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Are we there yet? – Use Cases and Requirements for the Industrial Metaverse

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***Abstract*—The manufacturing industry is constantly looking for new technologies to improve their structures, optimize processes, maximize profit, reduce cost, and improve quality. One such new technology is the metaverse. The metaverse uses a fully interconnected set of Digital Twins (DTs) that spans all parts of industrial production processes and company administration, thus enabling complex company and production insights. Implementations of metaverses in industrial processes are currently still rare, although there are concepts that promise major benefits. So why have these concepts not yet been used on a large scale in industrial production? To investigate this, we collect and discuss industrial use cases and derive requirements for a metaverse at industrial scale. With these requirements, we analyze existing architectures with respect to their applicability not only within big enterprises, but also at small and medium enterprises (SMEs). Furthermore, we present a vision for the Industrial Metaverse (IM) which fits current and future industrial needs. Finally, current open research questions are highlighted and future research directions are presented, with the ultimate goal of providing not only a further theoretical framework, but a broadly usable IM implementation.**

***Index Terms*—Industrial Metaverse, Industry 5.0, Digital Twin**

I. Introduction

A growing number of enterprises and researchers worldwide refer to a metaverse as the next stage of the industrial revolution [1]–[4]. In the last few years many variants of metaverse structures, architectures, and frameworks have been proposed. Most of them are high-level structures that lack potential for industrial application because they do not take into account the strict requirements for machine control by the industry, but only focus on a specific use case. Therefore, a detailed analysis of the current state in the industry, use cases, and requirements has to be performed to develop an industrially applicable framework.

Despite the frequent use of the term ”Metaverse”, there is no unified understanding of what a metaverse is, does or enables: For some parties [3]–[7], a metaverse is a human centered virtual universe where a user interacts with other users or objects in this virtual environment. Often, every participant is represented as an avatar in the metaverse. This metaverse variant is frequently focused on a 3D immersive user experience for socializing, entertainment, communication or education with the possibility of monetization to some degree. Other parties [8] describe a new form of professional training and maintenance through the metaverse. This concept mostly relies on DTs to store data and on virtual reality (VR) or extended reality (XR) to display relevant parts of this data to a user. A third group [1], [9] describes a fully connected metaverse with its focus on data integrity, data analysis and decision making. In these approaches, DTs are used to model relevant aspects of the real world and provide necessary data for further analysis. Further combinations of those metaverse interpretations are found throughout the literature [2], [10], [11].

The metaverse can be seen as a top-down approach to realize the Industry 5.0 (I5.0) vision as proposed by the European Union [12]–[14], the Industry IoT Consortium [15] or the Industrial Internet Consortium [16]. A corresponding bottom-up approach, on the other hand, can often be found in the literature under the keyword ”Industrial Internet of Things (IIoT)” [17]–[20]. IIoT is deliberately not covered here, as the focus is usually only on data acquisition by Internet of Things (IoT) devices in an industrial environment. Nevertheless, IIoT is a core building block for the IM, as it most likely offers solutions for industrial requirements in terms of real-time capability and sensor communication.

The focus of this paper is clearly on the role of the metaverse in industrial applications, as the metaverse brings a great economic advantage to enterprises by enabling a better understanding of overall production processes under consideration of external factors. The remainder of this paper is structured as follows: In Section II, definitions of common terms in the metaverse context are provided for clarity. Later, in Section III the state of the art in industrial production and the remaining challenges towards smart manufacturing are discussed to point out deficits in existing implementations. Section IV analyzes use cases for smart manufacturing technologies, and Section V derives requirements that must be satisfied by a metaverse to enable the previously proposed use cases. Afterwards, in Section VI existing solutions, frameworks and architectures are examined and evaluated in terms of their coverage of the requirements for industrial production. Subsequently, in Section VII, our vision for an industrially applicable metaverse – the IM – is presented. Finally, Section VIII identifies gaps in the current research that need to be addressed in future work.

