most important problems in building and implementing a Digital Twin in manufacturing? How can all the required data be obtained? Who are the owners of the data? And how does the Digital Twin reduce resource usage?

3. Research methodology

Manufacturing systems aim to use state-of-the-art technologies to achieve more accurate, sustainable, secure and efficient, and finally, smart products. Making an accurate virtual model of a physical product that imitates all aspects of the physical object requires the use and integration of multiple methods and technologies.

The research in this work is based on a literature review of articles about the Digital Twin concept and its application in manufacturing carried out over the period 2016-2018. First, the evolution of the definition of Digital Twin from 2010 to 2016 was investigated, and then the latest digital models in manufacturing were examined. Although the different methods and technologies described are known methods that have long been used in modeling of manufacturing processes, even before 2010, combining them to create Digital Twin blocks can be considered an innovative achievement. For instance, Henssen and Schleipen [18] used AutomationML for communication and exchange of data in manufacturing, and Cai et al. [15] presented how to collect data and transfer such data to build a database for creating Digital Twin blocks [5]. Botkina et al. [1] used a Line Information System Architecture (LISA) to transfer information into usable data in different applications in 2018. An integrated digital simulation, data transfer and genetic algorithm to create a Digital Twin model of the assembly line is described in [5]. After choosing suitable methods to make comprehensive Digital Twin blocks able to fulfill the requirements for building a Digital Twin of the manufacturing process, architecture must be found to generalize the model for different cases. Some simple architectures have been proposed for CPS, such as CPS 5 components architecture or intra CPS architecture [19]. The C2PS architecture used in this work is more inclusive and more suited for manufacturing processes and efforts to make such processes intelligent.

The framework of the Digital Twin presented in this work is based on a combination of a five-layer Digital Twin definition and C2PS architecture. The cyber-physical store data layer, primary processing layer, models and algorithms layer, analysis layer, and visualization and user interface layer are the defined layers for this structure. Although the layers have previously been defined in [6], there remains a need to determine the exact components used in each layer. The physical layer comprises the physical model and environment in real space; the data store layer comprises the database, exchanged information based on standards and tweeting, and the knowledge base; the models and algorithms layer consists of models of different fields such as the mechanical model, electrical model and so on. The analysis layer contains analysis, simulation, prediction and optimization operations. The user interface should provide a user-friendly surface for customers, engineers and companies. In the next section, each layer and its components are described.

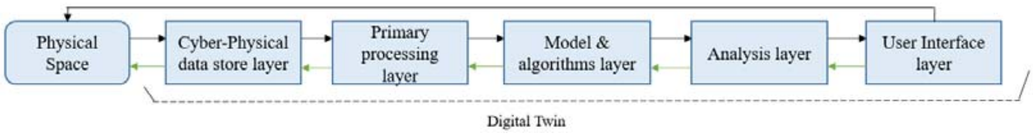

Fig 1. Overview of the 5-dimensional structure of the proposed Digital Twin.

4. 5-Dimensional definition of Digital Twin

Based on the literature review undertaken as part of this study, we did not find a comprehensive framework for a Digital Twin for Manufacturing. This research introduces an extensive Digital Twin model that consists of five layers covering all requirements to represent the physical space in the virtual space. The specific information needed in the model is based on collecting and converting the acquired data using novel and existing technologies and methods.

The 5-dimensional structure of the Digital Twin is depicted in Figure 1. The basic layer is the cyber-physical data store layer, which contains collected data from the physical model, historical data and data from the enterprise's manufacturing systems. In the next layer, the primary processing layer, suitable processes on the collected data are executed. The primary processing layer carries out operations like conversion of data to information to enable information flow between different levels of production. This layer can be performed by implementation of OPC (Object linking and Embedding for Process Control), AutomationML and other methods of relaying messages to and from the machinery. Mathematical, statistical, and CAD models are stored in the models and algorithms layer. The fourth layer is the analysis layer to perform prediction, optimization, reconfiguration, monitoring and control. The last layer is the visualization and user interface layer, which provides users with access to the Digital Twin via a graphical interface [6]. Figure 2 shows the components of the proposed Digital Twin manufacturing framework based on a 5-dimensional definition of Digital Twin. In following section, each layer is described in more detail.

