Digital Twin Implementation in Transition of Smart Manufacturing to Industry 5.0 Practices

Yuriy Skorenkyy[a], Roman Zolotyy[a], Sergiy Fedak[a], Oleksandr Kramar[a] and Ruslan Kozak[a]

[a] *Ternopil Ivan Puluj National Technical University, 56 Ruska St, Ternopil, UA46001, Ukraine*

Abstract

A viability and a rationale for implementation of digital twins with augmented reality interface for further development of the smart manufacturing ecosystem is discussed. Different aspects of the problem of design and implementation of digital twins for industrial applications are considered. An approach for constructing the secure-by-design augmented reality-enhanced interfaces for digital twins is proposed. Benefits and cautions for use of augmented reality-enhanced digital twins in Industry 4.0 and prospects for Industry 5.0 are discussed.

Keywords 1

Smart Manufacturing, Digital Twin, Industry 5.0, Augmented Reality, Information Security

1. Introduction

Digital twins are integrated nowadays into various spheres [1, 2] due to the recent developments of augmented reality (AR) and virtual reality (VR) technologies [3] which enable the development of realistic 3D copies with rich functionality. The current technological progress allows for wide use of AR assets and VR environment swith various interfaces. In the spirit of Industry 5.0, enhanced collaboration experience can be ensured by novel human-machine interaction interfaces based on augmented reality applications. This approach has received some educational applications [4, 5] and revealed substantial benefits for the involved stakeholders. The interaction between humans and machines can be facilitated by IoT sensors, cameras, microphones and touch triggers in an intuitive and inclusive way. However, the cost of substituting real production line equipment with its realistic digital twin is moderate only if the digital twin and its responses are not expected to be exactly like the real system, therefore, there are restrictions on digital twin application to be taken into account.

At the same time, in today's digital era, it is essential to take necessary measures and use appropriate technologies to ensure information security in every smart domain due to the prevalence of user privacy issues. Information security is critical for businesses and individuals as it prevents data breaches that can result in financial losses for organizations, frauds, extortion and identity thefts for individuals.

Transition to a more digitized industrial value chains is to have important outcomes for sustainable development, increase the energy efficiency of energy-intensive industrial processes and contribute to achieving the climate neutrality goal, using the creative potential of human enhanced by abilities of AI-based information systems. Despite the opportunities presented by digitalization and Industry 4.0 to 5.0 transition, which includes efficient use of IoT components and energy-efficient solutions that reduce pollution, there remain various aspects that can be integrated into these systems in order to further improve process operations. Important direction for the utilization of digital twin solutions is to optimize manufacturing lines and technologies specifically for the energy-intensive processes, especially in spatially distributed manufacturing chains. Furthermore, making the utmost use of raw

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EMAIL: skorenkyy.tntu@gmail.com(A. 1); zolotyy@gmail.com (A. 2); srigfd@gmail.com (A. 3); kramaroitntu@gmail.com(A. 4); ruslan.o.kozak@gmail.com(A. 5)
ORCID: 0000-0002-4809-9025 (A. 1); 0000-0002-9435-264 (A. 2); 0000-0003-3654-9161 (A. 3); 0000-0002-8153-2476 (A. 4); 0000-0003-1323-0801 (A. 5)

materials and energy can aid in decreasing waste-generation, amplifying access to recycled materials, lowering the levels of energy consumption and greenhouse gas-emissions and leading to cost-reductions.

Modern production lines are multifunctional physical systems consisting of intelligent machines, materials, products and containing a large number of multi-level connections between various elements. In the process of digital design of such systems, a kind of division is often carried out - digital models of various kinds are arranged separately in the digital space, while physical products and production processes exist in the physical space. A study of the development process of such smart factories indicates [6] that in order to fill the gap between the area of design and the area of operation of smart factories, the necessary element is the improvement of the technology of digital twins. This concept of creating unique virtual copies of real objects is gaining more and more importance due to the rapid development of simulation and modeling capabilities, the development of sensitive sensors, their better compatibility and the development of the Internet of Things (IoT). One of the key assistive technology solutions mentioned in this connection is the use of intelligent systems with augmented reality to support engineers in the design and operation of production lines.

2. Digital Twins in Smart Manufacturing

According to the widely used definition by the National Institute of Standards and Technology, Smart Manufacturing systems have to be collaborative manufacturing entities able to respond in real time to condition and demand changes. Such communication of production system units is also a characteristic feature of digital twins, which are digital representations of physical elements, usually using IoT and sensor data to monitor operations, control physical elements and support decision-making processes [7]. Digital twins are designed to be used across multiple stages of the product or the manufacturing system lifecycle [8]. For an implementation of a digital twin, model and software are designed [9] to operate with the information collected from physical objects.

