Industrial Metaverse for Smart Manufacturing: Model, Architecture, and Applications

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***Abstract*—Smart manufacturing has been transforming toward industrial digitalization integrated with various advanced technologies. Metaverse has been evolving as a next-generation paradigm of a digital space extended and augmented by reality. In the metaverse, users are interconnected for various virtual activities. In consideration of advanced possibilities that may be brought by the metaverse, it is envisioned that industrial metaverse should be integrated into smart manufacturing to upgrade industry for more visible, intelligent and efficient production in the future. Therefore, a conceptual model, named IMverse Model, and novel characteristics of the industrial metaverse for smart manufacturing are proposed in this article. Besides, an industrial metaverse architecture, named IMverse Architecture, is proposed involving several key enabling technologies. Typical innovative applications of the industrial metaverse throughout the whole product life cycle for smart manufacturing are presented with insights. Nonetheless, in prospect of future, the industrial metaverse still faces limitations and is far from implementation. Thus, challenges and open issues of the industrial metaverse for smart manufacturing are discussed, then outlook is provided for further research and application.**

***Index Terms*—Cloud manufacturing, cyber-physical-social system, digital twin (DT), industrial big model, industrial metaverse, metaverse, smart manufacturing.**

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I. Introduction

METAVERSE, as a virtual universe mapping and interacting with the real world, is regarded as an ideal embodied version of Internet in the future. Integrated with advanced technologies, the metaverse is enabled to be a virtual space extended and augmented by physical reality. Users are linked in virtual universe for immersive interacting experience and interconnected with each other for plentiful social activities. Since the concept of the metaverse was proposed in science fiction "Snow Crash" [1], people are gradually getting accustomed to virtual and online activities instead of in physical and conventional way, especially due to the aftermath of COVID-19 pandemic [2], [3]. Fortunately, with the emergence of multiple technologies, the metaverse is significantly developed to be a hotspot for academia and corporations to follow. Nowadays, the metaverse has been widely applied in various aspects [4], including industry, education, healthcare, office, arts, video games, tourism, etc.

Among these aspects, industry is one of the most significant components for economic lifeline [5]. Since Industry 4.0 was proposed [6], [7], industrial manufacturing has been transforming toward smart manufacturing [8], [9], especially throughout the product life cycle, covering research and development (R&D), production, test and experiments, sales and transactions, and services and maintenance [10], [11]. With advanced information and communication technologies (ICTs) [12], extended reality (XR) technologies and artificial intelligence (AI) [13], [14], smart manufacturing is empowered with higher-production efficiency and enhanced users' virtual interactivity [15], [16]. Furthermore, as a novel manufacturing paradigm, cloud manufacturing conveniently provides users with on-demand services. Distributed manufacturing resources are virtualized and managed in a unified, optimized and configurable manner, enabling highly virtual collaborative and innovative manufacturing [17], [18].

Although remarkable progress has been made, there are still a few limitations of the conventional smart manufacturing. The modeling and simulation (M&S) of the manufacturing devices, processes and the distributed workshops is labor-intensive. Virtual manufacturing still lacks seamless and immersive human-in-the-loop experience. Meanwhile, there are plenty of intangible assets stored, processed and transacted in traditional manner, which hinders circulation and transactions in market. To tackle the challenges aforementioned, the industrial