II. Definitions

A. Metaverse

The term metaverse was first mentioned in 1992 in the novel ”Snow Crash”, in which people live, work and interact in a parallel virtual world [21]. In recent literature the metaverse is described as the ”Internet of 3-D worlds” [9]. According to [1], ”The metaverse can be defined as the gathering of data and information surrounding users and objects, collected from various locations and devices (e.g., homes, work, and IoT devices), and presented in an immersive manner while being accessible through XR, including AR, VR, and mixed reality (MR), for a more tangible, visual, and interactive experience". We follow this definition with some additions and further explanations under the term IM as discussed in Section II-E.

B. Digital Twin (DT)

Throughout the literature, DTs are described as virtual representations of parts of the real world which can be used to simulate the behavior and the entire product life cycle of their real-world counterpart [11], [22]–[24]. According to [25] a DT "integrates ultra-high fidelity simulation" to a product and enables "unprecedented levels of safety and reliability". DTs can be used to perform analyses with traditional algebraic methods or with machine learning (ML) methods such as artificial intelligence (AI). The results can be used, for example, to optimize decision-making, improve certain processes or optimize cost. For further use in our research, we define a DT according to the literature as a) a virtual representation of parts from the real world. In addition, similar to [5], [26] and [27], we require that b) a DT must be able to receive and transmit data from the real world or another system within the IM. Furthermore, a DT must also be able to c) store data for further use and predict current and future states of its real-world equivalent. [28] discusses five archetypes of DTs. This classification of DTs is particularly useful, although the definition of DT and IM is different. Their archetype "AT 5" corresponds to our vision of an IM.

C. System model

The main function of a system model is to describe and predict the behavior of a system. This can be done either by analytical or data driven methods like AI. We define a system model as the part of a DT that is responsible for the relationships that describes the behavior of the (physical or virtual) system.

D. Data representation

In addition to system modeling, the DT must process various data and record it for further use. Therefore, a data representation is an integral part of a DT. The data representation stores data collected by various sensors, but also internal data such as model states and predictions, control commands or optimization parameters. Together, this data can serve other components of the metaverse as a basis for further analysis and optimization.

E. Industrial Metaverse (IM)

The IM is based on the above metaverse definition (Section II-A) and specifies an industrially applicable version of the metaverse. It is intended to implement the use cases from the manufacturing industry for both large enterprises and SMEs and enables improvements in all industrial processes. Essential elements for this are interconnected DTs like defined in Section II-B. These DTs contain a system model (Section II-C) to calculate the behaviour of the real-world equivalent and a data representation (Section II-D) to manage various data. This combination of data and system model can be used to perform optimization. The optimization can be carried out either for one local machine without additional information from the metaverse or in a global context for entire industrial processes with several participating DTs. For these (cross-enterprise) optimizations and further analysis, data driven methods such as ML and AI as well as classical analytical methods could be used. Furthermore, a high fidelity model of the entire production environment can be used to generate a large amount of high-quality synthetic data to train ML-based algorithms. In addition to advanced analytics, optimization and data generation, the IM enables advanced scheduling, simulation and prediction of processes, sensitivity analyses (what-if), and generally an optimized day-to-day business. This can be achieved by considering not only a small subset of data, but all data available in the whole IM. Furthermore, the DTs enable predictive maintenance and improved quality assurance, as a wide range of process parameters can be monitored and analyzed (see Section IV).

III. State of the art in industrial production

Industrial production is in an ongoing change and attempts to optimize production processes through smart manufacturing by integrating IoT, cloud computing and data driven analytics. More than ten years after the emergence of Industry 4.0 (I4.0) in the year 2011, the reality is still painting a different picture and many enterprises are still stuck in inflexible automation [29], [30]. While I4.0s successor I5.0 is getting more and more attention, the transition between both technologies is blurry [31], [32]. Over the years, many guidelines for I4.0 and I5.0 implementations have been proposed (see Section I) and the topic has been covered extensively in research. Reference architectures like the "Industrial Internet Reference Architecture" (IIRA) [15] or the German "Reference Architecture Model Industrie 4.0" (RAMI4.0) [33] have been proposed [34]. However, the implementation of the proposed concepts in industry has not yet taken place on a large scale. This raises the question of why large parts of industry are not using the proposed technologies and are missing out on the benefits.

