Perspective

Parallel Manufacturing for Industrial Metaverses: A New Paradigm in Smart Manufacturing

Jing Yang, Xiaoxing Wang, and Yandong Zhao

***Briefing*:** To tackle the complexity of human and social factors in manufacturing systems, parallel manufacturing for industrial metaverses is proposed as a new paradigm in smart manufacturing for effective and efficient operations of those systems, where Cyber-Physical-Social Systems (CPSSs) and the Internet of Minds (IoM) are regarded as its infrastructures and the "Artificial systems", "Computational experiments" and "Parallel execution" (ACP) method is its methodological foundation for parallel evolution, closed-loop feedback, and collaborative optimization. In parallel manufacturing, social demands are analyzed and extracted from social intelligence for product R&D and production planning, and digital workers and robotic workers perform the majority of the physical and mental work instead of human workers, contributing to the realization of low-cost, high-efficiency and zero-inventory manufacturing. A variety of advanced technologies such as Knowledge Automation (KA), blockchain, crowdsourcing and Decentralized Autonomous Organizations (DAOs) provide powerful support for the construction of parallel manufacturing, which holds the promise of breaking the constraints of resource and capacity, and the limitations of time and space. Finally, the effectiveness of parallel manufacturing is verified by taking the workflow of customized shoes as a case, especially the unmanned production line named FlexVega.

***Keywords*:** Parallel Manufacturing, Digital Workers, CPSS, Smart Manufacturing, Industrial Metaverses.

I. Introduction

SMART manufacturing is an advanced manufacturing pattern with the characteristics of self-perception, self-learning, self-decision, self-execution and self-adaptation, where intelligent technologies are used for dynamic response to personalized demands, rapid and stable product manufacturing and R&D as well as real-time optimization of production and supply chain networks [1], [2]. For the realization of smart manufacturing, some strategies such as Industry 4.0, Made in China 2025 and Industrial Internet are launched by different countries, which are based on Cyber-Physical Systems (CPSs) and characterized by networking, aiming at promoting the deep integration of informatization and industrialization, and accelerating the development of advanced manufacturing and social economy [3]–[5].

With the advance of various technologies in control, computer and communication, human society has been continuously incorporated into the manufacturing industry. CPS-based smart manufacturing can realize the passable interactions and integration between physical spaces and cyberspaces but is no longer adequate for dealing with human and social factors in systems [6]–[13]. As a consequence, the infrastructures of smart manufacturing have been converted from CPS and Internet of Things (IoT) [14], [15] to Cyber-Physical-Social Systems (CPSSs) and the Internet of Minds (IoM) [16], [17], whereby society will step toward the next stage of Industry 4.0, namely, Industry 5.0. CPSS-based smart manufacturing has attracted extensive attention [18]–[22]. Parallel manufacturing is an emerging CPSS-based manufacturing pattern, where the "Artificial systems", "Computational experiments" and "Parallel execution" (ACP) method is used for bridging the modeling gaps between actual manufacturing systems and their models, which are caused by complex human and social behaviors [20], [23]–[25]. However, the current research only stays at the theoretical levels and the solutions to small manufacturing problems, and the systematic application of manufacturing models should be further explored, especially the human-computer collaboration process.

In addition, as stated in [26], [27], CPSS is the abstract and scientific name for the hot term "metaverse". The industrial metaverse is a new industrial ecology where all the elements such as humans, machines and objects are connected and integrated seamlessly into the physical industry through a series of technologies such as blockchain, social computing, digital twins and Decentralized Autonomous Organizations (DAOs) [28]–[35]. The most important feature of industrial metaverses is the interactions between actual spaces and cyberspaces to broaden the operations in the physical industry. Obviously, the true realization of smart manufacturing in CPSS is a vital part of industrial metaverses.