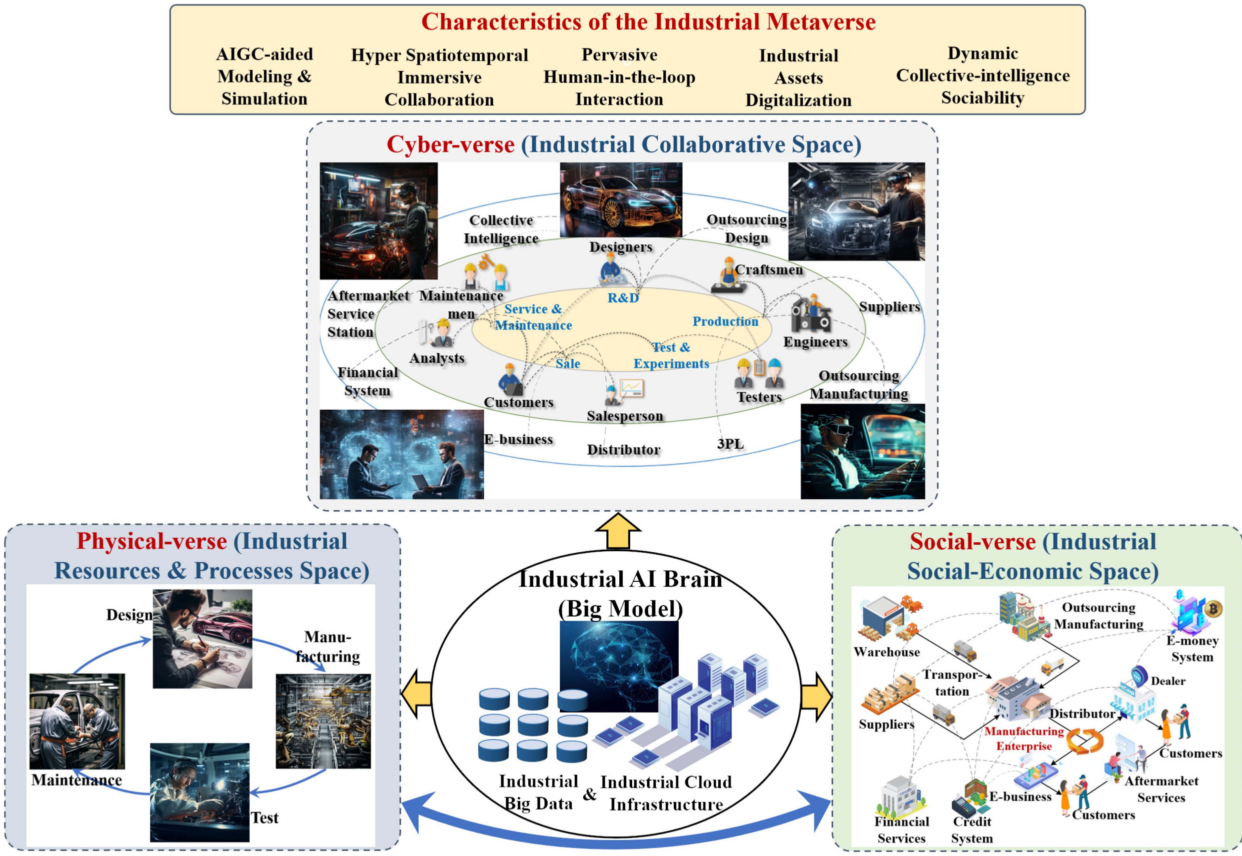

Fig. 1. IMverse model and characteristics of the industrial metaverse.

metaverse may bring some new advanced possibilities to the next-generation paradigms in smart manufacturing.

1) *Customized Parallel Simulation Scene Generation:* In the industrial metaverse, it is feasible to generate simulation scenes from customized demands intelligently and automatically. The generated scenes will be utilized throughout the whole product life cycle for more effective and customized production.
2) *Massive-User Hyper Spatiotemporal Immersive Collaboration:* Based on the generated scenes and instantaneous simulation capabilities in the industrial metaverse, massive numbers of users from all over the world are able to collaborate in a hyper spatiotemporal space. Interaction between humans and the industrial metaverse will be immersive for more effective collaboration.
3) *Seamless Human-in-the-Loop Manufacturing Participation:* Humans in the manufacturing processes have corresponding virtual roles to play seamlessly throughout the whole product life cycle. The virtual roles can guarantee the stability of the industrial metaverse, and further optimize the production according to immersive observation and human sensory experiences.
4) *Digital Assets Circulation and Transactions:* In the industrial metaverse, there are plentiful intangible assets that can be digitized as valuable properties for circulation and transactions in a decentralized economic system with privacy, security and trustworthiness.

Therefore, in consideration of the novel characteristics of the industrial metaverse, it is promising to integrate the industrial metaverse with the next-generation smart manufacturing [19], [20]. In this article, we propose a conceptual model named IMverse (Industrial Metaverse) Model and demonstrate the novel characteristics of the industrial metaverse for smart manufacturing. Then, an architecture named IMverse Architecture is proposed with the analysis of several key enabling technologies. Moreover, typical innovative applications with insights of the industrial metaverse throughout the whole product life cycle in smart manufacturing are presented. In spite of advantages of the industrial metaverse, there are challenges and open issues, so these and outlooks are provided for further related researches and applications.

II. Conceptual IMverse Model and Characteristics of the Industrial Metaverse for Smart Manufacturing

In this section, as illustrated in Fig. 1, a conceptual IMverse Model, is proposed to divide the industrial metaverse into cyber-verse, physical-verse and social-verse [21]. In the industrial metaverse, the physical-verse refers to a space with the physical industrial resources and processes. Numerous industrial physical resources are managed, scheduled and utilized to support various industrial processes throughout the product life cycle in the physical world. Social-verse describes industrial socio-economic space, where manufacturing enterprises, customers, distributors, suppliers, institutions, etc., in the supply chain together constitute a society with various socio-economic activities. Cyber-verse is in collaboration with all industrial elements in both virtual and physical space, including all the virtual and physical characters, resources, activities, and processes in smart manufacturing. Concentrating on the product life cycle, various characters and resources are distributed in the cyber-verse to realize plenty of activities in the manufacturing processes. These three verses are supported by an industrial AI brain, and the industrial AI brain is supported by industrial big data and cloud infrastructure. The physical-verse, social-verse, cyber-verse and industrial AI brain together form the industrial metaverse. Moreover, some main key characteristics of the industrial metaverse for smart manufacturing are summarized and described next in this section.

A. AIGC-Aided Modeling and Simulation

In the industrial metaverse, a large-scale virtual environment is fundamental to support users immersing themselves in various virtual activities. With the prevailing trend of AI foundation models (big models), generative capability and AI-generated-content (AIGC) are growing and can be fully exploited for simulation scenes generation [22], [23], [24] in many industrial applications. It is feasible to intelligently generate large-scale scenes with interactive models with the aid of foundation (big) models with more precise modeling, autonomous simulation and realistic interaction. Without the labor-intensive modeling process, simulation efficiency and convenience in manufacturing are significantly enhanced throughout the product life cycle. In the R&D, test and experiments, and services and maintenance phases, product design, and test and maintenance schemes can be verified with performance metrics in AIGC-aided scenes to simulate and upgrade products. In the production process, upgrading production line and products technique also needs simulated scenes for optimization. Moreover, generated simulated scenes enable salespersons to provide customers with an immersive experience in product trials for product promotion. Generally, various activities are boosted by *AIGC-aided modeling and simulation* in the whole product life cycle.

B. Hyper Spatiotemporal Collaboration

Hyper Spatiotemporal Collaboration is a characteristic, integrating space expandability and time scalability to allow users in the industrial metaverse to collaborate without boundaries of space and time [25].

From the perspective of hyper spatial dimension, on the one hand, every physical asset, such as prototypes, can be digitized. Then, the digital assets will be delivered and interacted virtually by designers in different departments and corporations via decentralized autonomous organizations (DAOs)-based collaboration [26]. On the other hand, it is feasible to expand the production space as many virtual infinite spaces which function independently [27], like parallel multiverses beyond mapping with the real world. The infinity of spaces in the metaverse enables countless simulation possibilities to enhance productivity without constraints from the real world.

