Journal of Manufacturing Systems 58 (2021) 52–64

Contents lists available at ScienceDirect

Journal of Manufacturing Systems

journal homepage: www.elsevier.com/locate/jmansys

Digital twin-based designing of the configuration, motion, control, and optimization model of a flow-type smart manufacturing system

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ARTICLE INFO

Keywords:
Smart manufacturing
Digital twin
Manufacturing system design
Industry 4.0
Cyber-physical systems

ABSTRACT

Digital twins can achieve hardware-in-the-loop simulation of both physical equipment and cyber model, which could be used to avoid the considerable cost of manufacturing system reconfiguration if the design deficiencies are found in the deployment process of the traditional irreversible design approach. Based on the digital twin technology, a quad-play CMCO (i.e., Configuration design-Motion planning-Control development-Optimization decoupling) design architecture is put forward for the design of the flow-type smart manufacturing system in the Industry 4.0 context. The iteration logic of the CMCO design model is expounded. Two key enabling technologies for enabling the customized and software-defined design of flow-type smart manufacturing systems are presented, including the generalized encapsulation of the quad-play CMCO model and the digital twin technique. A prototype of a digital twin-based manufacturing system design platform, named Digital Twin System, is presented based on the CMCO model. The digital twin-based design platform is verified with a case study of the hollow glass smart manufacturing system. The result shows that the Digital Twin System-based design approach is feasible and efficient.

1. Introduction

The research on the manufacturing system design began in the 1990s. The manufacturing system design always aims at satisfying the individualized requirements of customers, establishes high-order abstract models of products, and invents new design schemes. Recently, with the rapid development of 3C products, an increasing number of flow-type smart manufacturing systems are built in the Pearl River Delta region of China under the prevalence of Industry 4.0 vision [1]. Although the flow-type smart manufacturing system is of less complex coupling relations among the equipment and resources compared to the discrete-type smart manufacturing system. The design of a flow-type smart manufacturing system still has a high industrial and technical threshold. On the one hand, it requires the designer to have a comprehensive understanding of both the manufacturing process and the execution engine. On the other hand, it is necessary to master the design knowledge and have the ability to develop intelligent algorithms. The traditional method is that designers combine best-practice experience with offline mathematical analysis to design. However, the smart manufacturing system is a typical discrete event system of many random factors, which is often large in scale and complex in structure [2]. From initial designing to actual implementation, there are complex decision-making problems with complex influencing factors and coupling relations. It is difficult to identify and solve the objective function in a conventional analytical way, which makes it challenging to achieve the expected effect of the design and implementation. According to our investigation in the Pearl River Delta region of China, up to 60 % of the newly-designed flow-type smart manufacturing systems put into operation fails to meet the desired objective due to unreasonable designing.

The design of a flow-type smart manufacturing system is driven by individualized requirements, such as the production capacity, construction cost, and integration of legacy equipment. And the design could be conducted at the three-level: 1) static physical configuration such as equipment selection, whole production line layout, and assembly; 2) dynamic operation such as equipment motion, work-in-process (i.

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https://doi.org/10.1016/j.jmsy.2020.04.012
Received 20 October 2019; Received in revised form 7 April 2020; Accepted 16 April 2020
Available online 28 April 2020

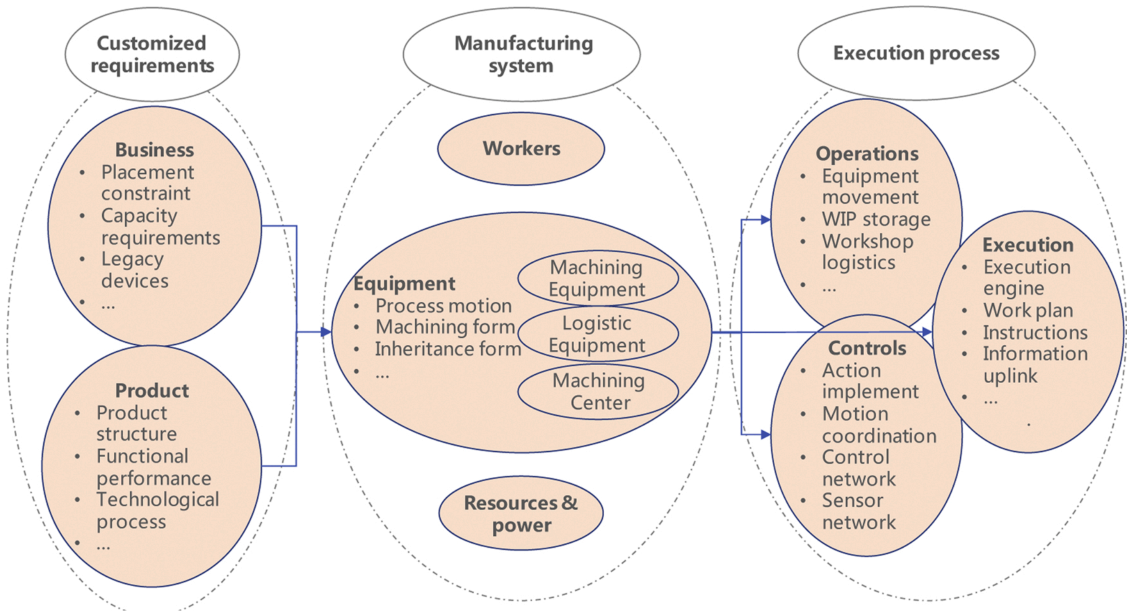


Fig. 1. Domain mapping relationships in the design of the flow-type smart manufacturing system.

e., WIP) movement, and workshop logistics; and 3) execution engines such as field control network, sensor layout, and manufacturing execution system (MES). Notably, the individualized requirements at different levels are interconnected and coupled with each other, and the optimization process requires coordination between design evaluation indicators and system operational metrics. If simply referring historical design of the existing manufacturing system, the differences of individualized requirements will lead to a configuration change, including equipment type selection, which may cause dramatic fluctuation of manufacturing execution efficiency. And the execution engine, control system, and sensor network must be adjusted and optimized, compatible with the differentiation of requirements. Compared with the design of a product, the design of a flow-type smart manufacturing system usually involves equipment selection, configuration design, motion and action planning, control script compilation, control network construction, and execution engine development. The design process of a flow-type smart manufacturing system brings substantial technical challenges to the automation of design knowledge and the coupling optimization of multi-discrete design problems. Moreover, under the mass customization and mass individualization manufacturing mode, the rapid changeover of the smart manufacturing system has become increasingly frequent, and significantly reduces the system design and configuration cycle. It is urgent to make breakthroughs and innovations in the design methods, technologies, and platforms for a smart manufacturing system in Industry 4.0.

To make the design methods adapt to Industry 4.0, more realistic cyber models mirroring the physical system are essential to bridge the gap between design and operation. Therefore, this paper proposes a digital twin-based design approach for flow-type smart manufacturing systems. Section 2 reviews the research progress of manufacturing system design research fields. Section 3 introduces the design logic of flow-type smart manufacturing systems for Industry 4.0, including quad-play CMCO (i.e., Configuration design, Motion planning, Control development, Optimization decoupling) architecture. Section 4 focuses on two key technologies for enabling the customized and software-defined design of flow-type smart manufacturing systems, including the generalized encapsulation of quad-play CMCO models and digital twin technology. Section 5 presents a digital twin-based design platform prototype, together with a case study of the flow-type smart manufacturing system of hollow glass. Section 6 draws conclusions.