To achieve smart manufacturing in CPSS, this paper not only introduces the basic framework of parallel manufacturing for industrial metaverses but also elaborates on its operation process and evaluates its application effect by taking the

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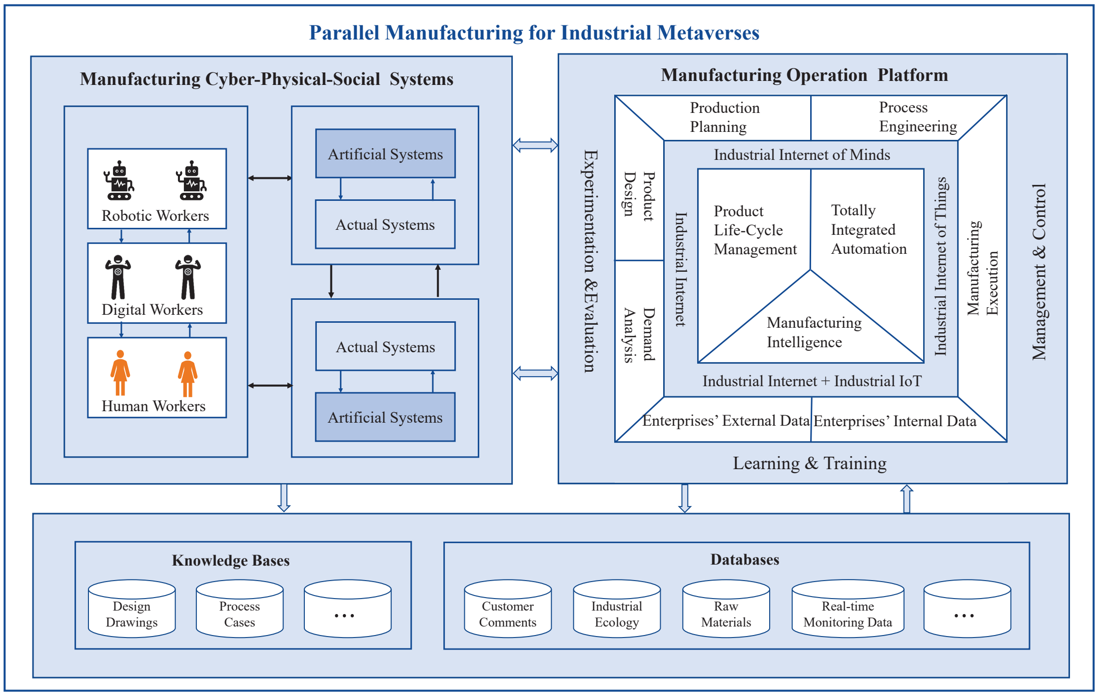

Fig. 1. The framework of parallel manufacturing for industrial metaverses.

workflow of customized shoes as an example. Therefore, the main contributions of this paper are as follows: 1) To deal with complex manufacturing systems involving human and social factors, ACP-based parallel manufacturing for industrial metaverses is proposed as a new paradigm in smart manufacturing, where CPSS and IoM are regarded as its infrastructures, Knowledge Automation (KA) is embedded to accomplish fundamental knowledge functionalities, and digital, robotic and human workers coexist and cooperate with each other for various tasks. 2) The whole manufacturing process is divided into five stages: demand analysis, product design, production planning, process engineering and manufacturing execution. The operations and benefits of every stage in parallel manufacturing are described in comparison with traditional manufacturing, respectively. 3) The workflow of customized shoes, especially the unmanned production line named FlexVega, is taken as a case for evaluating the application effect of parallel manufacturing. It has been shown that FlexVega really solves the most difficult core problems for the realization of flexible manufacturing.

The rest of this paper is organized as follows. Section II elaborates the framework, operation process and key technologies of parallel manufacturing for industrial metaverses. A case study of parallel manufacturing is described in Section III. Finally, the conclusion is given in Section IV.

II. Parallel Manufacturing

In this section, the framework of parallel manufacturing for industrial metaverses is introduced and then its operation process is elaborated. Finally, key technologies for realizing parallel manufacturing are briefly summarized.

A. Framework

The basic framework of parallel manufacturing for industrial metaverses is illustrated in Fig. 1. Based on the ACP method and KA technology, parallel manufacturing systems are constructed to achieve parallel evolution, closed-loop feedback, and collaborative optimization of a series of processes such as production planning, process engineering and manufacturing execution. The manufacturing operation platform analyzes and extracts social demands from social intelligence and gathers collective wisdom to design products that meet those demands in favor of rapid response to market changes. Digital workers, robotic workers and human workers cooperate to perform a variety of tasks, contributing to high efficiency and low manual intervention. As a typical class of CPSS, manufacturing systems are composed of physical systems for totally integrated automation, cyber systems for product life-cycle management, and social systems for manufacturing intelligence.