From the perspective of hyper temporal dimension, on the one hand, uninterrupted modular production is realized by collaboration of several teams in multiple countries, regions and different time zones. On the other hand, time is scalable to set as it is not always linear and parallel to the real world. In this manner, simulation experiments can be implemented and accelerated by speeding up time to support parallel intelligence, where it is possible for every entity to repeat the past and deduce the future for endless possibilities in the industrial metaverse.

C. Pervasive Human-in-the-Loop Interaction

Compared with digital twin (DT) factories or Industrial Internet of Things (IIoT) platforms in preconceived stages of smart manufacturing, the industrial metaverse is envisioned as a human-fully participated platform instead of merely promoting automatic production. In *Pervasive Human-in-the-loop Interaction*, almost all activities are realized by humans who immersively play through avatars corresponding to their identities, such as experts, analysts, laborers, operations engineers, and salespersons in smart manufacturing.

Specifically, designers virtually collaborate with each other utilizing immersive inspiration based on collective intelligence. Experts analyze the virtual production process through their human sensory capabilities, and evaluate AI-generated optimization and scheduling schemes. Operators are enabled to virtually cultivate and practice their skills in manufacturing and various craftsmanship for implementation in the real world. Maintenance workers observe and monitor real-time status for fault diagnosis, and analyze faults prediction results from the industrial AI to prevent accidents. Salespersons promote sales of products by providing customers with immersive and firsthand experience of trial. Generally, compared with manufacturing in full-automation, the safety, stability and interoperability throughout the whole product life cycle is enhanced and upgraded by *Pervasive Human-in-the-loop Interaction* without compromising production efficiency in the industrial metaverse.

D. Industrial Assets Digitalization

With a cyber-verse totally composed of data, every entity is represented in digital form. Therefore, the industrial metaverse has one of the most essential characteristics, *Industrial Assets Digitization*. Aside from traditional assets like physical equipment, there are more assets that can be digitized and transacted, such as data, knowledge [28], models [29], products, and services. Throughout the product life cycle in manufacturing, there are many intangible and valuable assets, such as design schemes, assembling processes, craftsmanship, and equipment operation methods. Design schemes and prototypes are digitized for convenient delivery, collaborative modification and further improvement. Assembling and craftsmanship processes are digitized as visualized references for training workers. All of these intangible digital assets in the industrial production can be digitized as valuable properties for protection and transactions. Thus, extensive transactions need foundation that realizes stable circulation in a decentralized economic system, which should also include a credit system. Besides, distributed and smart digital contracts are also parts of the assets digitized in the ecosystem for privacy, security and trustworthiness.

E. Dynamic Collective-Intelligence Sociability

Considered as the future version of the Internet, the metaverse is ubiquitous, immersive, tactile and embodied. With a social-verse inside, the industrial metaverse is characterized as *Dynamic Collective-intelligence Sociability*, where all units constitute a society and interact with each other in a more integrated way than the Internet. Nonetheless, *Dynamic Collective-intelligence Sociability* is not only a social attribute, but also an effective manner to boost production and customization in an online community. Enterprises are able to release designing demands for products to dynamically stimulate collective intelligence from users in the online community. Customers for specific product can also get involved in the design and test processes to immersively experience the performance of ordered product with multisensory options. Then, designers can further modify the production scheme based on experience and demands from customers. Afterward, it is also feasible for customers to chat with salespersons to sign smart digital contracts, comment on products online as reference for other customers, and enjoy customer services like remote maintenance. It is also supportive for small and medium-size enterprises (SMEs) to release regular recruitment for maintenance services from specialized outsourcing teams, if SMEs have complex equipment that are expensive to maintain themselves.

III. IMverse Architecture and Key Enabling Technologies for the Industrial Metaverse

In order to support the industrial metaverse, there should be an architecture to picture the whole establishment process of the industrial metaverse, and also several key enabling technologies to serve as pillars for the industrial metaverse.

A. IMverse Architecture of the Industrial Metaverse for Smart Manufacturing

Multiple distinguishable layers are vertically arranged in the IMverse Architecture from the systematic engineering perspective as illustrated in Fig. 2, and these eight layers are briefly described as follows.

1) *Physical Layer*, as a physical manufacturing world, is the foundation to support the whole industrial metaverse. Generally, there are two main components, including manufacturing enterprises and industrial chain. Within the manufacturing enterprises, the most significant components are human, machine, material, method and environment. Specifically, humans are playing various roles utilizing hard manufacturing resources (machine tools, robots, etc.) and soft resources (software, platform, data, knowledge, etc.) throughout the product life cycle. Externally, multiple enterprises are interconnected together with the industrial chain, which contains outsourcing manufacturing, 3rd-party logistics (3PL), etc. The *Physical Layer* is both the data collection source and the control target of the *Perception and Communication Layer*.
2) *Perception and Communication Layer* acts as a layer for perception and communication between the *Physical Layer* and the *DT and Digital Native Model Layer* via industrial networking in the industrial metaverse. The main activities through the *Perception and Communication Layer* are classified as ascending data collection from the physical world, descending feedback control from the virtual world via industrial networking, and edge computing responsible for operation of massive end devices in manufacturing.
3) *DT and Digital Native Model Layer* includes DT modeled from physical entities and digital native without mapping to real objects. Generally, DT models have digital entities precisely mapped from the data of physical entities collected in the *Physical Layer*. In DT models, there are virtual environment, avatars, digital assets and businesses. Data generated by the DT will be input to the *Industrial Data and AI Layer*. Compared with DT models, the digital native is defined to present models and scenes directly created in the digital world based on the creators' intention without a complete dependence on physical entities. In digital native models, virtual characters are empowered to act like nonplayer characters (NPCs) to perform given tasks. Digital native scenes are utilized for simulation of parallel unprecedented activities. Thus, in the digital natives, it is feasible to create massive data and information, which supports knowledge extraction and parallel intelligence acquisition in the *Industrial Data and AI Layer*.
4) *Industrial Data and AI Layer* acts as the data and knowledge base, and the industrial brain to provide intelligence for the industrial metaverse. Data storage and usage are supported by the data center and computing power infrastructure. Based on the industrial data and knowledge collected from the previous layers, the industrial foundation model (big model) and industrial domain AI model base will be constructed. The industrial brain is able to realize learning, inference, perception, recognition, prediction, detection, schedule, optimization, etc. These capabilities are acquired partly from data in the *DT and Digital Native Model Layer* and partly from the *Physical Layer*. Then, the industrial brain will provide intelligence for various activities in the industrial metaverse.
5) *Metaverse Engines Layer* is providing several engines for inner systems in the industrial metaverse. These engines are mainly classified as visualization and interaction, Simulation, Intelligent Decision-making, Assets Digitization and Cloud Services engines. For instance, visualization and interaction has capabilities, such as scene generation and rendering. This layer supports operation of the whole industrial metaverse and