2. Related work

Under the trend of product individuation, the manufacturing system design cycle gradually becomes the key factor that determines market competitiveness [3]. Rapid design technology emerges at the moment. Rapid Design is also known as Rapid Response Design or Agile Design. Ashley [4] expounded the characteristics of rapid response design and its relationship with agile manufacturing, virtual manufacturing, and flexible manufacturing. Singh et al. [5] proposed a centralized rapid design architecture based on knowledge engineering, which integrated production and assembly in the design stage to reduce product development time. Reynerson [6] introduced the rapid design center for the whole design work. In the design, as long as the requirements, such as size, power, weight, and load, are provided, the rapid design system can calculate rapidly according to the process. Chapman and Pinfold [7] used knowledge engineering to design a system aimed at improving the ability of body-in-white (WIB) design capability, which can dynamically respond to design changes in a short period of time. The new generation of artificial intelligence technologies is combined with the classical Axiomatic Design (AD) [8] methods, such as Computerized Relative Allocation of Facilities Technique [9], LOGIC (Layout Optimization with Induced Cuts) [10], and MSDD (Manufacturing System Design Decomposition) [11].

Typical manufacturing system design research focuses on the system configuration aspect, uses the modularization strategy for forming configuration space, and combines the reasoning and optimization technology for establishing a design scheme to meet individual needs [12]. The knowledge-based design includes the formalization, mining, and reuse of knowledge. Knowledge formalization usually involves the ontology and agent network models. Knowledge reuse and inferencing often require case-based reasoning, axiomatic design, and data mining methods. There is a lot of research on the knowledge representation and design of products. Ahmad et al. [13] proposed an ontology representation method of product-process-resource for the design process of products. Kretschmer [14] adopted the approach of data mining to extract knowledge and design for the assembly process of agile manufacturing.

Recently, the demand for the smart manufacturing system design extends to the adaptive correction of the execution engine setting and its efficiency, and the key is to perform modeling and optimization of coupled design goals and decision variables. Digital twinning is an

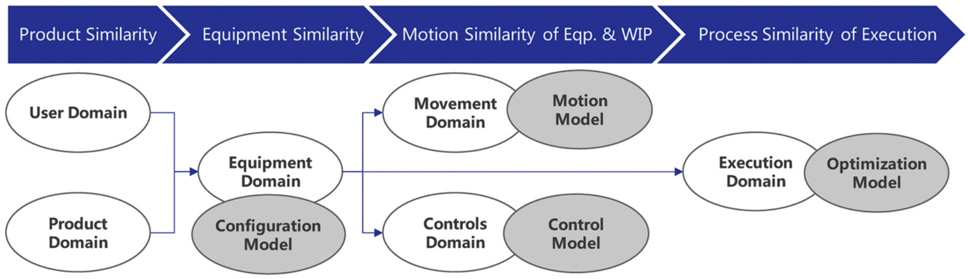


Fig. 2. Similarity transferring among configuration, motion, control, and optimization.

effective solution [15,16]. In the whole operation process of a physical system, the relevant knowledge could be accumulated to realize the optimization of a physical system based on the digital twin model [17,18]. Through the integration of all kinds of data of the physical system, digital twin comprehensively maps the entire life cycle of the physical system and co-evolutes/optimizes with the physical system based on analytic algorithms [19]. Digital twins can accumulate relevant knowledge continuously to realize the sustainable optimization of physical manufacturing systems [20]. Siemens advocates the concept of digital twins, constructs a production system model integrating manufacturing process in information space, realizes the digitization of the whole process from product design to manufacturing execution in physical space, and thus more accurately predicts product performance at each stage in the development process. Alam et al. [21] proposed a cloud information physical fusion system based on the digital twin reference model, discussed the computing interaction mechanism in the model and the method of generating a reconfigurable complex system controller. At present, the application of digital twin technology has been extended from operation to design of the manufacturing system [22].

Improving the adaptive ability of the execution engine is strictly dependent on its engineering analyzing capability of the critical problems in the field. It requires the higher-level mathematical modeling of the coupled optimization problem in the manufacturing execution. The digital twin is a potential technology to address the above issues. However, it is hindered by the lack of a conceptual theory and a sound technique basis. Therefore, this paper proposes a digital twin-based design approach for flow-type smart manufacturing systems in the Industry 4.0 context.

3. The architecture of digital twin-based designing of a flow-type smart manufacturing system

3.1. Domain mapping during the manufacturing system design

As shown in Fig. 1, the essence of the design process of the flow-type smart manufacturing system is to build the entity to meet the individualized needs, such as the placement constraint, production capacity, integration of legacy equipment, and production efficiency. In this process, the individualization needs from the business domain and product domain are transmitted to the manufacturing system domain and its execution process domain, driving the customizing of smart manufacturing in the dimensions of manufacturing equipment, operations, controls, and execution.

3.2. Basic definition of the quad-play CMCO design model

As shown in Fig. 2, there exists similarity transferring among product geometry, manufacturing process, equipment motion, WIP movement, manufacturing execution, and coupled optimization structure. The similarity could be expressed abstractly at a higher level. Making use of the similarity of the product, together with its flow-type smart manufacturing system, can effectively improve the customization

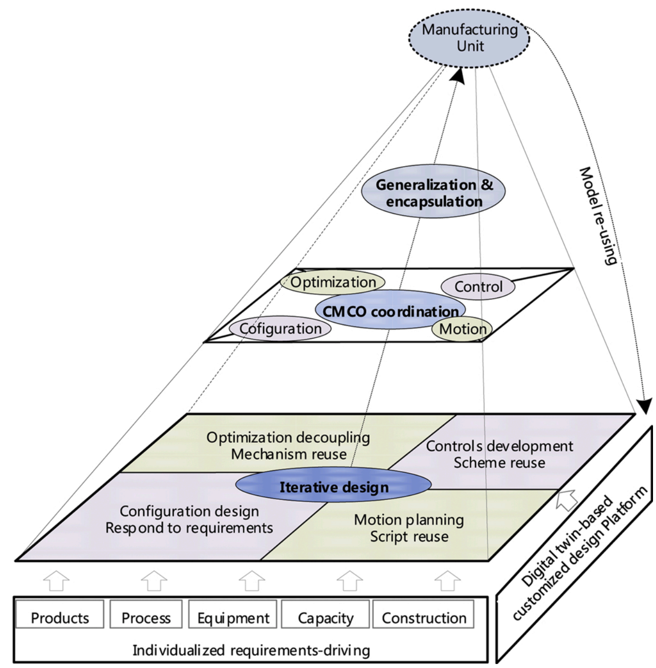


Fig. 3. The architecture of the quad-play CMCO design model.

efficiency and design accuracy. This paper defines the quad-play CMCO (i.e., Configuration-Motion-Control-Optimization) design approach to characterize the similarity of a flow-type smart manufacturing system abstractly.

Definition 1. Configuration model refers to the topological structure and static configuration of the flow-type smart manufacturing system, including the process planning, the typology and spatial layout of the system, the selection and allocation of the equipment, and the connection relationship and constraints between equipment.

Definition 2. Motion model refers to the movement form of the flow-type smart manufacturing system, including the motion form of equipment and the movement form of WIP.

Definition 3. Control model refers to the control system structure and autonomous system of the flow-type smart manufacturing system, including industrial control network structure, data acquisition and processing model, autonomous unit division, and unit control settings.