The cyber-physical data store layer is the first layer in the 5-dimensional Digital Twin definition. Provision of an accurate description of the physical object and its data is a basic and crucial phase in creation of a virtual model. Modern manufacturing has access to and utilizes a wide variety of data resources, such as equipment data, material and product data, environmental data, management data, and internet data. Some of these data can be shared through the IoT by different owners. Equipment data contains information about real-time performance, operating conditions and equipment properties. Material and product data include performance, inventory or context of use. Environmental data consists of temperature, humidity and air quality. Management data is collected from manufacturing information systems and computer-aided systems. Internet data includes user data collected from ecommerce and social networking platforms and public data from open websites. Big Data is state-of-the-art analytics and technology to collect and use data for business development and smart manufacturing. Therefore, Big Data can serve the Digital Twin. The main function of Big Data is data processing to identify behavior features and patterns [17].

The primary processing layer is the second layer in the model. Data are collected throughout the product lifecycle and the collected data should be converted to usable information for the various software operating during the manufacturing process or production line. Using standards for information conversion increases information exchange efficiency and communication quality. The standards define the information structure used to describe data about the system or process [1]. Accessibility to the data of each production stage makes the system flexible and allows it to respond efficiently without human control. In modeling of a manufacturing process, conversion and mapping of data in the digital space is complicated due to the large volume of data and variety of data types and forms of information, and their complex communication patterns. LISA is a flexible information architecture that provides communication between data sources of various origin, capabilities or ages. LISA is an event-driven manufacturing information system architecture for modelling information and transforming data into knowledge to make smart automated decisions. LISA contains message formats, communication, service endpoints and the message bus. The message bus enables LISA to transform events into usable data in a sufficiently flexible way [1]. The key properties of LISA are its ability to rapidly integrate devices and services on all levels and its support of continuous improvement in information visualization and control. However, nearly any messaging channel can be used to relay messages, including instances of using the Twitter microblogging service as a message channel [1]. The real-time data obtained from the system is used in analyses, reduction of processing flaws, quality improvement and decision making [1]. AutomationML is an open standard series to describe components and production plants. AutomationML is an XML based data format that can interconnect components in different disciplines and lifecycle phases to create a virtual mechanical and electrical design. It supports technical information in the manufacturing process and contains geometry, kinematics and logics. OPC UA is a method to exchange real-time data of the production line between control devices or IT systems and among different manufacturers. OPC UA is a full mesh network that contains nodes, their properties and relations. Therefore, users can organize data and information models for their OPC UA servers manually. Thus, OPC UA provides online communication and AutomationML acts like offline engineering data [18]. The knowledge base is a further component in this layer and contains the rules. These rules can be anything from physical data transfer to rules from analysis of the digital model.

The models and algorithms layer is the third layer. The graphic model of the machine or production line and the environment is created in CAD software such as SOLIDWORKS, CREO, and CATIA. In this layer, the mechanical,

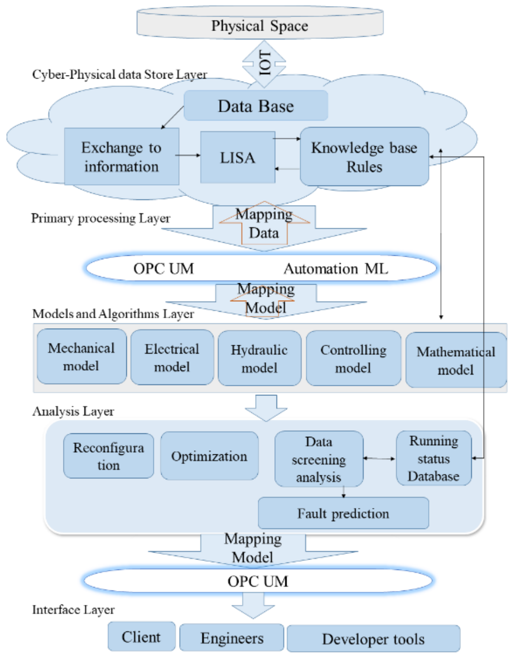

Fig 2. Proposed Digital Twin manufacturing framework based on 5-Dimensional definition of Digital Twin