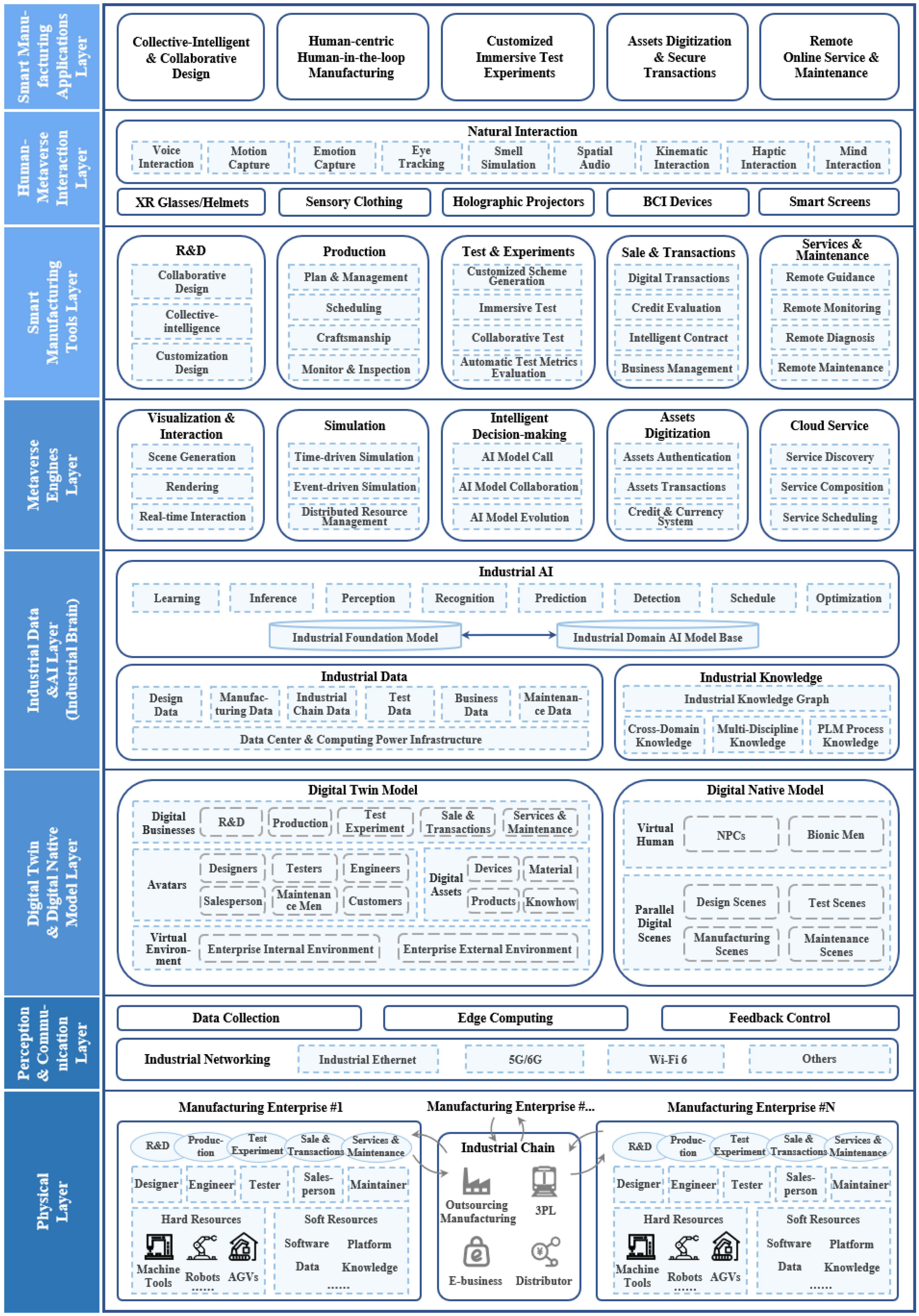

Fig. 2. IMverse architecture.

serves as the foundation of the *Smart Manufacturing Tools Layer*.

6) *Smart Manufacturing Tools Layer* is providing several tools for users to participate in various activities of the industrial metaverse, to realize human-in-the-loop interaction. This layer is supported by the *Metaverse Engines Layer*, and these tools are distributed throughout the whole product life cycle, including R&D,

production, test and experiments, sales and transactions, and services and maintenance. For instance, in R&D, the participation of designers in designing activities are supported by tools for collaborative design and intelligence collection. In services and maintenance, maintenance men are provided with tools for immersive activities, including remote guidance, monitoring, and diagnosis.

7) *Human-Metaverse Interaction Layer* is bridging the gap between humans and the industrial metaverse. With the aid of hardware, including XR devices, sensory clothing, holographic projectors, brain-computer interface (BCI) devices, and smart display terminals, a human is enabled with various natural interactions, such as voice interaction, motion capture, emotion capture, and mind interaction. Based on these interactions, it is feasible for users to interact with everything immersively and seamlessly in the industrial metaverse, and utilize the aforementioned tools to participate in human-in-the-loop activities.
8) *Smart Manufacturing Applications Layer* contains applications distributed throughout the whole product life cycle. Every application is the integration of humans, interaction technologies in the *Human-Metaverse Interaction Layer*, and tools provided by the *Smart Manufacturing Layer*. Five typical applications in this layer will be discussed later in Section IV.