To acquire data, analyze and optimize energy consumption of a smart manufacturing production, for which material flows, data flows and particular processes are shown in Figure 1, design and deployment of an analytics platform is absolutely fundamental. It is crucial to put in place data management systems for the purpose of storing and managing energy data scenarios, consumption and production process parameters. By gathering data, identification of the most energy-consuming aspects of particular processes will be possible, which will then facilitate the integration of new digital technologies, distributed procedure management and data-powered optimization. The power consumption by equipment and processes can differ substantially due to various specific factors including the type of machinery, the conditions under which it operates, and the schedule of production. In order to determine the energy-intensive processes or equipment, it is necessary to gather data on energy consumption, production and efficiency, using specifically selected smart sensors, meters and other monitoring devices which will be linked to manufacturing machinery.

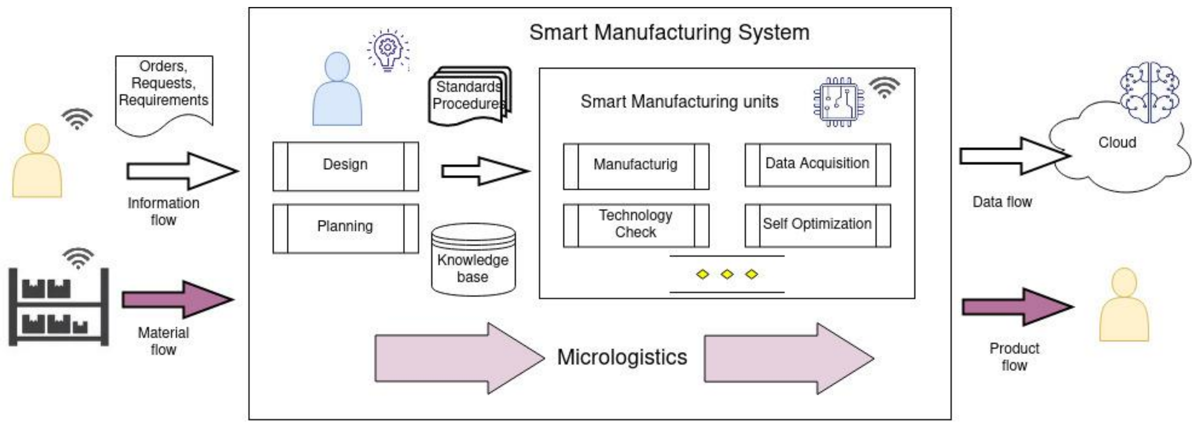

Figure 1: Processes, flows and artifacts for smart manufacturing use-case

There are various possible energy data that can be collected from smart manufacturing line components, namely

- Physical material data / visual material data,
- Process control data / machine data,
- Environmental data,
- Synthetic and measured operational data.

Classification of these data types is proposed in Figure 2 for a generic smart manufacturing facility using different types of raw materials and multiple sources to meet the energy demands in compliance with regulations and policies of green and digital transition [10-12]. Specific choice of the meters and sensors depends on the peculiarities of the manufacturing process. For example, while for some production elements where the heating is moderate and uniform, the point measurement of temperature with semiconductor-based sensors is accurate enough, informative and sufficient, for the case when the spatial thermal distribution is essential, the thermography usage is preferred. This implies that the amount and velocity of the harvested data can differ even for physically equivalent characteristics.