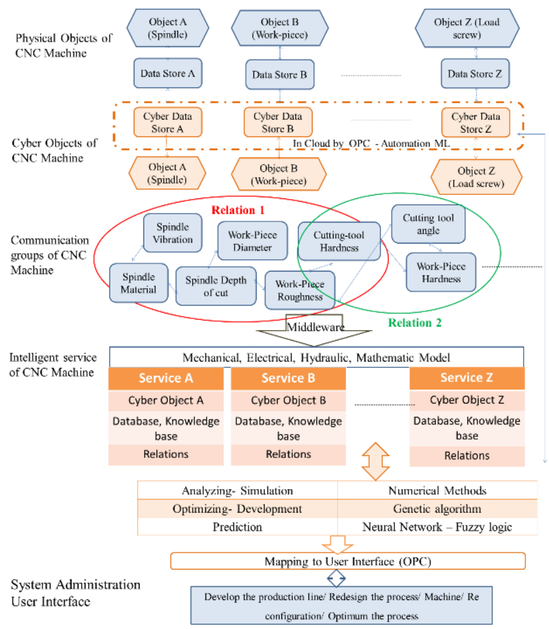

Fig 3. C2PS architecture of the Digital Twin in manufacturing process for example CNC Machine

electrical, hydraulic and mathematical models of the whole components are built. The layer is in bidirectional contact with the previous and next layer.

The analysis layer is the fourth layer. Several methods are used to develop, improve, redesign and reconfigure the production line or process. For example, machine-learning techniques such as neural networks are used to generate predictions. Fuzzy methods can be applied for diagnosis. For instance, Luo et al. used a B-spline fuzzy neural network to predict faults in manufacturing systems. It is trained by fault phenomena and fault reason, rules are then created based on training by the algorithm model, and the rules are stored in the knowledge base. This neural network is connected to the physical system so it is updated by new real data, which is mapped to the algorithm model [3]. In addition, PLC methods and XML codes are used for process control, and a genetic algorithm can be used in optimization [5]. The analysis layer is in bidirectional contact with the first and second layers.

The visualization and user interface layer is the last layer. This layer presents the results to customers and to experts for development purposes. In [6], this layer is divided into three types: rich-client, thin client, and developer tools. The rich-client tools provide an AWP interface as technical schemes, screens such as SCADA (Supervisory Control And Data Acquisition) and a HMI (human-machine interface). The thin-client provides an analytic screens interface for experts and includes functions such as statistical model analysis and object monitoring. Developer tools provide tools for model and algorithm development [6].

5. C2PS architecture in the Digital Twin

Alam et al. [19] introduce a C2PS architecture for a Digital Twin and this architecture is selected in this work as a suitable intelligent Digital Twin architecture model for manufacturing. Figure 3 illustrates the proposed comprehensive C2PS, which contains a five-layer structure of the Digital Twin. It is important to be mindful that the system, manufacturing process or production line consists of several dependent or independent parts. Therefore, each part has its own Digital Twin model. In the first level of the C2PS, the physical system is divided into a number of parts called physical objects. Each physical object is represented by a cyber object in the cyber environment. Data and information from the physical object are collected directly by sensors or enterprise manufacturing systems and then preserved in the physical data store. The physical data store is connected to a cyber data store in the cloud. There is a bidirectional connection between the cyber object and the physical object in first and second layer.