From the perspective of ACP, in parallel manufacturing, one or more software-defined artificial systems are constructed as social laboratories for computational experiments, where various manufacturing behaviors and phenomena are analyzed for acquiring their occurrence reasons and evaluating related solutions. It is worth emphasizing that artificial systems are not direct, mechanical, passive and mirror reflections of actual systems. Consequently, artificial systems do not have to be completely consistent with corresponding actual systems and they are regarded as some alternative realities. For dealing with insufficient and unbalanced data faced during computational experiments, virtual data is built and generated based on real data by some means such as Scenarios Engineering, Generative Adversarial Networks (GANs), Variational AutoEncoder (VAE) and Diffusion models (DMs) [36]–[43]. Once the

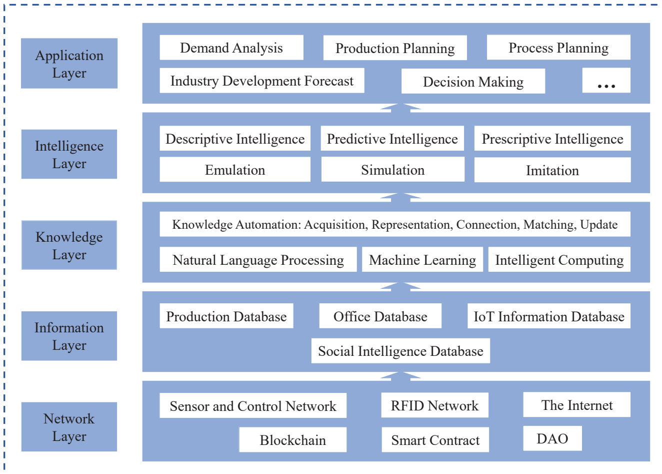

Fig. 2. The hierarchical structure of parallel manufacturing.

optimal solution is chosen, it is applied in actual systems. But the solution is not static and optimized dynamically through parallel execution and real-virtual interactions between actual systems and artificial systems, which takes into account unanticipated changes in some external factors. Furthermore, the actual system and its artificial counterparts can be connected in three modes for different purposes: learning & training, experimentation & evaluation, and control & management [44], of which the efficient operations are strongly supported by the hierarchical structure of parallel manufacturing, as illustrated in Fig. 2.

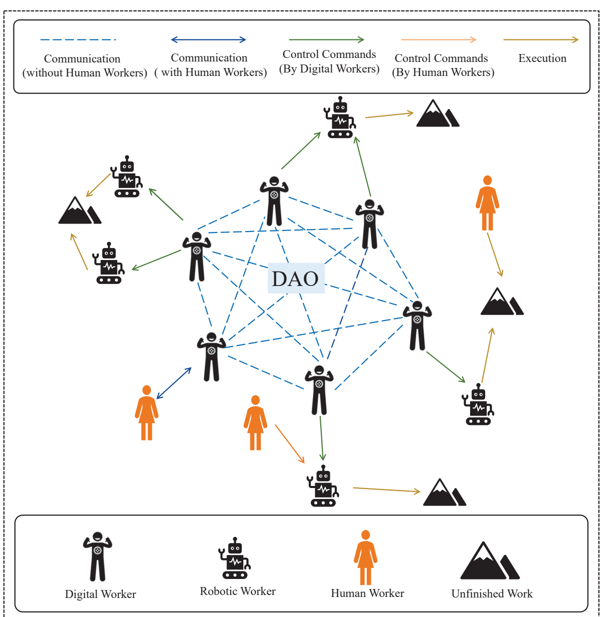

Fig. 3. DAO-based interactions and organizations between digital workers, human workers and robotic workers in enterprises.