B. Key Enabling Technologies for the Industrial Metaverse

From the perspective of developers, some key enabling technologies are classified and arranged based on the sequence of the development process. Exploration of how these technologies aid in deployment of the industrial metaverse will be discussed as follows.

1) *IIoT:* IIoT in the industrial metaverse is defined as the combination of sensors, software, communication technologies and infrastructure. In the industrial metaverse, IIoT is fundamental for data sensing, exchanging, communication and synchronization among virtual and physical things, systems and users. Sensors are embedded with massive physical devices and deployed in large-scale networks to collect and transmit abundant data to realize real-time bidirectional synchronization between the virtual and physical worlds. Except for sensing and networking, IIoT also has a role to play in communications for real-time, seamless and immersive interaction services [30]. Vivid 3-D scenes should be accessed by massive numbers of users all over the world with high speed and low latency. Transmission will be realized via scene streaming delivery like cloud gaming [31] instead of directly rendering, which is a highly demanding graphics rendering and computation capability in mobile edge devices.
2) *Industrial Cloud Manufacturing:* In the industrial metaverse, industrial cloud manufacturing is fundamental to provide manufacturing enterprises, customers and third parties with services by manufacturing capabilities servitization [32]. The process of cloud services begins from cloud resources, including computing resources, virtualization for centralized management, then the cloud service is able to be discovered and called [33]. Meanwhile, some tasks may need composition of many cloud services for further scheduling, collaboration and optimization among various services [34]. Moreover, cloud manufacturing is essential for the public to fully participate in the manufacturing collaborative processes. Generally, industrial cloud manufacturing functions as a service-oriented platform where services are provided for highly collaborative manufacturing.
3) *Industrial DT and Digital Native:* Industrial DT in the industrial metaverse is true description of the physical manufacturing entities with fidelity, robustness and traceability [35], [36]. Integrated with real-time data collected by Industrial Internet, industrial DT is fundamental for physical-virtual mapping, synchronization and interaction between industrial metaverse and real world. As a mirror synchronized with reality, equipment in the metaverse can be monitored, predicted and optimized via their real-time status provided by the industrial DTs. Moreover, with integrated mechanism models and simulation capabilities, it is feasible for the industrial digital native to create a virtual environment and characters like NPCs to dynamically evolve and adapt to avoid unprecedented situations in parallel simulation.
4) *Industrial XR:* Industrial XR covers virtual reality (VR), augmented reality (AR) and mixed reality (MR) technologies to offer seamless, immersive and multisensory interactive services among humans, machines and the environment. Specifically, AR overlays and superimposes digital information in the physical world, VR digitizes a virtual world to immerse users, and MR blends AR and VR together. Technically, XR-aided interaction is also enabled by 3-D construction [37], [38], [39], spatial computing, light field displays, front-projected holographic display, haptic feedback, and BCI [40]. By means of the above related technologies, users connected with avatars will immersively experience multiple senses, mainly including haptic, visual, and auditory senses. Aside from XR technologies, fine-grained human-specific information perception [41] is physically and ubiquitously assisted by head-mounted displays (VR glasses, headsets, helmets and hats), wearable devices (smart watches, fitness trackers and smart clothing), handheld devices (smartphones, tablets, and handles), cameras and projectors.
5) *Industrial Blockchain:* Blockchain is the enabling technology for an advanced economic system, which is especially significant in the industrial metaverse with numerous valuable assets, transactions and industrial chains inside it [42]. With the assistance of industrial blockchain, the economic system will be decentralized to prevent inflation, transparent for users to access, and immutable to be falsified and anonymous for guaranteed privacy protection. In the industrial metaverse, as a distributed ledger, the industrial blockchain

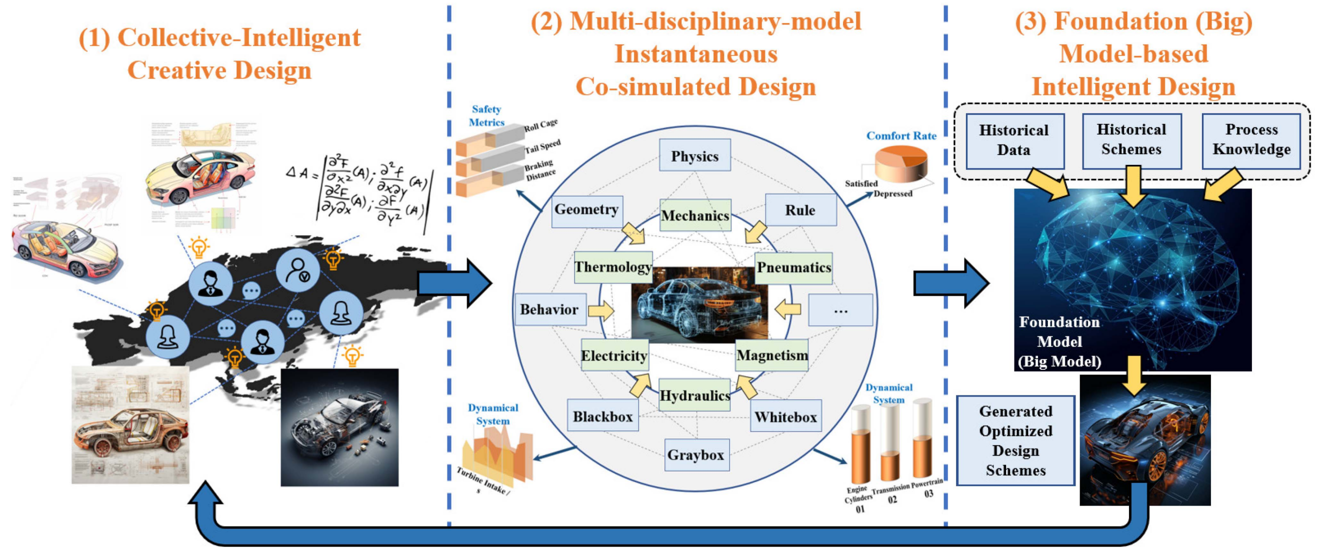

Fig. 3. (1) Obtain collective-intelligence from users all over the world, (2) design with instantaneous co-simulation from multiple disciplines and models, then finally (3) intelligently generate optimized design schemes from foundation model. The above process repeats for more optimized designing version if necessary.