The core technology of I4.0 and I5.0 are DTs [10]. Unfortunately, implementing DTs comes with high efforts. Furthermore, an easy integration in existing production processes is rarely possible. Although intelligent manufacturing offers significant advantages, its introduction also poses further technical, economic, and social risks. These include, for example: (i) availability of digital services, (ii) effort and cost for realization, (iii) critical machine control and (iv) the ability to integrate the new services into existing processes. Especially for SMEs, these risks prevent them from adopting new technologies and moving away from proven processes [35]. Some of the promised cost savings by optimizations can only be achieved with great effort and investment. Enterprises must be able to clearly see the decision support and the direct benefits in their daily business. Therefore, an easy-to-use framework for enterprises is required. The framework must be easy to integrate into existing production environments, otherwise many enterprises might be reluctant to invest time and resources in implementing smart manufacturing.

IV. Use Cases

This use case analysis focuses on industrial processes where an IM could provide benefits for enterprises. Further investigations and a more detailed analysis of the use cases from I4.0, I5.0, DT, and smart manufacturing towards industrial applications can be found in [16], [36]–[38].

A. Scheduling

With Job Shop Scheduling, the goal is to find out when which product is to be produced, and in which order. Many factors are taken into account, such as delivery date, machine setup time, employee availability, rework, joint processes with other jobs, energy cost and much more [29]. To capture all this, a production plan may be developed and adopted manually by a skilled worker as seen in many SMEs. For enterprises with larger production processes, manual development of production plans is not efficient. These complex problems require formulating and solving optimization problems [38], [39]. However, when using optimization problems, quality and availability of input data is crucial. Often, only manually acquired, basic data about production and transportation times are available. Obviously, this type of data collection is prone to errors. Therefore, only limited and incomplete knowledge about the whole production process is available for optimization. Inter-dependencies between processes and jobs are not known. Ultimately this can cause a suboptimal production schedule.

Next to an optimized production schedule, dynamic employee assignment can be performed. In order to be profitable, the idea of dynamic employee assignment is to have an employee working on a machine only when needed, but not occupying him, when the machine needs no attention, thus to utilize each employee to the full potential [39]. To achieve this, every machine needs to be monitored constantly. With this data, the time to the next human intervention can be predicted and an optimal processing order for every employee can be determined. Different employees with different abilities, preferences, and habits need to be taken into account, as these factors influence the execution of the respective tasks.

The IM can perform automated production planning and employee scheduling since all necessary data is available in the metaverse. To improve the accuracy of scheduling, the calculated plan can be evaluated against the real process data. The calculated schedules can be based on historic data such as order volumes or logistics capacities, but also real-time parameters such as energy prices or employee utilization can be used.

B. Simulation, prediction and sensitivity analysis (What-If)

Many processes are simulated in order to create a basis for decision-making or predict the outcome for changes in production parameters. Often, these simulations are inaccurate because of inadequate input data and system models which cannot represent all aspects of the problem. Data-driven approaches using AI / ML to optimize the models are an important innovation, but require a large amount of data [29], [40]. Interconnected DTs, together with continuous process monitoring and simulation enable sensitivity analysis with much greater accuracy [41]. Furthermore, this leads to a reliable and continuous prediction of process parameters, production rates and thus to a better utilization of available capacities [42].

C. Predictive Maintenance

Advanced maintenance concepts play a major role in modern intelligent manufacturing [32]. Maintenance work is currently carried out regularly (preventive) or after a failure (corrective). Preventive maintenance involves replacing parts before the end of their service life which results in ineffective use of the components. Corrective maintenance, on the other hand, makes maximum use of a component, but at the cost of production downtime. Predictive maintenance combines the best of both worlds. Components are used until shortly before they fail. To determine this point, extensive knowledge about the whole system is necessary [43].