In comparison with traditional manufacturing, there are human workers, digital workers and robotic workers in parallel manufacturing for industrial metaverses in collaboration for accomplishing tasks, as illustrated in Fig. 3. Robotic workers replace human workers to cope with tedious work, and digital workers are equivalent to the "brain" of human workers to command robotic workers' actions; while human workers are only responsible for the maintenance of equipment and conditions as well as the correction of errors caused by the former two. As a result, human workers barely interfere with the production process unless digital and robotic workers make mistakes, but with a small possibility. It is obvious that human workers should have the highest priority, so they can modify the digital workers' decisions and directly guide the robotic workers' movements. The correspondence between robotic workers and digital workers or tasks can be one-to-one, one-to-many and many-to-many, depending on the amount of computation required or the complexity of tasks. As the center of production, digital workers are organized into the DAO-based community and communicate with each other for sharing information. Every digital worker can compute and judge whether they can complete the work alone or collaboratively, and how much time and resources may be taken, which serve as metrics for ranking different work. Proposals about the assignment of work can be started by any digital members and discussed among the community, passed when the majority of the members vote yes, and recorded by smart contracts. Subsequently, digital workers carry out the assigned work according to smart contacts.

B. Operation Process

In terms of the aforementioned framework, we divide the whole production process into five stages: demand analysis, product design, production planning, process engineering and manufacturing execution, to describe the operation logic of the framework in detail.

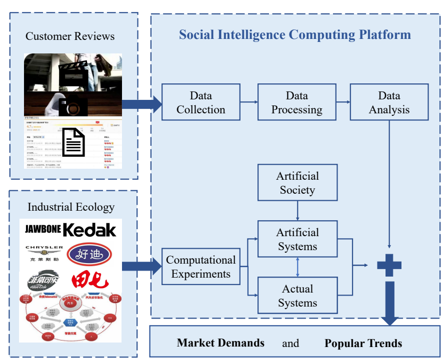

Fig. 4. Social demands analysis for social data.

Demand analysis is to conduct intensive and meticulous research and analysis on industrial information such as customer reviews and industrial ecology in order to accurately understand the customers' specific requirements for product functions, performance, reliability and so forth. Its core target is to integrate and convert customers' informal expressions of demands into professional expressions that are convenient for professionals to understand and communicate, so as to provide theoretical foundations for subsequent product R&D and production planning. This paper takes footwear and garment manufacturing as an example. Due to the randomness and uncertainty of changes in popular trends, traditional production patterns are difficult to deal with the issues that are unpredictable from historical data because they must predict popular trends and produce shoes or clothes at least six months in advance [45]. This means that traditional production patterns are insufficient for responding quickly and effectively to rapid market changes.

Parallel manufacturing perceives, crawls and analyzes data from various fashion communities and media platforms to extract important popular features by applying data processing and IoT technologies, as illustrated in Fig. 4. Based on industrial information, artificial systems are constructed to model and simulate the changes in the industrial ecology such as the dynamics of influencers, publication and revision of national policies as well as measures and benefits of competitors and related enterprises. With the help of computational experiments, fashion trends can be efficiently calculated to adapt to market changes in a timely manner, which could never have been accurately predicted. Demand analysis in parallel manufacturing is capable of meeting social demands quickly and avoiding producing obsolete products, which puts the enterprise at an advantage in competition with others.

Product design generally refers to integrating the needs of people, the possibilities of technology and the requirements for business success to create new products, that is, the transformation from ideas to product drawings. The traditional product design is extremely confined within the enterprise and is carried out only by the employees. The success of product design depends on the professional level of designers and their understanding of demands. The limitations of individual wisdom and the communication barriers caused by the long physical distance between designers and customers increase the failure rate of product design and make it hard to comply with individual requirements.

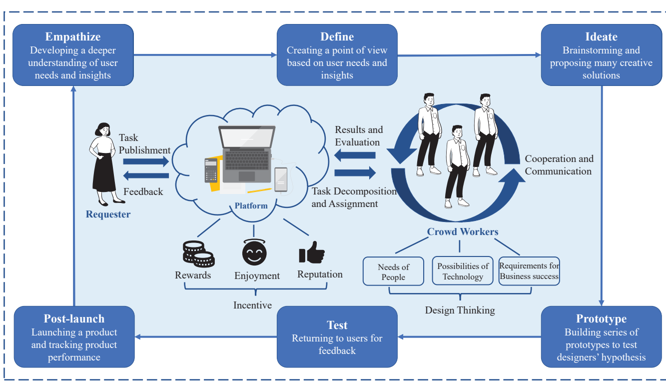

Fig. 5. Product design based on collective wisdom.