Objects are described in seven categories: Data storage, sensors, functionality, capability, mechanical behavior, actuators and action. Actuators apply the inputs from one object to another object, and sensors provide the output from the physical object to the corresponding database. Data storage contains data and information about design parameters, material features, defined and constant parameters of performance, functionality and capability. These components of an object are interrelated. For instance, functionality provides different capability for the object and depends on the specific functionality; sensors provide information pertinent to a specific capability; capability is related to properties and parameters; and mechanical behavior depends on design parameters, functionality and capability. In the last level, all the different model components affect or define the action.

The third layer of the C2PS is a peer-to-peer relation layer in which cyber objects that are related form a communication group. All the communications in a group are delivered between members of the group. Each cyber object can be in multiple groups. The objects in the physical layer are connected with each other as in the cyber layer. The peer-to-peer relation layer can act as an interaction layer between the cyber and physical object or the cyber and physical data store. A smart connection controller needs to make a decision about the suitable interaction mode for system context. Machin learning methods can enable the system to make decisions, which gives the system self-configuration ability. Use of a Bayesian network is an acceptable method to model uncertainty of context awareness. A Bayesian network is a probabilistic graphical model that represents a set of variables and their conditional dependencies via a directed acyclic graph. In this case, the network makes rules based on Multiple Input Single Output (MISO) fuzzy logic [19]. The rules from the connection are stored in the knowledge base to be updated in real-time.

The fourth layer of C2PS is an intelligent service layer comprising a number of services. Each service contains the corresponding object, data and relations and permits analysis, simulation, optimization and prediction. This layer acts as middleware layer, which means it uses the database in the operating system. The last layer is a system usage layer that uses the outputs of the previous layers that contains a service manager, service integrator, generated data consumption and data visualization. The physical model is connected to the Digital Twin via this layer, and redesign, development or reconfiguration are done by users, customers, engineers and experts based on the Digital Twin results.

6. Results

In The following section describes the procedure of making a Digital Twin using the example of a CNC machine. The first step in creating the Digital Twin of a CNC machine is to divide the machine into its components, that is, spindle, chuck, chip pan, apron, saddle, clutch, feed rod, lead screw etc. Each component is represented as an object in the first layer of the Digital Twin. The corresponding data store contains geometry, material and operation parameters (speed, spin delay time). In addition, machining operation, cutting tools and the workpiece are represented as an object as well. These data are exported to the cloud by the Internet of Things and then to the cyber data store.

The cyber data store consists of three parts: a) the database, b) the exchange information standard and LISA, and c) the knowledge base.

Each physical object has its own cyber object in the digital space, hence the cyber data store is connected to the cyber object, and data and information should be transferred to the cyber object. OPC UA is applied for exchange of real-time data. Automation ML helps to define all the parts, data, information, actions and their relations for use in the digital model. Subsequently, this collection is connected to the corresponding cyber object. There is some connection between cyber objects, physical objects and physical and cyber objects. For instance, the spindle as a component of the CNC machine is represented by seven blocks which collect and transfer data to the cyber data store. This data contains design parameters (geometry of parts such as housing shaft, drawbar and motor), material properties (modulus of elasticity, yield strength, passion ratio, shear strength) and turning geometry (which covers turning and tool angles, cutting angle and cutting strength). Next, sensors collect data during working time. These data are values like load, speed, power and cutting force. Mechanical behaviour comprises, for example, stiffness, vibration, stress and strain. The data from sensors has a close relation with parameters in the data storage and mechanical behaviour. For instance, the cutting force is related to the friction angle, anterior angle, cutting angle, cutting strength, distortion factor, cutting depth and cutting width. The cutting force data contains information about the circumferential cutting force and the radial cutting force. Capability contains a variety of factors that affect other components such as angular contact, contact angle, thrust races, taper rollers and cutting tools. Functionality is defined to fulfil the specific capability. In the last level, the role of the actuator is to control the whole system and its actions define the output of the system. Due to the crucial role of capability in the defined task of the spindle, other components are changed for different capability. Design requirement and customer demands define capability; therefore, it is important to use the correct process parameters to ensure that the desired product quality characteristics are achieved. Performance is determined according to the capability. For instance, work material properties and geometry define the capability. Soft or hard material, diameter, length, weight of the work-piece and other properties of the material affect the cutting tool, cutting angle and rotation speed, and, in turn, the spindle bearing. Material removal rate (removed volume over time) is the most common parameter for defining capability and spindle speed is usually based on the work-piece diameter and material. This parameter is used to adjust the control system to achieve desired outcomes and to ensure that the process remains stable. Therefore, fuzzy logic methods are applied on the connection to make the system intelligent and permit smart decision making when the work-piece is changed. Afterwards the data are transfered to the middleware layer for analysis, optimization, development or prediction. The middleware layer should contain mechanical, electrical, hydraulic and mathematical models of the CNC machine. Numerical methods and soft computing methods are used to simulate the process. Once more, OPC maps results for the user interface to allow experts to utilize the results for development, re-design, re-configuration and optimization of the system.