In the context of IM, DTs or smart manufacturing, predictive maintenance is often referred to as a core technology [2], [38], [44], [45]. Nevertheless, it requires a large amount of data. The IM provides all this data and can contain DTs for each individual part. These DTs represent the condition of the components, their expected wear and the predicted lifetime.

D. Quality Assurance

Another application for an IM is improved quality assurance [16], [23], [38]. During the production process, various sensor readings can be tracked and stored in DTs. These process parameters can be used to draw conclusions about the expected product quality [15], [46]. Additionally, quality is randomly checked by quality assurance (QA) employees, and the results are stored in the respective DTs as well. If the results determined by the QA employee match the expected qualities from the DT, the test interval can be increased until the process parameters change. This saves a lot of time and effort for the QA employee, who would otherwise have to spend more time checking further parts.

V. Requirements for an Industrial Metaverse

In order to understand the requirements for an IM, the different use cases were analyzed (Section IV). Various requirements are derived and evaluated in terms of their importance for the respective use case. Finally, we ranked the requirements on a scale from one to three to create a basis for further analysis, as shown in **Table I** (High resolution graphics are available at https://github.com/IndustrialMetaverse/

IM-Graphics/blob/main/UseCase-Reqirements.pdf). The ratings for each requirement are in the following range: 0 not necessary; 1 beneficial, but neither important nor necessary; 2 important, but not necessary; and 3 absolutely essential.

A. Optimization

For all use cases, knowledge of upstream and downstream processes (Req. 1) was identified as an indispensable function. Upstream and downstream processes can be, for example, other machines and processes within the enterprise, but also processes outside the enterprise such as delivery or distribution. With this knowledge, not only the direct effects on one subsystem, but also the effects on all upstream and downstream processes within the IM can be analyzed. To generate benefits from these analyses, the ability to perform optimization at a global scope (Req. 2) is required as well. For some use cases, such as predictive maintenance (Section IV-C) or QA (Section IV-D), immediate knowledge of unexpected situations (Req. 3) within the plant is crucial information, as immediate action may be required. For other use cases such as sensitivity analyses or general simulations (Section IV-B), no immediate reactions are required, so Req. 3 is not necessary here.

B. Machine Control

A comprehensive and accurate data basis is necessary for all use cases. Therefore, data must be handled with a consistent timing (Req. 4). Otherwise, potentially incorrect data may be used for calculations and the IM will make incorrect recommendations. Use cases like scheduling (Section IV-A) or predictive maintenance (Section IV-C) intend to improve the machine itself or its surrounding. Therefore, the metaverse must execute machine control commands to adjust production parameters and achieve the desired results (Req. 5). Traditional machine control systems are bound by strict requirements in terms of reliability, time accuracy and synchronicity [47]. This is most likely not achievable directly through a decentralized IM. Therefore, near real-time machine control with low latency in the millisecond range must be performed locally (Req. 6). Additionally, the availability and reliability of data and connections must be taken into account. One one hand, missing information in the IM can negatively affect modeling, simulation and prediction (Sections IV-B and IV-C). On the other hand, the production should not come to a stop when the IM in not available. The role of the IM is to supervise and optimize the local machine control and provide additional data and advice within a reasonable short time, but not to interfere with time or safety critical tasks.