Product design applied in parallel manufacturing is a design pattern that gathers collective wisdom to create a product rather than individual wisdom via the Internet, as illustrated in Fig. 5. Benefiting from its fast speed and cost effectiveness, crowdsourcing is treated as a popular paradigm for accomplishing a large volume of tasks from crowd workers [46]. Requesters publish tasks via computers or mobile phones and specify budgets such as how soon they expect those tasks to be completed. Platforms that act as brokers take into account reputation and interests for assigning decomposed tasks to crowd workers, aiming at making requesters obtain maximum benefits. Generally, those platforms are open to everyone without relying on contracts. Consequently, some extrinsic and intrinsic incentives must be adopted to attract crowd workers, e.g., rewards, enjoyment and reputation. To accomplish complex tasks that are difficult for one individual, crowd workers communicate with each other for efficient cooperation. Clearly, the design pattern connects customers and workers via the Internet, which even engages customers in the design process, i.e., prosumers [28], [47], breaking through the limitation of individual capacities and the communication barriers caused by spatial distance.

Production planning is devoted to planning and managing resources and capacities, ensuring that appropriate materials and forces are available to produce the expected number of goods or services on the specified schedule [48]. Traditional production planning is extremely dependent on managers' experience and insights. Although the Enterprise Resource Planning (ERP) system can fulfill the requirements for production scheduling [49], it cannot comprehensively consider the actual governance capabilities of enterprises so that the developed scheduling plans cannot be completely suitable for the current situations. In addition, the attainment of production plans is susceptible to various factors such as dynamic changes in market conditions, high fluctuation in resource usage and high rates of changes in customers' requirements, while the processes of production are not flexible because they are hard to change in any time after starting new production lines [48].

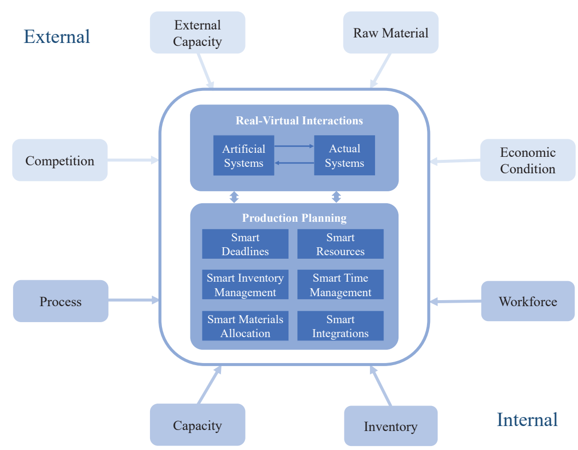

Fig. 6. Parallel production planning with strong robustness.

Parallel manufacturing constructs artificial production planning systems, which are leveraged to compute, test and evaluate different schemes for choosing the optimal. After that, the optimal scheme is applied to actual systems and adjusted to suit real conditions during production. Fig. 6 illustrates the framework of parallel production planning with the outputs of material plans and capacity plans. Different artificial systems represent different possible situations, so as to take into full consideration and quickly respond to a variety of internal and external changes. Parallel execution and real-virtual interactions between systems improve robustness for operations of actual systems against disturbances and also allow some flexibility in the production process.

Process engineering mainly denotes a process that transforms design drawings into detailed instructions and specific applications on exactly how to manufacture the products, of which the core step is process planning [50], [51]. Computer-Aided Process Planning (CAPP) systems are widely used to design process plans, but they ignore the availability of any change in resources, and are difficult to realize the self-updating and self-learning of process knowledge [50], [52]. Furthermore, the process plans must be applied to the actual manufacturing process for testing and evaluation, resulting in a huge cost. Once the chosen process plans have been adopted, they are immutable and have difficulty in adapting to some disturbances during manufacturing.

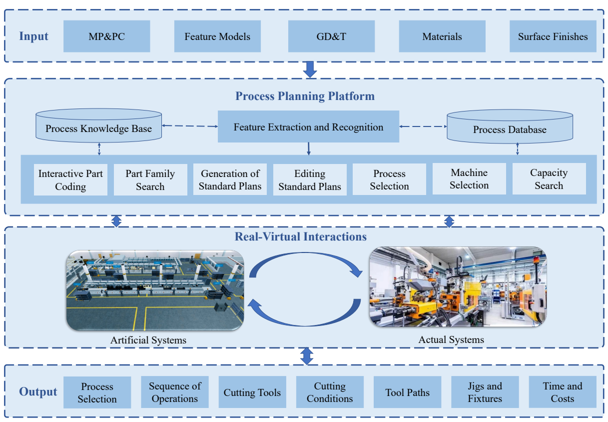

Fig. 7. Parallel process engineering with self-updating and self-learning.