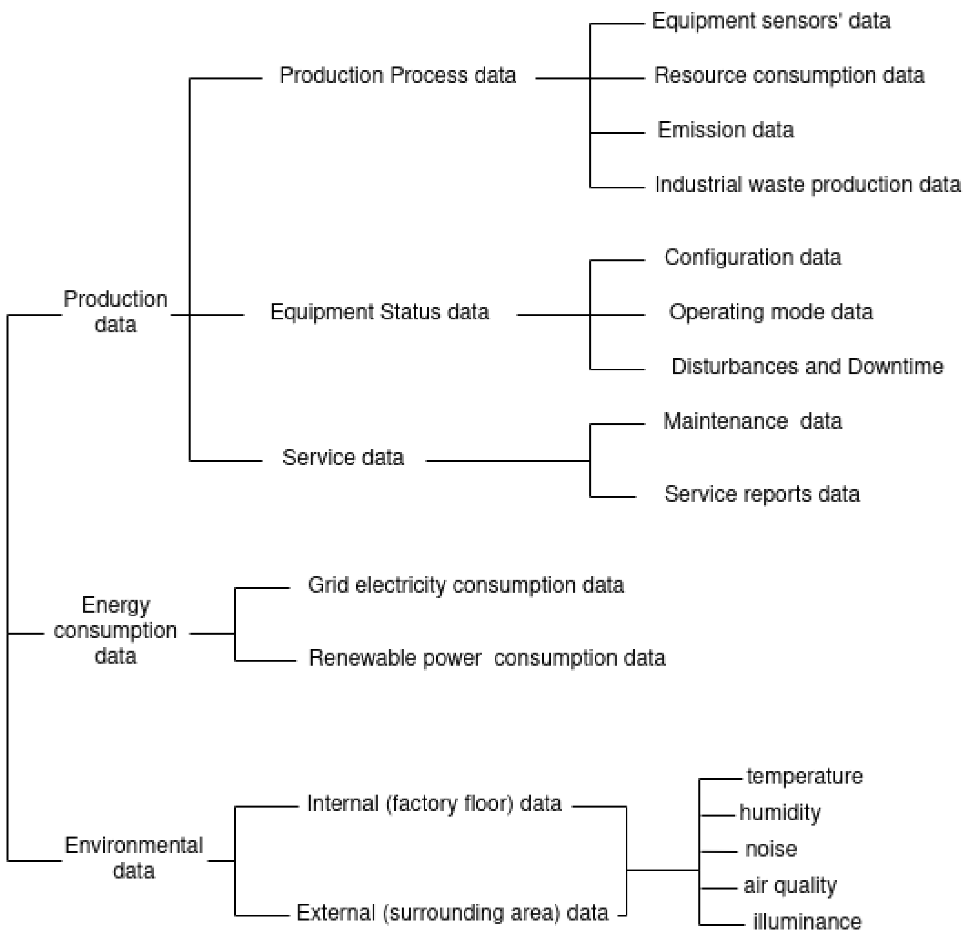

Figure 2: Data typology for industrial applications

The power consumption by each individual machine in the production line is one of the crucial data points to gather. Modern machinery can have IoT sensors to measure their energy consumption in real-time and this information can be utilized to identify units and processes where the equipment consumes more energy than is required and to optimize energy consumption as a whole as well as to reduce waste heat production. With the help of digital twins, the industrial data platform can track the manufacturing line's energy usage even if it is distributed among several different physical sites.

There are a few sorts of environmental data that need to be gathered. Some smart manufacturing processes (such as 3D printing and molding of plastic materials) call for precise temperature management, thus keeping track of temperature information is essential to both maintaining high-quality output and maximizing energy efficiency. Dataflow from the temperature sensors of the machine's heating and cooling systems can be used to both feed a digital twin that simulates the thermal behavior of the machine to predict potential problems and optimize the manufacturing processes and maintenance as well as to trigger edge-system controls in case of overheating.

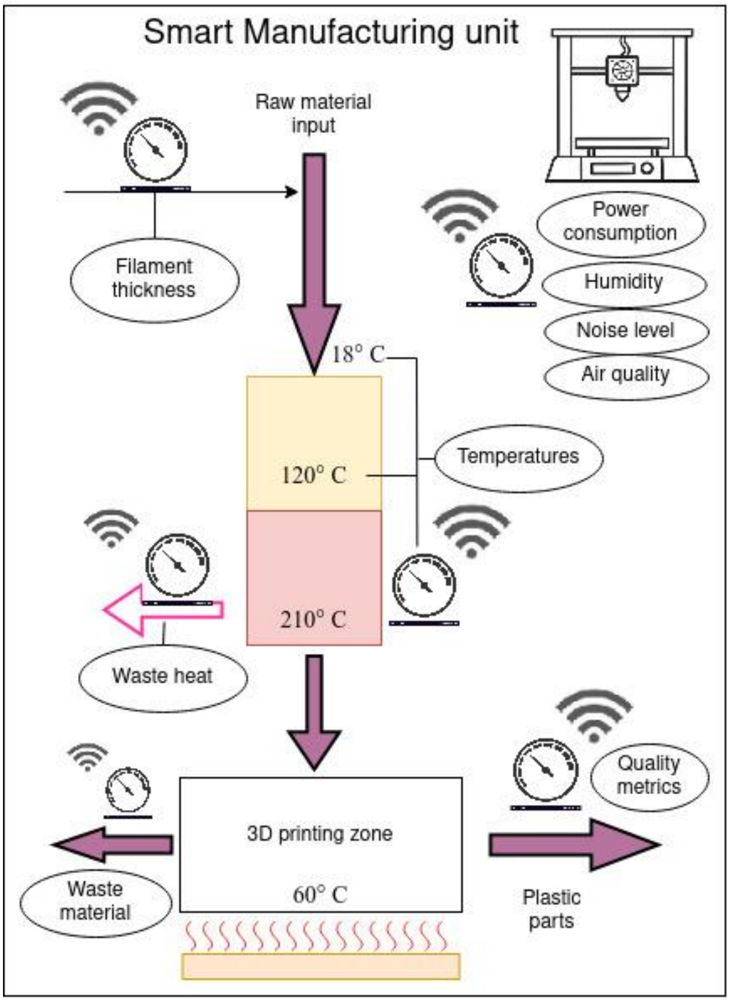

Figure 3: Exemplary Smart Manufacturing unit to be monitored and controlled by Digital Twin

Algorithms can improve the machine's performance to consume less energy by assessing data on the operating parameters and the amount of material being used. Vibration sensors on machine parts can make it possible to spot potential concerns before they become serious ones. Likewise, information regarding hydraulic system pressure will be gathered by sensors and used to modify energy usage as necessary. Through the machine's digital twin, information on the quantity of parts produced, cycle duration and downtime will be gathered and used to improve energy use.

Another benefit from digital twin implementation in smart manufacturing is predictive maintenance that can be used to maximize equipment time in service. The information gathered through sensors regarding the machine's state, encompassing data points such as vibration and temperature, allows for the prediction of maintenance needs, detecting causes of unanticipated interruptions to operations. By utilizing data analytics to schedule maintenance tasks, the workflow can be optimized for better performance, decreased energy consumption, and improved efficiency.