Definition 4. Optimization model refers to the optimization problems and their coupling structure in the whole operation process of the flow-type smart manufacturing system.

The similarity of the geometric shape of products determines the similarity of process planning. Taking board-type products as an example (Board-type products are characterized by the manufacturing feature of plane processing and lightweight assembly), the

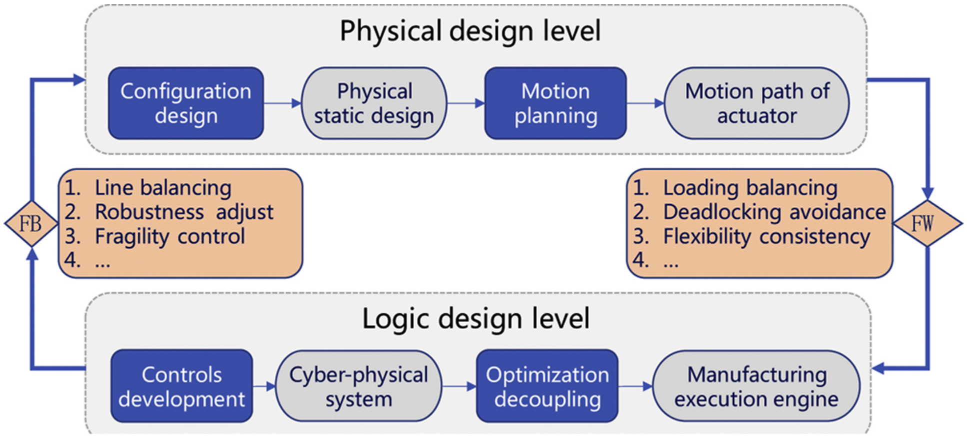


Fig. 4. A bi-level iteration perspective of the quad-play CMCO design model.

manufacturing process often involves point-to-point machining (e.g., drilling and dispensing process), straight-line/plane-curve processing (e.g., cutting, grinding, slotting, and chamfering), plane-integral processing (e.g., plating and coating) and other processing forms with highly-approximate movement type. The logistics form of board-type WIP is characterized by lifting, reversing, partitioning, laminating, vertical/horizontal storage, sorting, stacking, and other operations with the same logic of action.

3.3. Architecture of the quad-play CMCO design model

In the design of a flow-type smart manufacturing system, the key to improve the correctness and rapidity of design includes effective knowledge reuse, parallelization of models, and coordination of processes. This paper presents a quad-play rapid design method in CMCO architecture. The rapid design of a flow-type smart manufacturing system could be concluded as four stages, namely, *configuration design*, *motion planning*, *control development*, and *optimization decoupling*. As shown in Fig. 3, the CMCO design architecture is executed in the form of a hierarchical iterative optimization manner, in which each iteration process obeys the specific design objective and constraints of the optimization.

Configuration Design refers to 1) requirements analyzing; 2) process planning; 3) determination of system typology; 4) geometric layout types (e.g., L-type, S-type, U-type) according to space constraint; and 5) the configuration of equipment and buffer according to operation priority, cycle time and loading balance in the process route. A reconfigurable machine tool model with the open architecture of a standardized

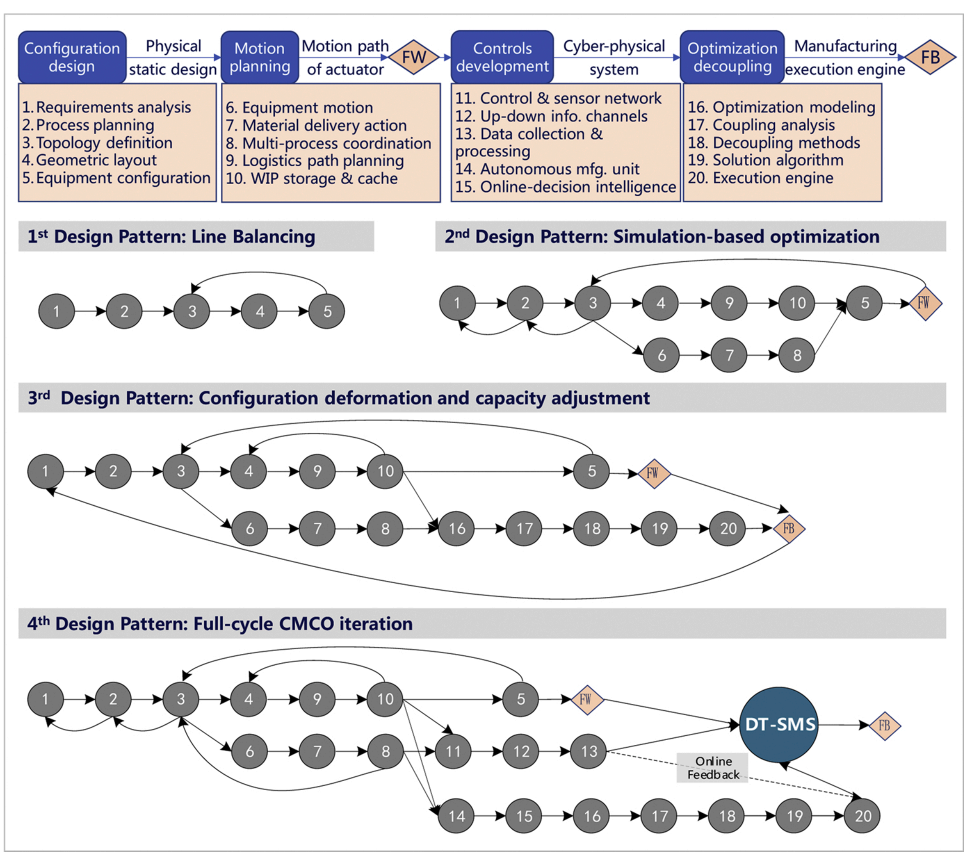


Fig. 5. Four patterns in the iterative design logic of the quad-play CMCO model.

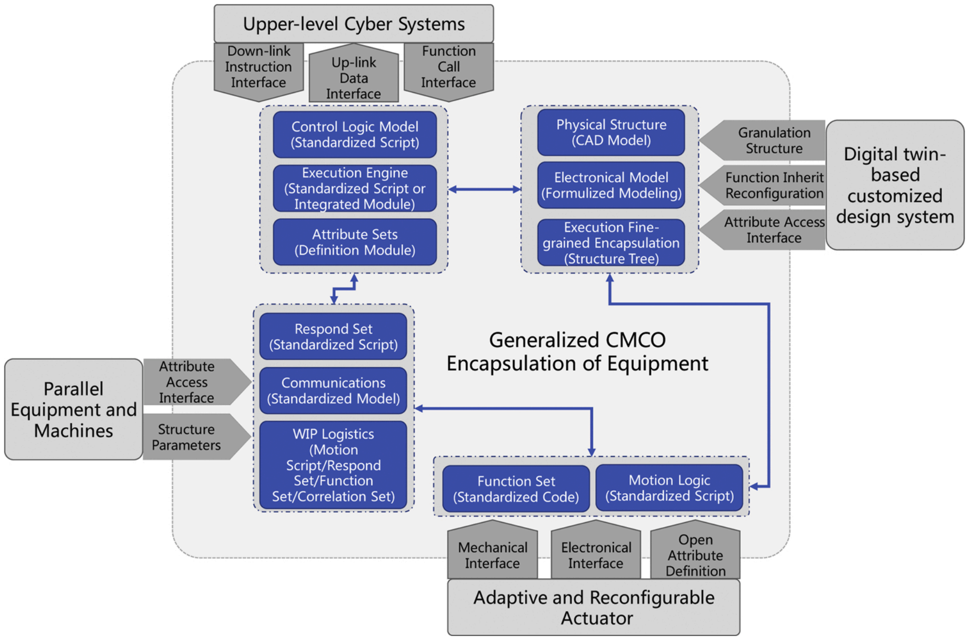


Fig. 6. A generalized encapsulation of the quad-play CMCO model.

plug-and-play platform, which can be rapidly integrated with various modules, is the foundation in this stage to achieve fast reconfigurability.