The data collection and data store is the fundamental of the proposed Digital Twin framework. Descriptions of virtual objects utilize a great deal of data from different sources; this data is owned by multiple resources. Such data typically concerns technical design, materials, tools, machines, operations, controller, software, maintenance and method of processing. As data and information in each area comes from different sources, data ownership is not clear. For instance, the manufacturer of the machine owns some data about the machine that is being used in the manufacturing process, however other data concerning the same machine is owned by the product design company and the company using the machine. Therefore, usage of the Digital Twin encounters issues with data ownership, responsibility for data, access, rights and control. Further questions include whether all the required data resources can be found and whether the required data will be provided.

7. Conclusion

This work has discussed creation of a Digital Twin model for the manufacturing industry. The Digital Twin represents a virtual model of the physical model and imitates performance, behaviour and changes in the real space. Due to the variety, complexity and volume of data and information in manufacturing processes, appropriate methods and technologies have to be integrated to achieve a comprehensive, smart Digital Twin.

The virtual model of the manufacturing process needs accurate data and information. As the data related to manufacturing of the product is connected and interacts, one missing part obviously affects the final results. A key difference between adoption of a Digital Twin and usage of digital simulation is that the Digital Twin uses real-time updated data, and, consequently, access to and permission for usage of the data is a crucial issue when creating a reliable digital model. The complex ownership structure of the data involving many different actors, such as the software data owners, tools data owners and machines data owners, can become an obstacle for engineers. Moreover, if it is possible to acquire and use all the data needed to create a Digital Twin, the model and results from the Digital Twin may be claimed by different owners. The underlying issue is how data, information and knowledge gained from the Digital Twin can be fairly shared between all the owners of the data used to construct and operate the Digital Twin.

Using a Digital Twin in manufacturing enables a reduction in waste and efficiency improvements to Lean Manufacturing. The results from the Digital Twin specify the type and amount of materials, and the processes and methods required to produce the desired product, which can reduce inventory and prevent overproduction. Furthermore, the Digital Twin can be used to plan a precise schedule for the whole lifecycle of the product from the design phase to marketing phase, thereby reducing downtime. Usage of a Digital Twin is a credible method for product and process development, and for decision making about tools, materials and processes, including plans for design, manufacturing, packaging and marketing.

In the next step of the work, a Digital Twin of a manufacturing process will be created and comparisons made between results from the Digital Twin model, experimental results and results from other simulations. However, to construct the data layer satisfactorily, ownership issues must be addressed. Ownership policy in manufacturing is complicated subject, however, to reach the full potential of Industry 4.0, a solution to issues related to data ownership must be found.

References

[1] Botkina D, Hedlind M, Olsson B, Henser J, Lundholm T. Digital Twin of a Cutting Tool. Procedia CIRP. 2018 Dec 31;72:215-8.

[2] Xu XW, Newman ST. Making CNC machine tools more open, interoperable and intelligent—a review of the technologies. Computers in Industry. 2006 Feb 1;57(2):141-52.