By implementing a specialized intelligent industrial data platform, it is possible to guarantee that the consistent and accurate data obtained from sensors will be utilized during subsequent analysis and modeling. The appropriate data governance practices must be used when gathering, retaining, and manipulating data related to industrial procedures. Properly accomplished data engineering (collecting, storing and preparing data) is an essential prerequisite for obtaining insight from the harvested data. Special attention is to be given to information security and the protection of privacy. This involves guaranteeing that data remains confidential, unaltered, and accessible, while also preventing unauthorized access, manipulation, and theft of data.

For an exemplary model of the smart manufacturing processes and units, specified by Figures 2 and 3, it is necessary to develop a model that represents the current state of the live production line through links to live data streams from the manufacturing floor and enterprise management or digital twin platform streams and provide options for decision-making based on mathematical models that allow characterizing both the resource consumption and process peculiarities. To identify the most effective and viable solution, several energy management scenarios can be simulated using the digital twin. A virtual copy of the smart manufacturing facility can enable real-time monitoring and analysis of the facility's performance and energy usage to optimize the process, resulting in a life cycle that is more sustainable.

3. Process optimization for Smart Manufacturing

Based on the data obtained from a set of embedded sensors and external data generators, a reference matrix would be developed consisting of the set of minimum parameters needed to mathematically describe each process and its dependencies, limits and boundary conditions. Target function built on this dataset may serve as a tool for optimization of the process and effectively the entire system. Optimization schema shown in Figure 4 illustrates the general approach which may help resolve the optimization problem in an efficient way. In the right panel, the business-oriented schematization is given. Inputs x and outputs y are the quantified characteristics of the material and information flows which the manufacturing system receives from the external entities and sends to the same or different external entities, respectively. Optimal control signal u^* is the solution of the optimization problem to fulfill the goals set by particular smart manufacturing use case. This optimal u^* is to be obtained following the procedure described in this section (the examples for particular use-cases will be presented elsewhere), to improve the initial control signal u based merely on the model description of the process and standard procedures. The distinctive feature of the proposed approach is the model refinement being the integral part of the optimization problem solving.

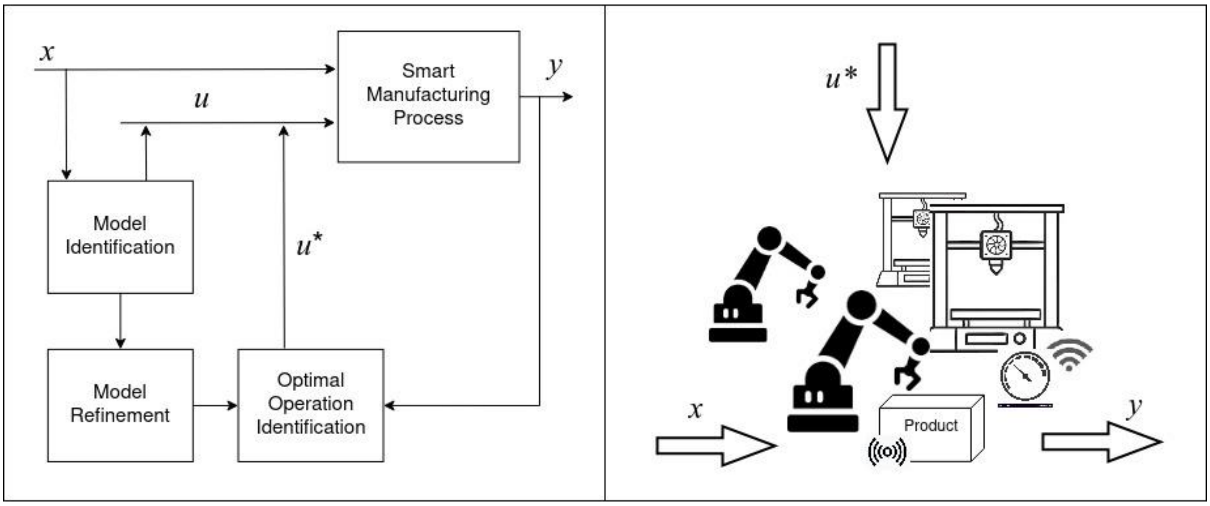

Figure 4: Optimization schema for digital twin-enabled smart manufacturing. Left panel: model representation. Right panel: inputs-outputs-controls representation

Solving the general optimization problem is quite complicated as it comprises functional relations of different types for numerous variables of various nature. However, the equations describing a particular process contain only variables of i^{th} subsystem and this feature allows a decomposition (see

Figure 5) and construction of the optimization recipe as a superposition of partial solutions for separate subsystems (for the detailed discussion on this approach applicability see [13, 14]). This approach also significantly reduces requirements for processing power used by the optimization engine. At the same time, if different partial optimization problems are self-contained, which may be the case of the distributed manufacturing system, the optimal solution for k^{th} subsystem may be incoherent with KPIs of the entire system, therefore no decision making may be done and no correcting actions may be taken before the full optimization solution is found for the entire system.