Motion Planning refers to 1) defining the motion sequence of equipment (manufacturing equipment and logistics equipment); 2) the material delivery action sequence; 3) the motion coordination of multiple processes according to the process route and process requirements; 4) logistics path planning to avoid unnecessary collisions and deadlocks effectively; 5) planning the suspension and cache mode of WIP according to the motion of equipment.

Control Development refers to 1) establishing the control & sensor network, up-down information channels, data collection, and processing mechanism according to the configuration and motion model of the manufacturing, so as to realize the interconnection and interoperability of cyber model, physical equipment, and control system; and 2) designing the division of control system for each autonomous manufacturing units according to the forms of process segment, so as to realize the online-decision intelligence in each unit control model. The middleware of REpresentational State Transfer (REST) architectural style could be used in this stage to allow the system to dynamically reconfigure and control equipment by using a uniform and predefined set of stateless operations.

Optimization Decoupling refers to 1) extracting the manufacturing process optimization problem of each equipment, the operation optimization problem contained in the manufacturing cell or process section, and the production planning problem; 2) analyzing their coupling relationship and establishing a decoupling system; and 3) developing the solution algorithm, which in turn serves as the execution engine driving the operation of the manufacturing system. This stage is crucial to achieving the "intelligent capabilities" of the manufacturing system in Industry 4.0.

Configuration Design responds to the customers' individual needs in the product, process, and equipment. *Motion Planning* realizes code-level reuse of equipment motion and WIP logistics logic. *Control Development* reuses the control network structure and control scheme. *Optimization Decoupling* reuses the decoupling mechanism and solution method. In a fine-grained flow-type smart manufacturing system, a coordination mechanism could be achieved in the abstract level of the CMCO model. The fine adjustment of configuration can drive the motion, control, and optimization model to adjust adaptively. Usually, the generalized encapsulation is a key enabling technique for supporting this coordination, including the encapsulation of the cyber model, action script, control network, execution engine, as well as the definition of communication, software, mechanical, electrical, and other interfaces.

As shown in Fig. 4, the CMCO design architecture could be reorganized as a bi-level structure. Configuration design and motion planning can be summarized as the physical design level. After the completion of physical design, the evaluation of loading balance, process deadlock, and flexible consistency can be carried out to guide the rationality of the physical design. Control development and optimization decoupling can be summarized as the logic design level. After the implementation of logic design, the evaluation of system performance, regulation of flexibility, and the system brittleness/robustness can be carried out to improve the operational performance of the logic design.

3.4. Four typical patterns of iterative CMCO design logic

According to the practical customization requirements of the flow-type smart manufacturing system, four typical iterative design paradigms can be concluded, as shown in Fig. 5. The "FW" and "FB" symbol in the bi-level of Fig. 4 are two vital indicators to judge the design patterns in Fig. 5. The notations of the 20 steps in the four pattern maps are mapped with the upper part of Fig. 5. The arrows among steps imply the design sequence.

The DTS-based iterative design would be used in each of the four stages of CMCO, as shown in Fig. 5, but the iteration logic will be different in the proposed four types of design patterns. The 1st design pattern is named as *Line Balancing*. In the 1st design pattern, the topology definition, geometric layout, and equipment configuration will be iteratively optimized from Step 3 to Step 5 to achieve the loading balancing for each equipment in the production line. The 2nd Design Pattern is named as *Simulation-based Optimization*. Compared with the 1st design pattern, the motion planning will be incorporated into configuration design based on the parallel iteration of system layout (network level) and equipment coordination (node-level) in a simulation-based optimization method. The 3rd Design Pattern is named as *Configuration Deformation and Capacity Adjustment*. Compared with the 2nd design pattern, the optimization decoupling will be directly integrated with configuration design and motion planning, without considering the control development. This design pattern is usually conducted in practical usage of DTS, since the control development is

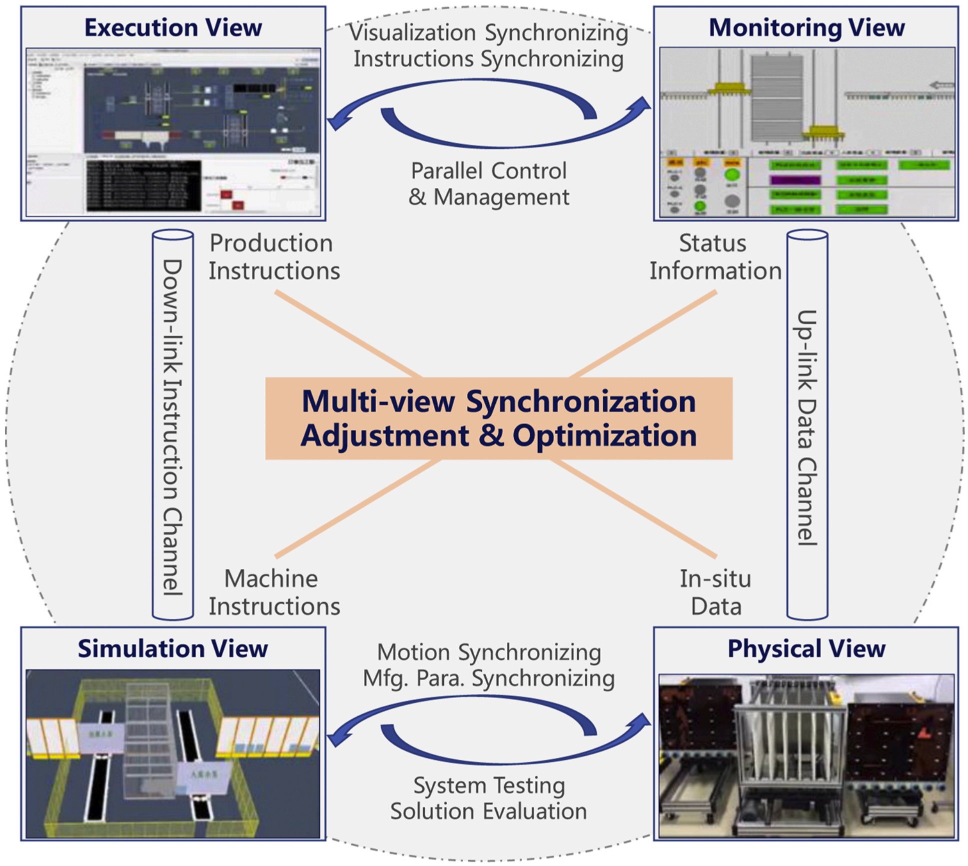


Fig. 7. Multi-view synchronization for building a digital twin of the flow-type smart manufacturing system.

less coupled with the other three stages in terms of the optimization space, besides it needs massive work on establishing the physical control network to form a digital twin. The 4th Design Pattern is named as *Full-cycle CMCO Iteration*. The optimization of the overall design scheme is carried out iteratively across four stages, including configuration design, motion planning, control development, and optimization decoupling. The 4th design pattern shows a full-cycle hierarchical iterative optimization design process of a digital twin-driven flow-type smart manufacturing system (i.e., DT-SMS), in which the parallel design task and the iteration of the design process involve the whole design process. The difference between the 4th design pattern and the traditional serial design pattern lies in the hardware-in-the-loop simulation of the software-defined manufacturing system and adequate coordination based on knowledge automation and artificial intelligence technique. A digital twin platform can support the semi-physical simulation of static configuration and dynamic execution behavior of the software-defined manufacturing system, and it can be used as a virtual integrated debugging platform to support the task collaboration of mechanical engineers, control engineers, and software engineers, effectively ensuring that design tasks can be executed parallelly.