is able to support various economic activities in the whole manufacturing process. In consideration of several enterprises in a common industrial metaverse, the industrial blockchain prevents centralized operation by few entities [43]. Industrial digital assets, like design schemes and craftsmanship, can be recorded as nonfungible tokens (NFTs) for proof-of-ownership and property protection in the new era of Web 3.0 [44], [45]. With DAOs, users' privacy and security will be protected, and their created value will be maximized [46], [47]. During transactions among enterprises and individuals, the industrial blockchain supports smart contracts with enhanced transparency and trustworthiness.

6) *Industrial AI:* To support plentiful autonomous activities and applications in the manufacturing processes, it is necessary to empower extensive agents with industrial AI [48], [49]. AI in the general metaverse provides functions, such as massive virtual scene creation, NPC chat communication, and user personalized guidance. In contrast, there are more values created by industrial AI for the manufacturing processes in the industrial metaverse. AIGC is capable of assisting designers and testers by generating designing schemes and test scenes intelligently. In the production processes, industrial AI acts as the brain to realize autonomous control, dynamic scheduling and intelligent decision-making [50], [51]. In sales activities, industrial AI integrating blockchain is able to support smart digital contracts and payment channel networks. Moreover, industrial AI helps in predictive maintenance [52], [53] and intelligent diagnosis [54] to prevent accidents. However, in order to remain sustainable, the industrial AI must achieve smart energy consumption and control for less carbon emission and greenhouse gas production.

IV. Typical Applications of the Industrial Metaverse Throughout the Product Life Cycle

With integration of the key enabling technologies in the industrial metaverse, several typical innovative applications cover the product life cycle in the next-generation smart manufacturing. In this article, the product life cycle is divided into five phases, including R&D, production, test and experiments, sales and transactions, and services and maintenance, in which corresponding typical applications are successively described. Aside from typical applications described below, there are also many other applications, including immersive product trials for sale, human-in-the-loop production optimization, data visualization and analytics, supply chain management, etc.

A. Collective-Intelligence-Based Collaborative Design

Since collective intelligence was first proposed for designing, diverse designing tools used by netizens lead to heterogeneous design schemes and problems for further convergence. Thus, only the optimal one is selected from these heterogeneous design schemes without merits from others.

With the industrial metaverse, the whole process of R&D is facilitated to be more convenient and efficient. The collective-intelligence-based collaborative design can be realized in a platform, such as NVIDIA Omniverse with compatible design scheme file format, which supports multiuser real-time visualization, simulation, and interoperability for industrial R&D. Thus, as illustrated in Fig. 3, many design schemes from collective intelligence can be modified in a compatible manner, with iterations by multiusers for the most ideal version of schemes. Then, due to the capability of instantaneous co-simulation, designers are enabled to obtain performance metrics for their design schemes with multiple disciplines and models. Finally, the foundation model (big model) is capable of generating optimized design schemes by inputting historical

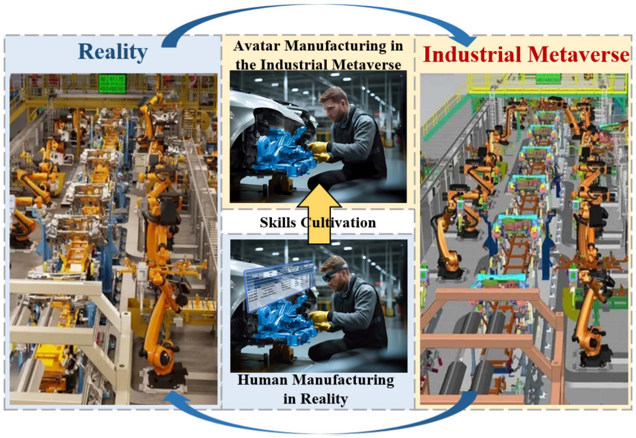

Fig. 4. Producers skills training in the industrial metaverse for implementation in reality [55].

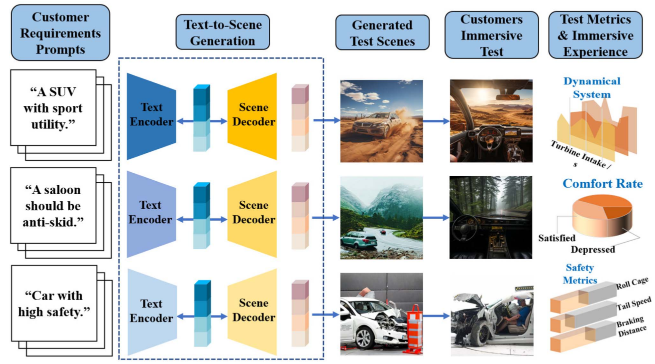

Fig. 5. Framework of customized and immersive test scenes generation from prompts in the industrial metaverse.

operational data, previous schemes and process knowledge. The above process always repeats for more optimized designs.

B. Producers Skills Training

During activities like assembly and welding, an XR system assists workers by rendering virtual-physical information, such as components detection, information, and assembly process. With accurate detection and localization algorithms, an AR system renders the virtual components into real ones, and further assists user cognition in assembly via a guidance system. Effective guiding information should be represented with geometric-level and information-level visualization, a data processing model and visual interfaces in an AR assisted system [56].