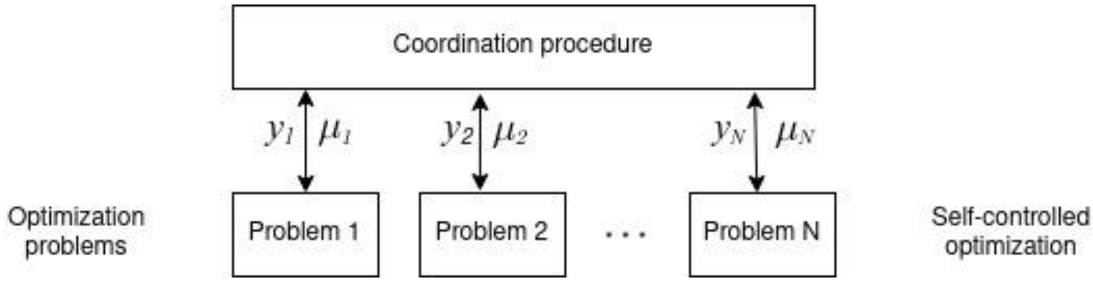

Figure 5: Optimization schema for digital twin-enabled smart manufacturing. Left panel: model representation. Right panel: inputs-outputs-controls representation

Taking into account the measured process state vector $\vec{x} = (x_1 \quad x_2 \cdots \quad x_n)$, control vector $\vec{u} = (u_1 \quad u_2 \cdots \quad u_n)$ and disturbances, the model choice is performed and the chosen model is refined. The initial control signal u is chosen on basis of the following considerations. First, the dimensionality of the state vector on the each particular subsystem does not exceed the dimensionality of the control vector for this subsystem. Moreover, particular u_n is constructed according to hardware specification for the n^{th} smart manufacturing system component, for example, as binary code or analog signal. For a complex system, in which every compact manufacturing process (i^{th} subsystem) is characterized by its own control vector $\vec{u}_i$, input vector $\vec{x}_i$, output vector $\vec{y}_i$ and transformation matrix c_{ij}, we consider the problem

$$max \sum_{i=1}^{N} F_i(\vec{x_i}, \vec{u_i}) \tag{1}$$

at conditions

$$\vec{x_i} = \sum_{j=1}^{N} c_{ij}\, \vec{y_j}, \vec{y_j} = \vec{f_i}(\vec{x_i}, \vec{u_i}), i = 1,2 \cdots N. \tag{2}$$

Lagrange polynomial for the above problem formulation is

$$R(\vec{x}, \vec{y}, \vec{u}, \vec{\lambda}, \vec{\mu}) = \sum_{i=1}^{N} \left(F_i(\vec{x}_i, \vec{u}_i) + \vec{\mu_i}^T \left(\sum_{j=1}^{N} c_{ij}\, \vec{y_j} - \vec{x_i} \right) + \vec{\lambda_i}^T \left(\vec{f_i}(\vec{x_i}, \vec{u_i}) - \vec{y_j} \right) \right). \tag{3}$$

Solution correction is performed on a higher level of the optimization, which corresponds to the overall system management. Coordination of the solutions obtained for separate subsystems is to operate the output vectors $\vec{y}_i$.Therefore, in the first stage the calculation of output vectors $\vec{y}_1$, $\vec{y}_2$, … $\vec{y}_N$ is to be done. In the second stage, the system of equations

$$\frac{\partial R}{\partial \vec{x_i}} = \frac{\partial F_i}{\partial \vec{x_i}} - \vec{\mu_i} + \vec{\lambda_i} \left(\frac{\partial \vec{f_i}}{\partial \vec{x_i}} \right)^T = 0, \tag{4}$$

$$\frac{\partial R}{\partial \vec{u_i}} = \frac{\partial F_i}{\partial \vec{u_i}} + \vec{\lambda_i} \left(\frac{\partial \vec{f_i}}{\partial \vec{u_i}} \right)^T = 0, \tag{5}$$

$$\frac{\partial R}{\partial \vec{\lambda_i}} = \vec{f_i} - \vec{y_i} = 0, \tag{6}$$

$$\frac{\partial R}{\partial \vec{\mu_i}} = \sum_{j=1}^{N} c_{ij}\, \vec{y_i} - \vec{x_i} = 0 \tag{7}$$

is to be solved and values $\vec{x}_i$, $\vec{u}_i$, $\vec{\lambda}_i$, $\vec{\mu}_i$ are to be determined. In the next stage the outputs vectors $\vec{y}_i$ are corrected with use of the condition

$$\frac{\partial R}{\partial \overrightarrow{y_\iota}} = \sum_{j=1}^{N} c_{ij}\,\mu_i - \overrightarrow{\lambda_\iota} = 0 \tag{8}$$

and the system of equation (4)-(7) is solved with the corrected parameters iteratively. The condition for interruption of the iterative procedure may be chosen as

$$\sum_{j=1}^{N} c_{ij}\,\mu_i - \overrightarrow{\lambda_\iota} \leq \vec{\varepsilon}. \tag{9}$$

When the acceptable solution is obtained with the desired tolerance, the procedure, which is well-suited for on-line optimization, is interrupted and the controls are enforced. Worth noting, the described correction procedure improves the intermediate solution for a defined target function, which itself may be a subject for correction. Even if the best solution is not reached in certain iteration, the current suboptimal solution is an improvement over the initial control signal u.