4. Key techniques for enabling the CMCO design model

4.1. Generalized encapsulation of quad-play CMCO models

Reuse and effective dissemination of design knowledge is the basis of implementing the rapid design of the smart manufacturing system. It requires designers to summarize existing design cases and encapsulate design schemes abstractly, covering the definitions of the 3D cyber model, action script, control structure, execution engine, and its corresponding interfaces. It also requires designers to encapsulate the quad-play CMCO models in a higher abstract level of representation for classification, retrieval, and effective dissemination. A generalized encapsulation of quad-play CMCO models is established, as shown in Fig. 6. It is the technical basis of the rapid customized and software-defined design of the flow-type smart manufacturing system.

The generalized encapsulation mechanism includes four key aspects: 1) Multi-dimensional high-order characterization for the adaptive and reconfigurable actuator of encapsulated objects. Generally, it is represented by standardized action and motion sequence, which needs to be combined with the manufacturing features of the product. For instance, the basic actions commonly used in the processing of board-type products are packing and stacking. 2) Attribute and access control systems for upper-level cyber systems. It is necessary to define user, role, interface function, control logic, execution engine, and operation category to establish a role-based access control system. 3) The granularity control of encapsulated objects for design. Coarse-grained encapsulated objects can be formed by superposition between encapsulated objects, which need to be realized on the basis of fine-grained encapsulation and cross-grained reconstruction. 4) Correlation trajectory of configuration/motion/control/execution for other parallel equipment and machines. The key to the quad-play coordination is the correlation of model, script, control, and execution engine of the multi-equipment system. Therefore, it is necessary to establish the correlation trajectory based on the parameter matrix correlation, variable evolution calculation, and parameter assignment changes. Finally, the generalized encapsulation will result in the parallelization of the software-defined design process.

4.2. Digital twin for hardware-in-the-loop simulation of a flow-type smart manufacturing system

The digital twin is established by building a real-time downlink instruction channel and the uplink data channel to realize multi-view (i.e., physical view, simulation view, execution view, and monitoring view)

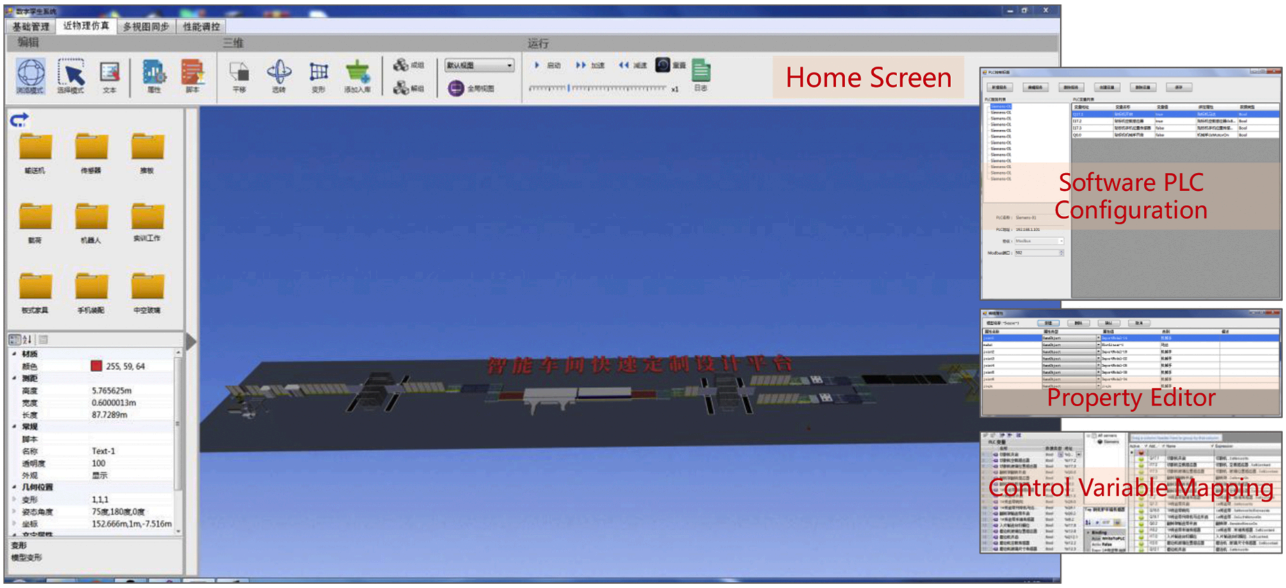


Fig. 8. Screenshot of the digital twin system prototype.

synchronization of flow-type smart manufacturing system [23]. Multi-view synchronization technology takes a software-comprehensible Programmable Logic Controller (PLC) as the bridge for establishing the interaction channel between cyber simulation, device model, physical PLC, and configuration software. The real-time synchronization realizes the interconnection and interoperability of cyber model and physical equipment, as shown in Fig. 7.

Different from traditional off-line simulation method, the digital twin integrates the hardware-in-the-loop simulation with optimized design model through 1) Synchronization of the cyber and physical system, namely, establishing the command and information channel between the execution engine (view) and the simulation model (view), so that the execution engine can control the movement of not only the physical equipment but also the simulation model; and 2) Iterative optimization between static configuration and dynamic execution, namely, conducting a repeated "execution-analysis-adjustment" to achieve a balanced optimization of the configuration scheme and the execution engine. The digital twin relies on 1) geometric modeling, namely, the flow-type smart manufacturing system and its equipment relationship is modeled geometrically and semantically; 2) mathematical modeling, which relies on the mathematical abstraction of the capacity parameters, control mode and equipment relations of the system; 3) optimizing computation, namely, the corresponding intelligent optimization algorithm is developed as the execution engine of the system according to the established mathematical model. On the one hand, the digital twin can reasonably realize the hardware-in-the-loop simulation for replacing the physical testing, reducing the verification cycle and cost. On the other hand, it can also optimize the configuration and execution synchronously, and finally output the design scheme and execution engine, which can support the rapid implementation of the flow-type smart manufacturing system.

5. Prototype system and a case study

5.1. A digital twin system prototype

The rationality verification of a flow-type smart manufacturing system is usually performed continuously in the process of design and deployment. The cost of the physical verification is expensive due to the costly transportation and assembling of equipment and the increasing of the design time [24]. Relying on the offline simulation platform is easily limited by the expression and calculation efficiency, so the rationality of the design scheme will be weakened [25]. It is needed to combine modeling and real time data to build a digital twin system to make the output system performance constantly verified and improved. Therefore, to improve the current insufficient analysis ability of the manufacturing execution process, a digital twin system prototype is proposed for the design of a flow-type smart manufacturing system.