Similar to parallel production planning, parallel manufacturing obtains the optimal solution through computational experiments in the process planning platform before manufacturing. One or more artificial process engineering systems are constructed to test and evaluate various solutions to different conditions. During manufacturing, artificial systems are executed in parallel and interact with the actual systems for real-time optimization of process solutions. After manufacturing, those process data and solutions are saved to process database and process knowledge base, respectively. Fig. 7 illustrates the framework of parallel process engineering with multiple inputs: feature models, dimensions and tolerances (GD&T), materials, surface finishes, and machining process and process capabilities (MP&PC) as well as multiple outputs: process selection, sequence of operations, cutting tools, cutting conditions, selection of jigs and fixtures, the tool paths for both rough and finish cycles, and the estimated time and costs. It is obvious that this framework can overcome the shortcomings of traditional CAPP methods for dealing with complex manufacturing environments, resulting in saving costs as well as achieving self-updating and self-learning of knowledge.

Manufacturing execution can produce actual products. Traditional automatic manufacturing systems include not only some automatic production equipment but also human workers in some segments, which states that relatively much manpower is still needed for mental and physical work. Human workers should obtain salaries for their efforts, bringing about an increase in costs. However, they cannot keep on working efficiently because they are vulnerable to external environments and their own conditions to make mistakes.

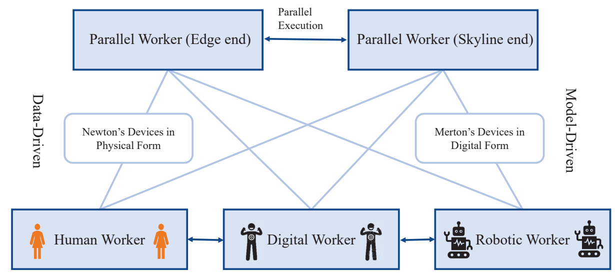

Fig. 8. Manufacturing execution in collaboration between digital, robotic and human workers.

Manufacturing execution in parallel manufacturing can enable robotic workers to replace human workers and automatic production equipment to perform most of the physical work. Digital workers instead of human workers accomplish most of the mental work for decision-making. Fig. 8 illustrates manufacturing execution in collaboration between human workers, digital workers and robotic workers. Obviously, robotic workers with the cooperation of digital workers are more flexible and adaptable than automatic production equipment. And they can continue working efficiently and do not require salaries in comparison with human workers, causing a reduction in costs. The only tasks that human workers are responsible for are the maintenance of the manufacturing environment and equipment as well as the correction of failed results.

TABLE I
THE DEFINITIONS OF KEY TECHNOLOGIES FOR THE REALIZATION OF PARALLEL MANUFACTURING.

Technology	Definition
Knowledge Automation (KA)	KA regards knowledge as the controlled object and realizes the cyclic process of automatic generation, acquisition, application and re-creation of knowledge [30].
Blockchain	Blockchain is a continuously growing list of records, called blocks, which are linked and secured using cryptography, with characteristics of decentralization, integrity, and auditability [31].
Smart Contracts	A smart contract is a computer program or a transaction protocol with self-verifying, self-executing and tamper-resistant properties [31], [33].
Industrial Internet of Minds (Industrial IoM)	IoM is an intelligent network organization, which is capable of accomplishing fundamental knowledge functionalities in a cooperative manner for automatic high-level applications. Industrial IoM is the industrial extension of IoM, which is characterized by "data-information collaboration", " knowledge-intelligence collaboration" and "sensing-control collaboration" [17], [20].

C. Key Technologies

Key technologies such as KA, blockchain, smart contracts, and industrial IoM, are considerably powerful tools for the realization of parallel manufacturing. The definitions of those technologies are shown in TABLE. I.

Almost every procedure in the manufacturing process, such as demand analysis, product design, production planning and process engineering, is inseparable from the help of human experience and knowledge, that is, KA which regards knowledge as the controlled object plays an essential role. The essence of KA is to take into account the characteristics of human behaviors and incorporate them into traditional knowledge representation and knowledge engineering. KA is considered as the core systematic form of IoM, achieving the cyclic process of automatic generation, acquisition, application and re-creation of knowledge [30].