C. Digital Twin

Data acquisition and data storage is the core of a successful IM [15], [48]. By using DTs, data is permanently recorded and made available for various services. All analyzed use cases require DTs. Logical connections between these DTs (Req. 7) are required to connect parts, transfer data, and draw conclusions across multiple systems. In addition, DTs must be created and managed when new physical machines are integrated into the enterprise (Req. 8). To minimize the efforts of creating a DT for a new machine (system-model, prediction, etc), an inheritance structure for DTs is advantageous, as a lot of production machines share the same or very similar parts. Inherited structures within DTs allow the core modeling to be reused to reduce the effort required to integrate subsequent units into the IM (Req. 9). In many cases it is not necessary to model the exact behavior of parts of a system. In this case, a basic DT with a few core functions might be sufficient. In some applications these core functions are not sufficiently precise. Therefore, the basic DT must be extended by an advanced DT to better model the system behavior. Consequently, an IM must support both basic DTs and advanced DTs (Req. 10). Secondly, most processes can be modeled by a set of sub-processes; a cascaded structure of DTs could be used to represent a complete DT by several subordinate DTs (Req. 11). Figure 1 describes this DT structure based on the example of a plant with a DT. The DT is divided into 2 sub-DTs, each containing respectively two or three further sub-DTs, which are inherited from templates.

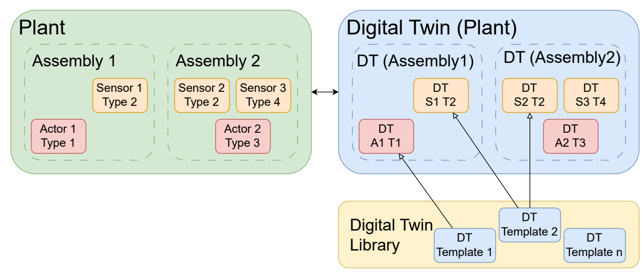

Fig. 1. Example of two DTs consisting of multiple sub-systems (sensors and actors) which share inherited system models (in blue)

Furthermore, an exchange format for DT-description is required as machine manufacturers can offer DTs for their products and machines (Req. 12). This could then even lead to an open source library for DTs. The DT stores data and makes it available for all types of services. At the same time, many different sources supply data to the DT. This data must also be stored and, if necessary, be further processed. We therefore propose a standardized interface for communication with DTs (Req. 13). These structures for DTs should reduce the complexity and effort of the entire modeling process.

D. Interfaces and Support

To truly add value for enterprises, the metaverse must enable optimizations that would otherwise not be possible. This requires comprehensive data acquisition and support for various analysis tools, including not only classic algebraic solutions (Req. 14), but also a wide range of data driven techniques such as ML and AI (Req. 15). In some cases, data is not recorded automatically, but manually. For example, certain parts are checked periodically during QA (Section IV-D) or maintenance. This results in valuable additional data about the produced parts or the state of the machine. This data must

TABLE I
RELATION BETWEEN USE CASES AND REQUIREMENTS

Use Cases \ Requirements	optimization			machine control			digital twins							interfaces & support				human-factor					visuali-zation	
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
	knowledge about upstream and downstream processes	optimization at a global scope	immediate knowledge about unexpected situations	consistent real-time handling of production and sensor data	control technology for the plant (timing independent)	Low Latency for time-critical tasks	logical connection between DTs	creating and managing DTs	inherited structure for DTs with varaints or configurations	basic DTs and advanced DTs	cascaded structure of DTs for subsystems	exchange format for DT-description	unified communication interface for DTs	algebraic optimization	AI / ML	manual input for additional data in DTs	AR / VR / XR	DT for humans	human interaction with the metaverse	protection of personal employee data	support of the employees in the execution of the work	real time notification of the employee	visualization of processes	visual guidance for tasks
Scheduling	3	3	2	3	1	0	3	3	1	1	1	1	1	3	3	2	1	2	2	2	2	2	1	1
Simulation	3	2	1	3	2	2	3	2	2	2	2	1	1	3	2	1	1	3	1	2	1	1	1	0
Prediction	3	2	1	2	2	2	3	2	2	2	2	1	1	3	3	1	1	3	1	2	1	1	0	0
Sensititvity Analysis	3	2	0	2	0	0	3	2	2	1	1	1	1	2	2	1	1	2	1	2	1	0	1	0
Predictive Maintenance	2	3	3	2	1	1	3	3	2	2	2	1	1	2	3	3	2	1	3	1	2	3	2	2
Quality assurance	2	2	3	3	1	1	3	3	2	1	1	1	1	2	2	3	1	1	3	0	1	0	0	1
Mean	2.7	2.3	1.7	2.5	1.2	1.0	3.0	2.5	1.8	1.5	1.5	1.0	1.0	2.5	2.5	1.8	1.2	2.0	1.8	1.5	1.3	1.2	0.8	0.7