As shown in Fig. 8, a Digital Twin System (i.e., DTS) for manufacturing system design is developed based on the free-to-use Unity3D engine. The visualization engine displays the simulation model configuration, layout and logistics path, equipment/WIP movement, and operation process of the flow-type smart manufacturing system. Given individualized products, the DTS could provide different designs of manufacturing systems. It can collect, gather, and utilize real-time data to simulate the manufacturing process. It comprises of Requirements Analyzing Module, Resource Analyzing Module, Decision Engine, and Deployment Module, which will be detailed via a case study in section 5.3. All these four modules are developed in the C# programming language based on two key enabling technologies described in section 4, namely, generalized encapsulation of quad-play CMCO models and the multi-view synchronization technology. The first one is the generalized encapsulation of quad-play CMCO models that could support remote on-line testing and reconfiguration of equipment from different suppliers [26]. A wide area network communication channel between the digital model and physical equipment is established to realize the synchronization of movement and motion between the digital model and physical equipment. The second one is a multi-view synchronization technology that ensures real-time interaction between physical equipment and digital model within the required accuracy range. It eliminates the influence of the asynchronous sampling period and PLC communication time between physical equipment and the digital model to achieve parallel transparent monitoring [27] of the manufacturing system. Besides the fundamental application as a high-fidelity hardware-in-the-loop simulation of physical processes and equipment, the DTS is characterized by its unique capability on the distributed integration testing of the whole flow-type smart manufacturing system, which supports multi-vendor equipment integrated with a digital twin model for avoiding the bottleneck, shorten integration cycle, and reducing integration cost.

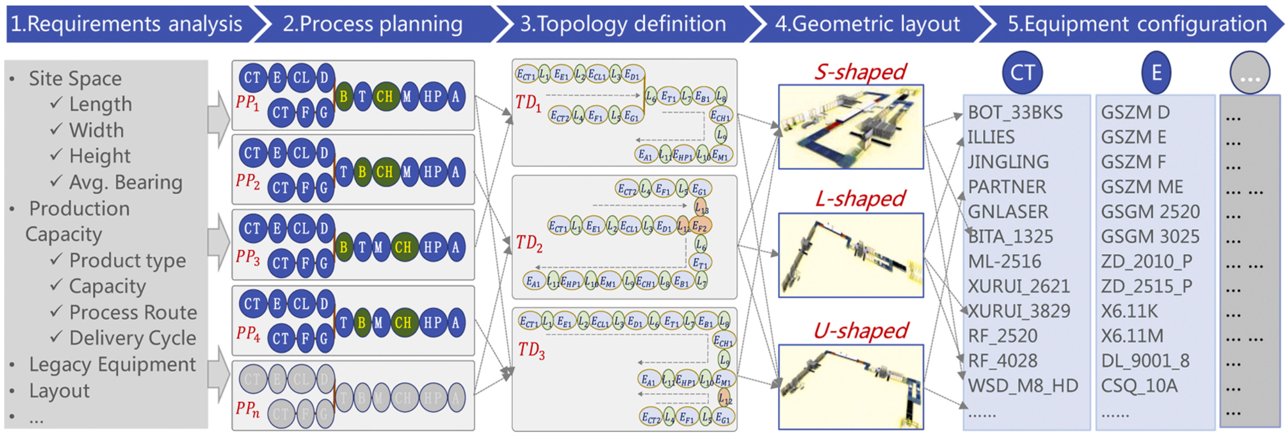


Fig. 9. Illustration of five steps in the configuration design stage.

5.2. A case study of the design of hollow glass smart manufacturing system

This paper takes a hollow glass processing enterprise in China as an example to illustrate the proposed approach and system. Hollow glass is a new kind of building material with good heat insulation and sound insulation. The hollow glass industry faces an urgent need to realize smart manufacturing in Industry 4.0. Appendix Table A1 provides an overview of corresponding hollow glass processing equipment. Due to high-pressure water washing cleaning and high-temperature tempering process, it is not allowed to mount labels on the surface of the glass in its manufacturing process. When making production plans, manufacturers must simultaneously optimize raw material blanking rate, equipment utilization rate, and delivery time. In general, it is challenging to achieve systematic coordination and optimization in the design of its smart manufacturing system.

5.2.1. Configuration design

Fig. 9 provides an overview of the first five design steps in the configuration design stage. The configuration design is started from the analysis of personalized requirements of site space, production capacity, process route, legacy equipment, and layout. Taking the characteristic of site space as an example, it directly affects the layout of the production line. For long and narrow areas, the production line is linear or L-shaped. At the same time, different locations of entrances and exits of the site space lead to varying flows of logistics, and the layout of production lines is also different. With respect to the process planning and typology definition, the production process of hollow glass includes material cutting (CT), edging (E), cleaning (CL), drying (D), batching (B), toughening (T), coating (CH), framing (F), matching (M), gluing (G), hollow hot pressing (HP), assembling (A), and other processes. The typology definition is to arrange the relation of manufacturing equipment according to the results of process planning. The matching machine is used as the batch-merge point and batch-split point. Its location determines the form of the manufacturing process and system typology, and thus is the primary design variable. The digital twin-based process planning has been well studied [28]. With respect to the geometric layout and equipment configuration, the layout of the whole production line needs to be planned according to the site conditions of the enterprise. The selection of equipment is depended on the capacity requirements, contextual takt coordination with other equipment [29], and the site space characteristics. In the smart manufacturing system, the equipment such as CNC machine tool could be designed and implemented with the capability of self-sensing, self-prediction, and self-maintenance based on digital twin [30].

5.2.2. Motion planning

The design of a hollow glass manufacturing system not only includes a selection of more than 70 physical equipment but also has to establish their logical relationships, namely, motion planning (Fig. 10). The basic actions of equipment and material delivery includes linear moving, rotation, lifting, *etc*. The design of equipment motion and material delivery action is to find an optimal combination of these basic actions for single machine equipment, as well as the action logic design for the whole production line. The equipment motion often is hierarchical and of relativity characteristics. For instance, the cutter truss movement will drive the cutter head and cutting tool movement. With respect to multi-process coordination, the parameter reference and control script could be retrieved from the established model library and script library, and then mapped to each other. The motion planning is based on hierarchical model processing. The hierarchical processing is aimed at the modeling of operation behavior in production lines such as cutting

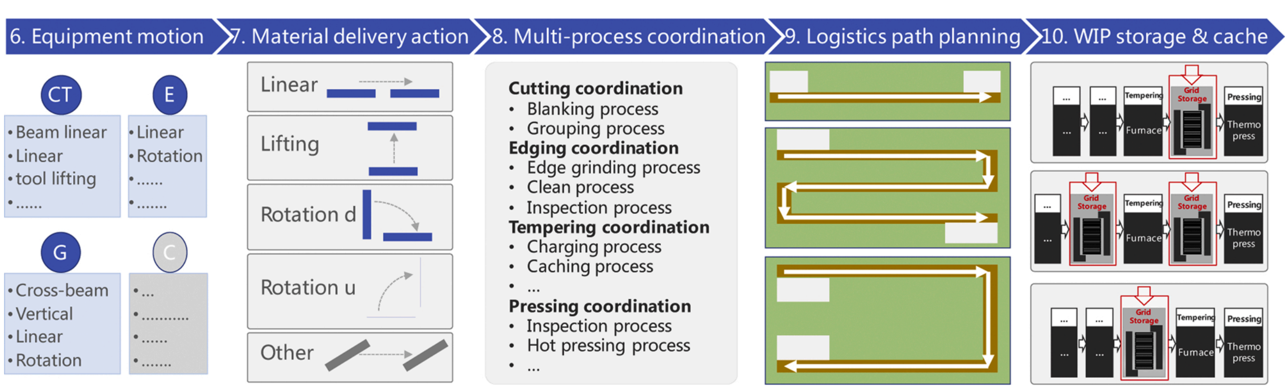


Fig. 10. Illustration of five design steps in the motion planning stage.