Industrial big data with the characteristics of heterogeneity, large flux and strong correlation suffers from a variety of interference factors during sharing, resulting in serious security risks. The advantages of blockchain are to be decentralized, difficult to tamper with and programmable, providing a technical foundation for guaranteeing the security of data. Through smart contracts and blockchain, a large network of intelligent entities runs with minimal operating costs without external supervision, which is known as a decentralized automation organization (DAO) [31], [32]. In DAO, a series of open, fair and equitable rules of system operations are recorded and implemented by smart contracts, achieving autonomous operation and evolution without management and supervision.

Based on the Internet, IoT and IoM, industrial IoM integrates a variety of resources and coordinates different departments for effective and efficient management and control. The technical foundations of industrial IoM are cutting-edge technologies of intelligent systems and engineering, including the intelligent management and control of real-virtual systems based on ACP, social communication and cloud computing based on KA as well as the achievement of DAO based on blockchain [17]. The most notable features of industrial IoM are "data-information collaboration", "sensing-control collaboration" and "knowledge-intelligence collaboration", whereby massive entities are connected to form socialized self-organizing, self-running, self-optimizing, self-adapting, and self-cooperative network organizations.

III. Case Study

Parallel manufacturing has been applied successfully in some footwear and garment enterprises. This section takes the workflow of customized shoes of SANBODY Technology Company (see Fig. 9) as a case, which has built a 3D computer vision-based unmanned production line for shoes (see Fig. 10) named FlexVega. The line leverages 25 vision sensors and 10 robots, causing that the number of human workers is reduced from 36 to 1 while the production capacity is doubled. Almost all the steps such as loading and unloading, grinding, spraying glue, sole attaching and removing shoe lasts, are automated so that the system is simple and easy to use for manufacturing shoes of various styles.

In order to describe the cooperative relationships between digital workers, robotic workers and human workers, we elaborate on the collaboration process by taking spraying glue on the soles as an example, as illustrated in Fig. 11. Based on 2D pictures and 3D point clouds of soles acquired via sensors,

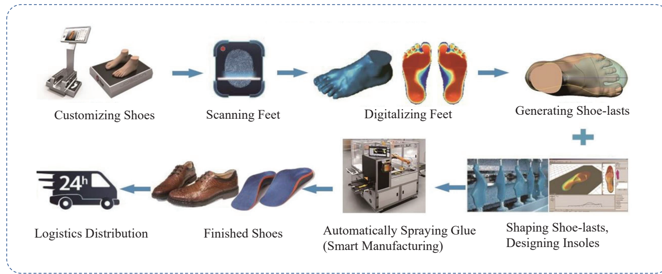

Fig. 9. Workflow of customized shoes based on parallel manufacturing: From demands to products

glue-spraying paths are computed by redefined algorithms and sent to the robotic workers, including coordinates and angles. On receiving commands from digital workers, robotic workers accomplish spraying glue according to those paths. Subsequently, sensors obtain 2D and 3D measured data of glue-sprayed soles for evaluating whether the effect is qualified via digital workers. If the answer is qualified, the step is successful, and the soles are moved to the next step; otherwise, digital workers conduct robotic workers to place the soles with bad spraying effects in a specified location that is convenient for human workers. Afterward, human workers try their best to modify the errors. During this step, an artificial neural network is constructed as the evaluation algorithm used by digital workers. After virtual data is generated by parallel perception [53], the network is trained based on parallel data including the real data and the synthetic data for good performance [54]. In the company, statistics indicate that the success rate of spraying glue through the cooperation between digital workers and robotic workers is approximately 99.9%. Consequently, digital workers and robotic workers instead of human workers perform most of the mental and physical labor, respectively, resulting in higher labor productivity, fewer employees, and lower production costs.

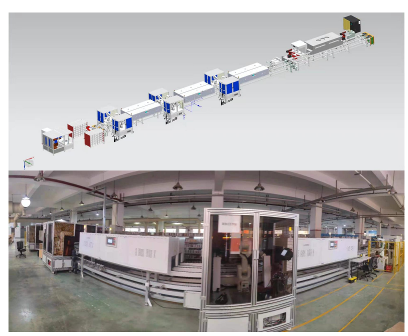

Fig. 10. A 3D computer vision-based unmanned production line for shoes (FlexVega): The 3D rendering scene and the real scene.