4. AR-enhanced Digital Twins

Augmented Reality is a technology that can bring significant change in the growth of an organization. When combined with Artificial Intelligence (AI) and the Internet of Things, AR opens new possibilities in product manufacturing, maintenance, support, and more. In Smart Manufacturing, AR can allow production managers to view production KPIs and have an intra-factory overview of workstations and production lines in real-time for monitoring, identifying, analyzing, diagnosing and resolving problems and flaws. AR can also be experienced via wearable smart glasses, or a mobile phone or tablet with a camera. The device may use computer-generated virtual objects to assist users in performing complex tasks and getting real-time insights for informed decision-making.

As a relatively new and rapidly developing information technology, AR is a powerful tool to facilitate the interaction and, to some extent, the merging of physical and virtual space objects, providing a variety of production services through the widespread adoption of digital twins. AR also provides much better effect of immersion in the industrial environment and a more natural way of interaction for the subjects of the production process. Let us point out that the objects of physical space and the applied level of extended reality technology can be quite organically linked through virtual space. However, one of the bottlenecks and problems faced by the technology of digital twins in production is the proper implementation of the full range of interaction between the physical space and the virtual twin [15]. That is why augmented reality plays a special role at the current stage of supporting the practical implementation of industrial processes. The combination of AR and digital twins can improve the performance of industrial systems in different areas and at different stages of their life cycle, including design, manufacturing, distribution, installation, active operational use, service and end-of-life. Depending on the goals of the industrial process, one can focus [16] on different levels of overlap and mutual influence between the real object and its counterpart. The concept of a passive virtual twin refers to the transfer of physical data into the virtual space for the purpose of observation, i.e. the implementation of basic functions of status monitoring and alerting based on sensor data. Compared to a traditional web-oriented digital twin, this process can be significantly improved due to the specifics of AR devices. Unlike the virtual twin, its hybrid subspecies focuses on virtual and physical analysis and feedback, which includes the processing of contextual information. After collecting data from the physical space, real-time data analysis must be performed, and this process includes modeling, prediction, diagnosis and optimization, as well as feedback from the analysis results from the virtual world to the physical world. AR support significantly enriches on-site data analysis by adding object detection, scene capture and processing of cyber-physical interaction (for example, with the help of the Microsoft HoloLens 2 AR headset, the workspace itself will be perceived much more fully). And finally, the cognitive twin has the most powerful high-level toolkit, as it allows you to combine human intelligence and machine computing. There is an opportunity to dynamically solve more complex and unpredictable situations with the help of advanced computing capabilities, to organize a creative process (design, interaction with robotised processes, machine learning, etc.).

For example, in work [17] it is noted that the modeling of the assembly of multi-element products is considered one of the key technologies in the process of designing and manufacturing complex systems. Note that AR-based digital assembly technology is used to implement the overlay of an additional information layer, perception of the assembly scene, navigation of assembly operations, joint design of the assembly process, etc. A digital assembly model based on a digital twin should realistically simulate the assembly behavior of physical objects in a real environment. Through the interaction between the virtual assembly objects and the real assembly environment, the quality of the assembly design is effectively improved.

The approach of digital twins has proven itself efficient for interaction with individual elements of production lines. For example, implementing [18] such a system on a CNC milling machine with remote process control, where control delay and virtual processing accuracy are monitored, can be applied as an important part of smart manufacturing, having a high potential for application on various industrial machines and smart systems. Augmented reality approaches are actively used to optimize control of robotic systems [19, 20] in industrial production.