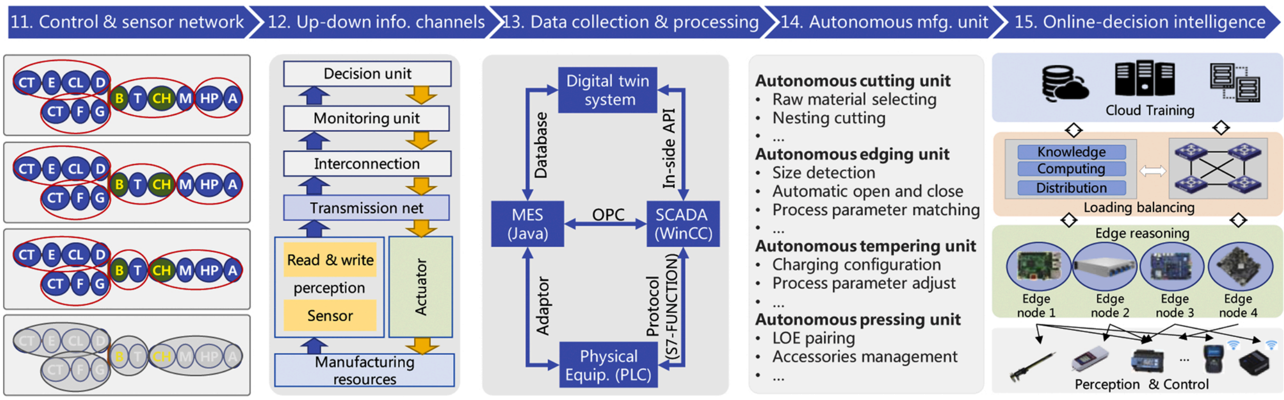


Fig. 11. Illustration of five design steps in the control development stage.

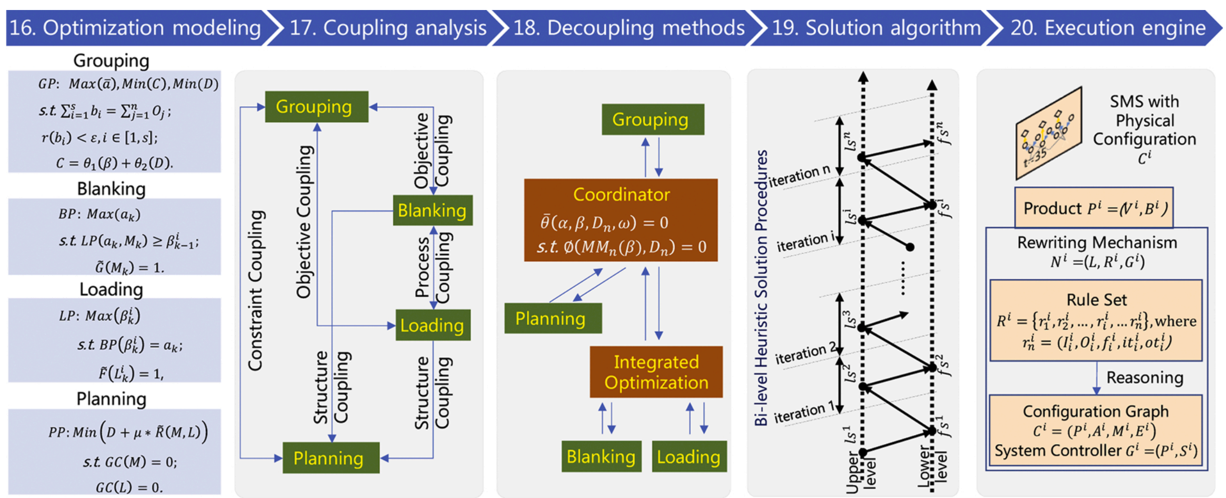


Fig. 12. Illustration of five design steps in the optimization decoupling stage.

machine. The behavior model of the equipment must also be established in a hierarchy manner. In the design of multi-process coordination, and the upper-level components relative to the lower-level components or elements are given higher priority. The relative motion relation between the moving parts in the equipment becomes the motion link relation, such as between the claw of the manipulator and the mechanical clamp. With respect to the logistics path planning and the WIP storage and cache, the hollow glass is a kind of blind operation object, which needs to form a logical label based on the mandatory flow sequence. A clear flow sequence requires accurate and robust path planning. The design variable about WIP storage and cache is the location of the grid storage, which could be located in the front or back of the tempering furnace. This decision will affect the tempering process.

5.2.3. *Control development*

Fig. 11 provides an overview of the 11th to 15th design step in the control development stage. The control in this case study majorly includes four units, namely, cutting unit, edging unit, tempering unit, and hot-pressing unit. The key to developing up-down channels for achieving multi-view synchronization is the control agent of the digital model, which is a kind of software-comprehensible PLC. It is a hybrid model by incorporating Object linking and embedding for Process Control (OPC) with the database, Industrial Internet-based protocols, heterogenous equipment-inside Application Programming Interface (API), and customized adaptor. The Deployment Module of DTS platform is configured to communicate with physical equipment, and the execution kernel is configured to communicate with physical equipment, and the DTS is configured to communicate with the control system. With respect to the online-decision intelligence step, it is to design the computing architecture to form the interplay of cloud training and edge reason. Usually, each autonomous manufacturing unit should be configured with at least one edge computing node to achieve online-decision intelligence, such as proactive fault diagnosis [31]. A discussion on how to combine permissioned blockchain with a holistic optimization model as bi-level intelligence (i.e., lower-level online-decision intelligence and upper-level holistic optimization intelligence) for smart manufacturing has been discussed in our previous study [32] and will be omitted there for a concise reason.

5.2.4. *Optimization decoupling*

Fig. 12 provides an overview of the last five design steps in the optimization decoupling stage. In detail, the production of hollow glass involves four typical discrete optimization problems: order-batch grouping, blanking optimization, tempering furnace loading, and operation planning. *Grouping* refers to the clustering order within the production cycle. It forms a reasonable production batch by balancing the use of raw materials and energy consumption. *Blanking* is a layout optimization to maximize the utilization rate of raw material. Usually, the layout scheme must meet the Guillotine-Cutting constraints. *Loading* is to optimize the capacity. *Planning* is to optimize the flow path and order of WIP for minimizing the makespan. Typical design variables are identified in Appendix Table A2. These four optimization problems are interrelated with each other, forming a complex coupling optimization problem of "grouping-blanking-loading-planning", which affects the