Various XR systems have been developed to address diverse problems during the manufacturing processes in aspects of ergonomics assessment, operation guidance, planning and training. As shown in Fig. 4, through establishing a virtual-physical environment, workers interact with both real components and virtual auxiliary information, including industrial instructions, visual aids, and virtual components. In the XR-aided skills training environment, both virtual contents and real feedback are transmitted to the user for completion of various manufacturing tasks with higher efficiency and fewer errors.

C. Customized Immersive Test Experiments

In the real world, testing experiments for the product are usually conducted in specific scenes. It is implied that products with different testing demands may need distinct scenes, because these scenes are fixed and hard to modify in reality. Typically, every task needs a specific testing scene, which increases the costs of humans and financial resources. However, in the industrial metaverse, some multitask combined scenario can be modeled and simulated for the product-level comprehensive and global tests, as illustrated in Fig. 5. For instance, automotive anti-skid, anti-collision and waterproof tests could be combined in one virtual rainy orographic scene, where single-task performance and synergy among tasks could be verified together. With help of attribute group editing [57], [58] and text-to-scene technologies [59] evolved from text-to-image and text-to-video technologies [60], test scenes will be generated intelligently and automatically from customized demands in text. These technologies have been verified in applications like Midjourney and Sora. Attributes, such as weather, air velocity, dustiness, lighting, force-field, heat, texture, and material, will be adjusted according to specific function and demands of product. Furthermore, it is feasible for consumers to participate in the process of the test as their avatars, such as drivers of a new automobile or passengers on an aircraft. This user-interacted test pattern not only provides the results of test metrics, but also immersive and embodied experience for consumers. During this process, some customized and specialized demands, which cannot be represented as test metrics, can also get verified by the consumers themselves.

D. Intellectual Property Transactions

Previously, the intangible knowledge in manufacturing used to be recorded in traditional ways as confidential information to prevent copying and plagiarism from competitors. Otherwise, these achievements could be patented to ensure intellectual property right, but the process of patent application, sharing and utilization is arduous and redundant. Recording skills or craftsmanship in words is also not vivid for the convenience of reference.

In the industrial metaverse, as illustrated in Fig. 6, intellectual property can be recorded and digitized in NFTs, which are more easily stored, shared and inserted in processes when it is necessary for reference to previous related works. When utilizing these digital assets, the valuable information can be visualized or announced, aided by XR, to provide guidance for key procedures in production. When any work utilizes digital industrial knowledge assets for reference, the owner of this intellectual property will be paid automatically in the decentralized economic system. Besides, the industrial knowledge from experienced engineers, especially celebrated craftsmen, will also become unique identification to create extra value for the products in sales. In this manner, property digitalization and transactions primarily contribute to improving production

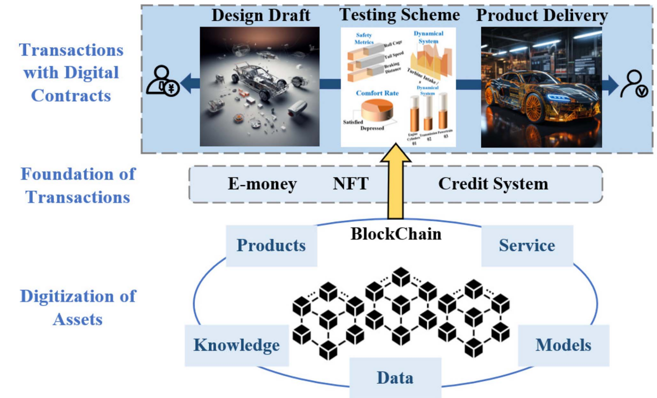

Fig. 6. Assets digitization for transactions in the industrial metaverse.

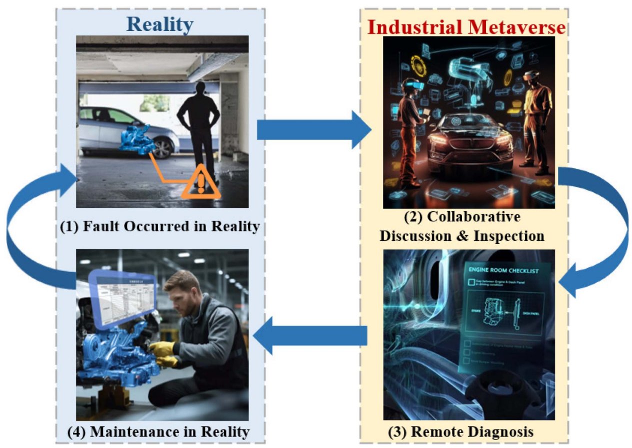

Fig. 7. Virtual remote maintenance in the industrial metaverse.

quality, enhancing circulation and creating extra value for products.

E. Virtual Remote Maintenance

For services and maintenance after transactions, the status of a product will be monitored automatically. Hence, when faults of any products occur in reality, maintenance workers will be notified via periodical monitoring or reports from customers. In the industrial metaverse, as shown in Fig. 7, customers and maintenance workers could describe and discuss anomalies remotely and inspect products collaboratively. Afterward, remote diagnosis and decision-making can be realized through the collaboration of many maintenance workers in a human-in-the-loop manner. Finally, the physical product will be maintained and virtual status will also be synchronized for the convenience of usage in both physical and virtual worlds.

V. CHALLENGES AND OUTLOOKS

In spite of advantages and prevailing trends mentioned above, the industrial metaverse is still far from industrial practice and there are several limitations. Therefore, six challenges and open issues are discussed in this section. Moreover, the corresponding outlook of the industrial metaverse for smart manufacturing is also provided.

A. Automatic Large-Scale On-Demand Modeling

In order to develop an industrial metaverse, the virtual space is the most fundamental to be modeled first. Nevertheless, the industrial metaverse needs to be spacious, covering the manufacturing environment, all devices and humans-in-the-loop. Therefore, it is extremely labor-intensive to model such a large-scale universal digital world.