0	not necessary	1	beneficial, but neither important nor necessary	2	important, but not necessary	3	absolutely essential

be stored in the corresponding DT, as well (Req. 16). For advanced maintenance and repairs (Section IV-C), as well as for process monitoring augmented reality (AR), VR or XR should be supported (Req. 17), although it is clear from the use case analysis that this should not be the main focus for an IM implementation.

E. The Human-Factor

In addition to technical requirements for a metaverse, there are also human-centered requirements that must be taken into account. In the IM, people are integrated as a resource into processes and optimizations. This requires a DT representation for each person. Characteristics and individual behavior, physical location, current task as well as availability and individual skills need to be modeled (Req. 18). Like machine parts, humans need to interact with the metaverse in a variety of ways to receive and transmit data (Req. 19). This level of human integration reveals a certain amount of personal data. This personal data must be protected to ensure that employees support the system and do not experience a feeling of being controlled and monitored (Req. 20). Instead the employees can benefit from the IM. By providing additional information when necessary, each employee can be optimally supported in the execution of their task (Req. 21). To inform employees about their next task, communication between the IM and employees is necessary. In some use cases like Scheduling (Section IV-A), it may be sufficient for this communication to take place once a day. In other cases like QA (Section IV-D), however, immediate action may be required. Therefore, a simple communication channel between the IM and employees in production must be created. This can be done, for example, via various cyber-physical systems such as smartwatches, VR or XR devices (Req. 22).

F. Visualization

To improve the user-friendliness of the metaverse, a detailed visualization is advantageous (Req. 23). This can be done through a detailed 3D model enriched with DT data. It can be displayed either on a monitor, on mobile devices such as smartphones and smartwatches or as an immersive model through VR, AR or XR [8], [22]. These immersive models in particular could be used to support employees in their work (Req. 24). Despite its great benefits, visualization is typically not required for most IM functions. This is very different to other metaverse implementations and therefore changes the focus for the IM away from visualization and human interaction towards optimization and analysis.

G. Additional Requirements

In addition to the presented requirements, some general requirements must also be met. For example, the metaverse has to integrate seamlessly into the existing production process. It is unlikely that enterprises will completely replace established workflows and thus risk production downtime during the implementation phase. Additionally, the initial implementation of basic metaverse technologies should be of reasonable effort and cost in order to increase acceptance. The complex processes in various industries must also be taken into account. DTs as the core element of an IM must be available for every relevant element of a process. This leads to a large amount of necessary DTs. Data collection and system modeling are the key factors for the creation of DTs. It must therefore be possible to implement these two aspects at a reasonable cost. To further reduce the effort for initial implementation, a basic library of DTs can be implemented. This library contains basic DTs for general applications such as robots, plants, employees and frequently used parts. These DTs can be used as a template for specific persons or processes within the system to be represented (see V-C).

VI. Framework and architecture analysis

There are already a few proposed metaverse architectures for industrial use in the literature. However, those often focus on only a few very specific use cases. Hence, most do not fulfill the requirements for a general metaverse in industry. In this section, the five most suitable proposed architectures are analyzed with regard to the fulfillment of the presented requirements (Section V). The requirements towards an IM are clustered into six sections, namely: (A) optimization, (B) machine control, (C) digital twins, (D) interfaces & support, (E) human-factor and (F) visualization. In addition, the remaining development effort towards an IM for a wide range of applications in various industries is estimated.