Additionally, to achieve good effects of spraying glue, two problems for increasing spraying errors (Criterion: less than or equal to 1mm) need to be handled: 1) Even for a class of shoes, every pair of shoes has a unique pair of soles and uppers according to the subtleties of shapes; 2) Soles and uppers are non-rigid and prone to deformation. Generally, other companies assume that different shoes in a class of shoes have the same soles and uppers, which are rigid and not deformable. As a result, in those companies, an engineer manually sprays

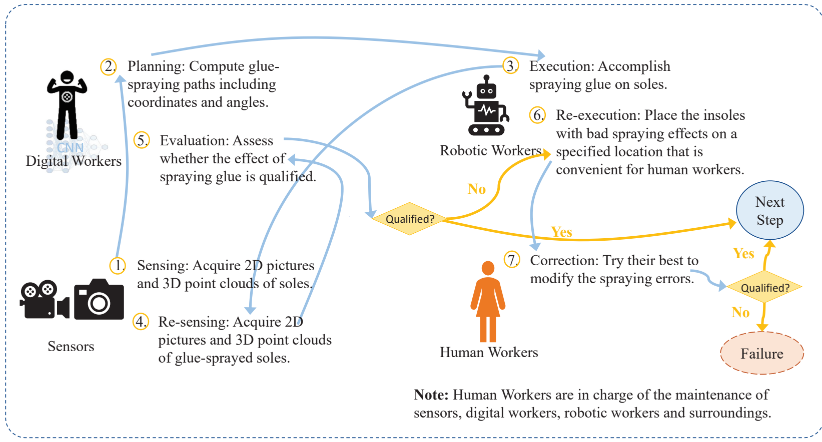

Fig. 11. Collaborative process of robotic workers, digital workers and human workers during spraying glue on the soles

glue on a pair of soles and uppers once for teaching robots, and then the robots strictly spray on all the shoes according to the path shown. It is obvious that the method suffers from large spraying errors and is only applicable to one or two classes of shoes with simple appearances. In SANBODY Technology Company, to deal with those problems, 3D visual scanning, 3D deformation simulation and path planning for deformations are applied as core technologies for the realization of flexible manufacturing in terms of glue-spraying. Every sole and upper are scanned through 3D virtual scanning technology to fully consider the subtle differences, and their deformations are predicted and simulated ahead of time through 3D deformation simulation technology, playing a vital role in reducing errors. Subsequently, path planning for deformations is conducted to calculate spraying paths, where deep neural networks are constructed for self-learning correction, and then robotic workers carry out spraying glue along the paths without the engineer's demonstrations. In conclusion, FlexVega really solves the most difficult core problems of flexible manufacturing for the first time, which is a revolutionary breakthrough in the real sense.

Fig. 9 illustrates the workflow of customized shoes from demands to products based on parallel manufacturing, making on-demand production possible. At first, the shapes of customers' feet are captured by 3D scanners, and 3D models of their feet are constructed. Subsequently, shoe lasts are generated and shaped automatically according to those 3D models. Afterward, the styles of shoes are designed by crowd workers including prosumers [28], [47]. After customers are satisfied with the shoe styles, the closest contracted factories to the customer are found according to customers' personal information for manufacturing shoes in a real-virtual interaction. As we can see, parallel manufacturing breaks the time and space constraints and avoids production waste caused by aesthetic discrepancies with consumers.

IV. Conclusion

In this paper, the framework of parallel manufacturing for industrial metaverses is proposed to achieve smart manufacturing in CPSS. In the framework, social intelligence is collected, analyzed and extracted into social demands, and collective wisdom is gathered to design products through online communication, contributing to achieving on-demand production and avoiding production waste caused by aesthetic discrepancies with consumers. The ACP method is utilized for parallel evolution and real-time optimization of a series of operations, such as production planning, process engineering and manufacturing execution, improving robustness and flexibility in the production process. Digital workers and robotic workers continue performing most of the physical and mental work instead of human workers, resulting in higher efficiency and lower costs. Finally, the effectiveness of the framework is proved by the workflow of customized shoes in SANBODY Technology Company.

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