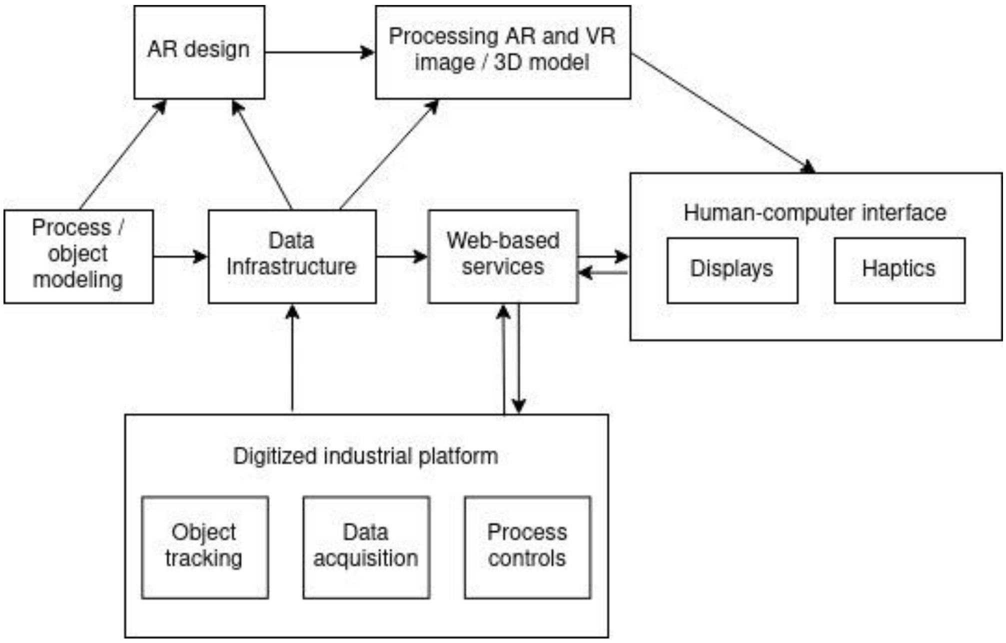

Figure 6: Components of the information system for the AR development

Augmented reality-enhanced digital twins will facilitate human-computer interaction and make it more natural and personalized within Industry 5.0 practices. As metrics to be included into the information layer of the digital twin for the human operator to make timely informed decisions, the characteristics of manufacturing processes performance as well as critical physical parameters, predictions of events, risks estimates are the most relevant candidates.

The workflow for developing AR tools has already been tested in educational use-cases [2, 4]. We propose the sequence of steps represented in Figure 6 for the design and implementation of AR tools for smart manufacturing. The initial step is to be the model development based on the system specification and appropriate regulations. AR design for the smart manufacturing system comprises the 3D modeling of the components and the produced items as well as embedding of the information layer for better informing of the authorized personnel and/or the decision maker. For the smart manufacturing line in operation, the digitized industrial platform performs tasks of the collecting and pre-processing of the relevant information, identified according to the methodology discussed in Section 2 and transmits the data to the custom-built data infrastructure. In the data infrastructure, parameters of the model developed in Section 3 are assigned the data points from the real production line for the subsequent optimization and control signals generation. For AR assets, the visual markers tracking allows the user to receive the insight into the process flow, visualized through the human-computer interface and promptly interfere with correcting actions transmitted via web-based services to the industrial platform. Current state and system changes cause re-processing of AR layers and reflect both the parameters evolution and optimization results. This way, the Industrial Digital Twin (IDT) allows for real-time optimization and informed decision-making by human operators for improved process efficiency. As one can see, in addition to the digital twin services and databases, external users, 3rd party services and physical devices can be involved which raises the issues of information security and privacy, to be addressed within secure-by-design ideology, with vulnerability and threat analysis based on detailed identification and characterization of the relevant data flows.

5. Information Security Concerns in Digital Twin Development

It is important to properly design and develop a security layer for the Industrial Digital Twin in cloud/edge environments. Addressing various aspects of information security and cybersecurity threats is required for assuring protection of the IDT and IoT devices from malicious attacks. Information, collected by the digital twins and processed by the industrial data platform, represents the valuable business asset and therefore is to be the subject of a thorough analysis in order to be appropriately secured. To address security concerns during the IDT development, deployment and use, the following aspects have to be considered.

Since the IDT itself and as being a part of Cyber Physical Systems operates with sensitive data and privacy data, the best security practice compliant with industrial standards and regulations should be followed by default. Secure-by-design principle for developing IDT implies security requirements to be identified, which is one of the most important stages of the system development life cycle that allow the engineers to develop a quality, cost effective and secure system. Among approaches to identify security requirements within information and cyber security domains there is threat modeling that allows to identify security needs, locate threats and vulnerabilities, score their impact and severity, and prioritize solutions. It can be applied to a broad range of systems, including software, networks, distributed systems, IoT and industrial processes. To identify and describe potential threats and vulnerabilities to the IDT and to individual's personal data, the STRIDE [21] and LINDUNN [22] threat modeling methodologies can be leveraged. Based on the IDT architecture, its applications and technologies analyzed in [23] we developed the general data flow diagram and the threat model shown in Figure 7.