Ref. [1] proposes the ”Enhanced DT-enabled Metaverse Framework”. A high level architecture where an immersive virtual world is connected with DTs and AI. The focus is set on socializing, communication and economy through a metaverse. Industry is just one possible application, but special industrial requirements are not considered. The ”Framework of DT-II” is proposed in Ref. [2]. DTs are discussed in the context of industrial production. The shop-floor is modeled by DTs with interconnections within one and among multiple enterprises. Additionally each product has a DT which models the whole product life cycle. Ref. [8] proposes an architecture for VR in smart manufacturing. The architecture is based on DTs to gather data from the real world and to provide a new way to work and learn collaboratively. The authors further provide the ”Unreal Engine Experiment Framework” to interact with the metaverse trough VR. The ”OpenTwins” open-source framework [11] is proposed for the integration of DTs. The framework is focused on communication and management of data in the context of DTs. Further the DT data can be represented in a 3D world. The framework also features data prediction with ML. In addition, the framework was implemented in a prototyping environment with real industrial data and tested with regard to latency. Ref. [19] focuses on reliable and low latency communications for DTs in the context of the metaverse. While most other approaches focus on an overall architecture for the metaverse, this approach deals specifically with the problem of communication, which other approaches do not address in detail. The outcome of the analysis of these architectures can be found in **Table II** (High resolution graphics are available at https://github.com/IndustrialMetaverse/IM-Graphics/blob/main/ArchitectureFramework-Reqirements.pdf).

Over all analyzed architectures and frameworks, it is apparent that each framework only focuses on parts of the requirements but does not take the whole IM into account.

Implementing process optimization is often the main driver for enterprises to implement an IM. That requires knowledge about adjacent processes. Surprisingly, only [2] mentions comprehensive optimization over multiple processes. [1], [11] and [19] discuss aspects of optimization at a global scope and knowledge about adjacent processes, but do not see optimization as a key feature. [8] does not mention optimization at all.

[1], [11], [19] and [2] discuss the control of machines by their framework, but do not perform a detailed analysis regarding industrial requirements for machine control. Only [19] considers applications with strict timing requirements.

Most literature addresses DTs as a core technology. The connection and interaction between multiple DTs are only considered by [11] and [2]. Except for [11] no approach discusses a simple structure to manage a large amount of DTs.

In order to perform various tasks, the IM must provide interfaces and support various technologies. While communication interfaces and data storage types are not mentioned in most approaches, the need to support AI, ML and VR, AR or XR is often discussed.

Most analyzed architectures discuss visual interfaces. [1] and [8], for example, directly suggest the use of VR as main interaction method with the metaverse. [11], on the other hand, does not define the technology used for visualization more precisely. Instead, they merely propose a ”3D representation”. The approaches [19] and [2] do not include visualization at all, since it is not necessary for the presented use cases.

In summary, none of the architectures examined fully meets the requirements for an IM. Most approaches are still in the concept phase. [2] comes closest to meeting the requirements for an IM, but lacks the detailed DT structures required (see Section V-C). Apart from [11], no approach is developed far enough to be used in an industrial prototyping environment. [11] uses structures from [41] and [49] to provide DTs with real production data. Additionally, data prediction and visualization are implemented.

VII. Vision for an Industrial Metaverse

An IM architecture for the use in enterprises should be able to provide the various benefits discussed in Section IV. Implementing the IM must be possible with low effort, cost, and production downtime during integration. To fully address the requirements of the industry and enable the proposed use cases, we propose an IM that is able to optimize the entire production process by taking into account not only machine parameters and data, but also the human factor. Additionally, an intelligent and simple structure to create, manage, and connect DTs is necessary. To reduce the effort for DT modeling, the proposed IM must support DTs according to Section V-C and Figure 1.