With the emergence of big AI models with remarkable generative capability, we foresee that a large-scale industrial manufacturing 3-D scene dataset will be created to support automatic large-scale 3-D scenes generation. It is envisioned that a big AI model, named contrastive language-scenes pretraining (CLaSP), will be proposed to learn 3-D scene concepts and representation from millions of text-scene pairs of data. CLaSP, as the discriminator to judge whether generative scenes are feasible, can be utilized in a generative adversarial paradigm [61], like DALL·E [62] or 3-D Gaussian [63]. Afterward, black box, white box and gray box models combining AI and mechanism models will be integrated in 3-D scene models, and applied for specific tasks in the industrial metaverse.

B. Highly Immersive, Precise, and Realistic Interactions

With universal 3-D scenes in the industrial metaverse, massive modeled devices and products are available for virtual-physical interactions. In order to offer immersive interacting experiences as much as possible, specific 3-D models should be geometrically precise to operate and be realistic in visual effects. Currently, mesh data representation is widely applied for 3-D modeling in interactivity applications. However, industrial products and devices contain complex geometric structures, materials, textures, and shaders, which require exploding computing resources during real-time rendering and displaying.

In future, on the one hand, for precise geometric structure, simplifying mesh triangular surface slices while maintaining model accuracy is one of the solutions. More mesh simplification strategies based on geometric features and topologies should assist in retaining more details of the 3-D model. One the other hand, for realistic visual effects, balancing the tradeoff between quality and speed of model rendering is important. One solution is to use adaptive sampling strategies to dynamically adjust light sampling density by applying NeRF [57] techniques, according to the change of model complexity and perspective. Afterward, fine post-processing can be performed through coarse-to-fine multiscale rendering process.

C. Low-Latency Real-Time Communication for Massive Users

With massive numbers of users and devices interconnected in the industrial metaverse, this presents an exceedingly heavy burden to the communication network. In order to ensure immersive and seamless physical-virtual interaction experiences for the users, low-latency and real-time communication is essential for ubiquitous, open and timely access. To deal with explosive amounts of data in user-generated-content

(UGC) and device-generated-content (DGC), improving the capability and speed of data collection and processing at edge devices to enhance response and analysis ability is urgently needed.

According to these challenges, it is envisioned that a more advanced communication network will integrate the following essential factors: 1) more efficient communication technologies, such as B5G, 6G, spectrum, or quantum communication [64]; 2) more reasonable distributed networking layouts and resources allocation; and 3) more unified communication protocols for heterogeneous end devices to enhance processing efficiency.

D. Industrial AI Foundation Model (Big Model)

AI models are integrated in smart manufacturing to promote production with significantly higher efficiency [65], [66]. However, AI models for many manufacturing devices in different phases are heterogeneous for various tasks or data modalities without transferability. Also, the problem of collaboration among multiple agents is another challenge that hinders efficiency in the whole production.

In consideration of these challenges, it is promising to integrate interdisciplinary knowledge with multimodal artificial general intelligence (AGI) for foundation models. It is also promising to support almost all downstream tasks [67], [68], and enhance collaboration among different agents via interdisciplinary multimodal perception [69]. Besides, it is essential to achieve semantic extraction and analysis from users' multisensory multimedia data. Large language models (LLMs) will be integrated in the manufacturing devices, which will accordingly act like NPCs to bridge the communication gap between machines and humans-in-the-loop.

E. Advanced High-Performance Computing

The tremendous volume of data collected from numerous interconnected users and manufacturing edge devices, is an important issue for computation. In order to enhance generalization of AI models on multimodal data, the capacity of AI big model is growing to contain billions of parameters, and the number of parameters will be getting exponentially larger beyond our imagination. Real-time rendering is another essential application for an immersive and seamless interaction experience. Additionally, sustainability of the metaverse will require lowering the computing power consumption for green energy efficiency.

In terms of computing power, high-performance computing (HPC) is prevailing to support the implementation of giant-scale AI models. Further development of HPC may integrate quantum computing, which is still in the prototype development stage and faces technical challenges, especially in large-scale many-body quantum systems. Once quantum processing units are deployed in HPC, the computing power would be unprecedented to reshape science and industry. In addition, the architecture of the computing network in the industrial metaverse should be designed with intelligent layout and allocation for better sustainability and green energy efficiency.

F. Privacy, Security, and Trustworthiness

In the industrial metaverse, with plenty of human-fully participated activities generating massive UGC biological data, the corresponding private information should be carefully monitored and secured. In addition, there are various digital assets containing intellectual value in the process of collaborations and transactions. Due to its close association with privacy for users and commercial security for corporations, the aforementioned data need both appropriate usage and also prevention from data abuse, attack and invasion.

As the industrial metaverse is a world built on data, the trusted data matrix (TDM) [70] is envisioned to be integrated in the industrial metaverse as an infrastructure for safe, efficient and reliable transactions and data exchange processes [71]. Inside the TDM, decentralized cross-chain governance, on-chain identification and adaptive risk evaluation are future research directions. The combination of AI and blockchain is another promising solution for self-adaptation in the block propagation processes [72], [73].

VI. Conclusion

With the recent prevailing trend of the metaverse, we envisioned that it is promising to integrate the industrial metaverse into the next-generation smart manufacturing to bring more advanced opportunities to industrial production. Thus, a conceptual IMverse Model of the industrial metaverse for smart manufacturing and its corresponding novel characteristics were proposed to serve as a solid base for further development of the industrial metaverse. Consequently, the IMverse Architecture was proposed with analysis of several key enabling technologies for real implementation of the industrial metaverse for smart manufacturing. Moreover, the industrial metaverse's typical innovative applications covering the whole product life cycle were presented with insights for advanced utilization. Finally, challenges, open issues and outlook were discussed as future directions of related researches and applications.

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