[3] Luo W, Hu T, Zhu W, Tao F. Digital twin modeling method for CNC machine tool. InNetworking, Sensing and Control (ICNSC), 2018 IEEE 15th International Conference on 2018 Mar 27 (pp. 1-4). IEEE.

[4] Rosen R, Von Wichert G, Lo G, Bettenhausen KD. About the importance of autonomy and digital twins for the future of manufacturing. IFAC-PapersOnLine. 2015 Jan 1;48(3):567-72.

[5] Vachálek J, Bartalský L, Rovný O, Šišmišová D, Morháč M, Lokšík M. The digital twin of an industrial production line within the industry 4.0 concept. InProcess Control (PC), 2017 21st International Conference on 2017 Jun 6 (pp. 258-262). IEEE.

[6] Ponomarev K, Kudryashov N, Popelnukha N, Potekhin V. Main Principals and Issues of Digital Twin Development for Complex Technological Processes. Annals of DAAAM & Proceedings. 2017 Jan 1;28.

[7] Knapp GL, Mukherjee T, Zuback JS, Wei HL, Palmer TA, De A, DebRoy T. Building blocks for a digital twin of additive manufacturing. Acta Materialia. 2017 Aug 15;135:390-9.

[8] DebRoy T, Zhang W, Turner J, Babu SS. Building digital twins of 3D printing machines. Scripta Materialia. 2017 Jul 1;135:119-24.

[9] Liau Y, Lee H, Ryu K. Digital Twin concept for smart injection molding. InIOP Conference Series: Materials Science and Engineering 2018 Mar (Vol. 324, No. 1, p. 012077). IOP Publishing.

[10] Moreno A, Velez G, Ardanza A, Barandiaran I, de Infante ÁR, Chopitea R. Virtualisation process of a sheet metal punching machine within the Industry 4.0 vision. International Journal on Interactive Design and Manufacturing (IJIDeM). 2017 May 1;11(2):365-73.

[11] Zhang H, Liu Q, Chen X, Zhang D, Leng J. A digital twin-based approach for designing and multi-objective optimization of hollow glass production line. IEEE Access. 2017;5:26901-11.

[12] Gabor T, Belzner L, Kiermeier M, Beck MT, Neitz A. A simulation-based architecture for smart cyber-physical systems. InAutonomic Computing (ICAC), 2016 IEEE International Conference on 2016 Jul 17 (pp. 374-379). IEEE.

[13] Schluse M, Rossmann J. From simulation to experimentable digital twins: simulation-based development and operation of complex technical systems. InSystems Engineering (ISSE), 2016 IEEE International Symposium on 2016 Oct 3 (pp. 1-6). IEEE.

[14] Glaessgen E, Stargel D. The digital twin paradigm for future NASA and US Air Force vehicles. In53rd AIAA/ASME/ASCE/AHS/ASC Structures, Structural Dynamics and Materials Conference 20th AIAA/ASME/AHS Adaptive Structures Conference 14th AIAA 2012 Apr 16 (p. 1818).

[15] Cai Y, Starly B, Cohen P, Lee YS. Sensor data and information fusion to construct digital-twins virtual machine tools for cyber-physical manufacturing. Procedia Manufacturing. 2017 Jan 1;10:1031-42.

[16] Hehenberger P, Bradley D, editors. Mechatronic Futures: Challenges and Solutions for Mechatronic Systems and their Designers. Springer; 2016 Jun 10.

[17] Qi Q, Tao F. Digital twin and big data towards smart manufacturing and industry 4.0: 360 degree comparison. IEEE Access. 2018;6:3585-93.

[18] Henssen R, Schleipen M. Interoperability between OPC UA and AutomationML. Procedia CIRP. 2014 Jan 1;25:297-304.

[19] Alam KM, El Saddik A. C2ps: A digital twin architecture reference model for the cloud-based cyber-physical systems. IEEE Access. 2017;5:2050-62.