When implementing an IM, a multi-layered structure with a machine-wide level and a process-wide level with DTs for every machine and process is required as proposed by [2]. The machine-wide level manages and optimizes all aspects related to the production machine itself. The process-wide level, on the other hand, manages and optimizes across all machines. Here, optimization takes place on a global level, as many different parameters from various sub-processes and machines are available. In a real-world scenario, parts of the overall cyber-physical system (metaverse, DT, and real-world entities)

TABLE II
FULFILLMENT OF THE REQUIREMENTS IN THE PROPOSED ARCHITECTURES AND FRAMEWORKS

Architecture \ Requirements		optimization			machine control			digital twins							interfaces & support				human-factor					visualization	
		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
		knowledge about upstream and downstream processes	optimization at a global scope	immediate knowledge about unexpected situations	consistent real-time handling of production and sensor data	control technology for the plant (timing independent)	Low Latency for time-critical tasks	logical connection between DTs	creating and managing DTs	inherited structure for DTs with varaints or configurations	basic DTs and advanced DTs	cascaded structure of DTs for subsystems	exchange format for DT-description	unified communication interface for DTs	algebraic optimization	AI / ML	manual input for additional data in DTs	AR / VR / XR	DT for humans	human interaction with the metaverse	protection of personal employee data	support of the employees in the execution of the work	real time notification of the employee	visualization of processes	visual guidance for tasks
[1]	Aloqaily et. al.	1	1	-	1	1	1	1	2	-	-	-	1	1	1	2	-	2	1	2	1	1	1	2	1
[2]	Cheng et. al.	3	1	2	2	1	2	2	2	1	1	2	1	2	1	1	1	1	1	1	-	1	1	-	-
[8]	Alpala et. al.	-	-	-	-	-	-	-	-	-	-	-	-	-	-	1	1	2	1	2	-	1	2	2	2
[11]	Robles et. al.	1	-	-	2	1	1	2	2	-	1	1	2	2	-	2	1	2	-	1	1	-	1	1	1
[19]	van Huynh et. al.	1	-	1	1	1	2	1	-	-	-	-	-	-	1	-	-	-	-	-	-	1	1	-	-
	Our metaverse vision	3	3	3	2	3	2	3	3	2	3	2	2	2	2	3	3	2	2	2	1	1	2	1	1

- not possible / not provided; 1 with major restrictions; 2 with minor restrictions; 3 fully supported

will be suspect to outages and thus suffer downtime. Hence, the architecture must be reliable and available enough, to perform time critical tasks, while being flexible enough to not restrict the possibilities of an IM. To allow a broad spectrum of technologies, the IM must support algebraic optimization methods as well as AI and ML. For example, for an improved QA, AI can be used to learn the relationship between quality and production parameters or sensor readings to support QA employees in their work and reduce manual effort. In order to be able to model every single aspect of the production process in the IM, not only machines but also humans must be represented by DTs. In the literature, these DTs of humans are often avatars that interact with a virtual world. In the context of the IM, the behavior and characteristics of people must be modeled in order to simulate and predict their influence on the production process.

VIII. CONCLUSION AND FUTURE WORK

Despite the large number of research projects, concepts and partial implementations in the areas of metaverse, I4.0 and I5.0, smart manufacturing, and DT, there is still no practicable, ready-to-use implementation for enterprises. Even core aspects such as the metaverse architecture itself or the functions and responsibilities of DTs are not uniformly defined in the various publications and implementations. Many approaches are focused on a specific use case instead of developing a universally applicable solution. The main contributions of this paper are: 1) the identification of industrial requirements for an IM taking into account possible use cases for enterprises and the current state of the industry, 2) an analysis of existing architectures and frameworks with regard to their ability to meet the stated requirements, and 3) the presentation of a vision for an industrially applicable IM.

To create an applicable metaverse for large enterprises and SMEs, we have defined requirements for an IM. Unfortunately, various approaches in the literature cannot be adapted for a wider range of industrial use cases without implementing a large number of additional functions. When implementing the IM, cost, benefits, and effort for enterprises must also be taken into account. A simple architecture that can be integrated into existing processes is therefore necessary. In order to realize the IM, future work should focus on the following aspects: 1) design of a cost-efficient and low-effort IM architecture; 2) development of a framework for realization of this architecture; 3) detailed DT development and utilization according to Figure 1; 4) machine control and optimization through the IM.

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