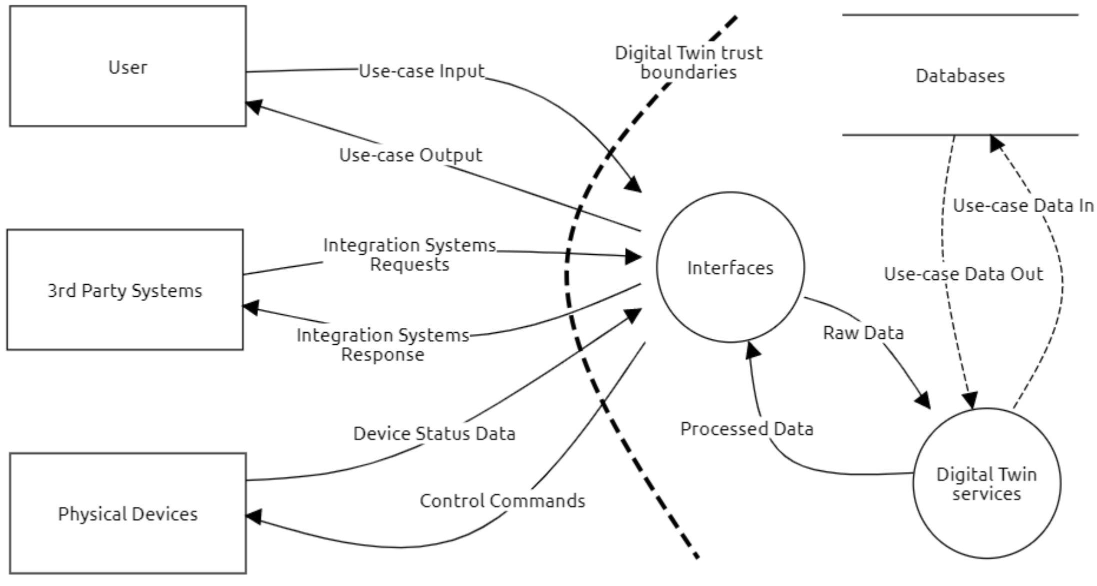

Figure 7: Digital Twin architecture data flow diagram

The potential threats to the IDT and the data being processed within the Smart Manufacturing facility have been analyzed. The corresponding threat descriptions and mitigation actions have been systematized in Table 1. The proposed countermeasures will help engineers and security specialists to reduce the time and costs while designing or upgrading the IDT platform and its components.

Privacy threat modeling within the IDT development is a process of identifying and assessing potential threats to personal information. It helps organizations involved in Smart Manufacturing as well as individuals to develop strategies to mitigate these threats and protect data privacy. Since the privacy threat modeling requires specific inputs of certain manufacturing implementations it will be analyzed in more detail in a separate research.

Table 1
Security threats and countermeasures for IDT platform

Type of Security threat	Element of IDT architecture the threat is applicable to	Countermeasures
Spoofing – Impersonating someone else or claiming a false identity	User 3rd Party Systems Physical Systems Interfaces Digital Twin services	Strong authentication mechanisms: MFA, biometric auth, certificate pinning, OAuth. Strong cryptographic protocols: PGP, AES, SHA-2, TLS 1.2 / 1.3, Elliptic-curve cryptography. Encryption usage
Tampering – modifying data in transit or at rest, or modifying a process maliciously	Use-case Input / Output Integration Systems Requests / Response Device Status Data Control commands Interfaces Databases Digital Twin services	Proper authorization mechanisms. Data hashing and signing. Secure communication protocols. Security Labeling
Repudiation – denying taking an action or that an event occurred	User 3rd Party Systems Physical Systems Interfaces Digital Twin services	Logging and audit trails.
Information Disclosure – sensitive data being leaked while it's in transit, at rest, or being processed	Use-case Input / Output Integration Systems Requests / Response Device Status Data Control commands Interfaces Databases Digital Twin services	Encryption usage. Proper authorization mechanisms. Strong cryptographic protocols: PGP, AES, SHA-2, TLS 1.2 / 1.3, Elliptic-curve cryptography. Secure coding best practices.
Denial of Service – an asset, service or network resource become unavailable or its their performance are reduced for purposive users	Use-case Input / Output Integration Systems Requests / Response Device Status Data Control commands Interfaces Databases Digital Twin services	Antimalware software / Security applications. Redundancy.
Elevation of Privilege – gaining access or privileges that are unauthorized	Digital Twin services Interfaces	Proper authorization mechanisms. Principles of least privilege. Logging and audit trails. Access certification.

Shift-left security approach adoption for the IDT development and usage will help to ensure the sensitive data and privacy information are protected from constantly increasing threat of cyber attacks on industrial systems. The solution provides the required traceability for cybersecurity and privacy auditing to demonstrate compliance with corresponding regulations.

6. Conclusions

Implementation of digital twins with augmented reality interface may become a powerful enabler for realization of human creative potential in smart manufacturing, which is a prerequisite for transition to Industry 5.0. Digital twins are especially valuable for improving manufacturing workflow when there are decisions which are to be made by a human operator. At the same time, collection of relevant information will allow continuous process optimization which may bring multiple benefits, including better quality of products, improved energy efficiency and efficient predictive maintenance, effective integration with smart city ecosystems [24, 25].

Different levels of digitalization [26] and stages of implementation of digital twins may be supported by augmented reality assets, from a virtual copy of a separate object, which can be remotely monitored to perform quality checks and control its behavior, to a virtual twin of the entire production pipeline, which not only allows the remote control in real time, but also provides an opportunity to apply the novel methods of big data processing for the purpose of predictive analytics and process optimization. In transition to principles and practices of Industry 5.0, where human creativity will play the central role in the production processes, novel human-oriented interfaces, such as those based on augmented reality technology, will be of the utmost importance. Specific examples of digital twins, discussed in the paper, their characteristic features and possible ways of further implementation of digital twins in smart manufacturing suggest the importance of adoption and proper implementation of secure-by-design approach for digital twins design.

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