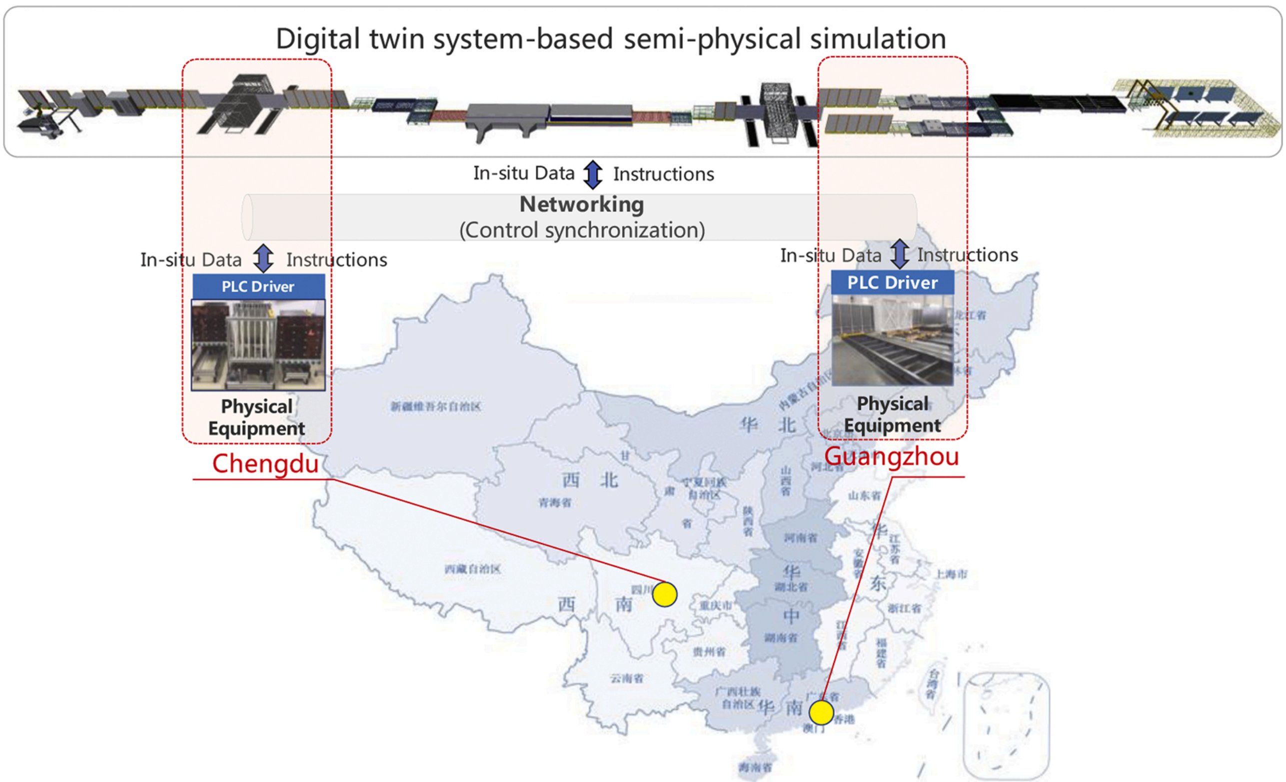


Fig. 13. Digital twin-based semi-physical simulation and design verification.

operational performance of the hollow glass smart manufacturing system. The coupling relation of joint optimization needs many nested computations and inevitably calls for multiple optimization variable combination calculations that satisfy the fast responsiveness needs [33]. The fundamental solution lies in the computational decoupling method using a hierarchical diagram calculation. The intersection relationship can be encapsulated into a kind of integrated optimization problem in combination with a unique internal negotiation mechanism. Through the topology deformation of the problem structure, a hierarchical-layered calculation diagram and a bi-level iteration coordination model were proposed to achieve optimal design performance in our previous study [34] and will be omitted there for a concise reason.

5.3. *DTS-based iterative design of the hollow glass smart manufacturing system*

Through the integrated semi-physical simulation method, the DTS could be used to achieve iterative "closed-loop optimization" of a hollow glass smart manufacturing system, guiding the rapid development of a complete set of execution systems, as well as the deployment and integration of hardware and control software.

Firstly, at the initial stage of design, the Requirements Analyzing Module is used to extract all the required manufacturing operations from the product design document, and creates an ordered list of required operations object. Secondly, the Resource Analyzing Module is used to capture all the needed machines in the smart manufacturing system

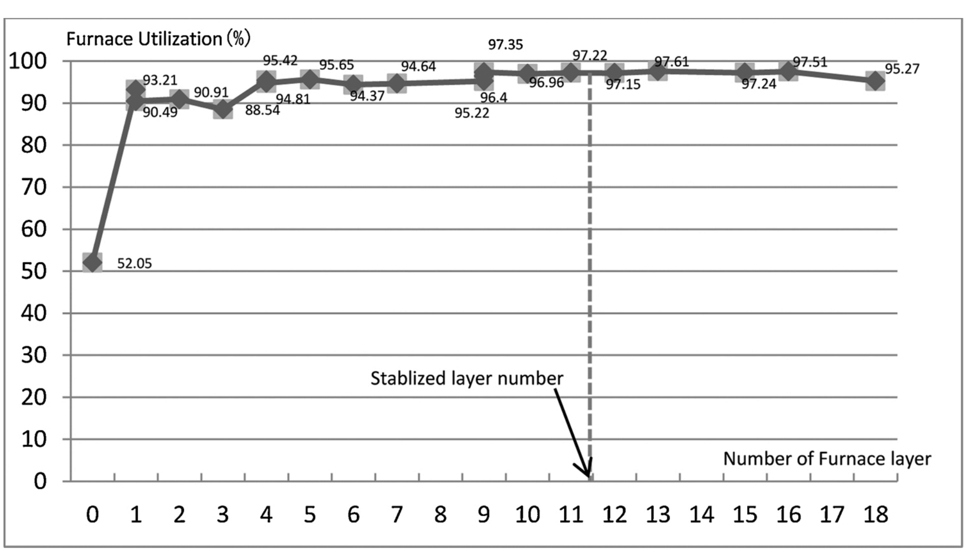


Fig. 14. The relation of furnace utilization and the number of furnace layer.

Table 1
Comparison of algorithms on the loading optimization problem.

No.	$M_{Silva(3E)}$	$M_{Puchinger(3E)}$	$M_{Silva(3NE)}$	M_{DTS}
1	–	15	15	**14**
2	14	13	14	**13**
3	13	14	13	**13**
4	6	6	6	**6**
5	8	8	8	**8**
6	8	8	8	**8**
7	15	12	12	**12**
8	12	12	11	**11**
9	12	12	12	**12**
10	–	16	–	**16**

from the workshop capability and capacity document, and then output the position in the system, the orientation of the machine and WIP flow, and the connections of one machine to another. Thirdly, the Decision Engine is used to produce a set of possible configuration and motion solutions that satisfy the given requirements by using the knowledge-based reasoning model. Through an "execution-analysis-adjustment" of the iterative optimization process in the Decision Engine of DTS, it finally outputs design schemes, and the production line is basically determinate except for its control, which is then obtained from the Deployment Module in DTS. Finally, after obtaining a design solution to the smart manufacturing system successfully, the Deployment Module imports the configuration on the decentralized controllers of the smart manufacturing system. The semi-physical simulation model is used to realize the final verification of the design scheme of smart manufacturing systems in the distributed integration testing method (Fig. 13). Some parts of the virtual manufacturing system model could be replaced into the physical equipment to analyze its coordination and matching degree with respect to other related equipment models in the smart manufacturing system. Adopt this kind of distributed on-line verification is a less-costly method to assist the design. It finally outputs the execution kernel as the core of the intelligent control system for realizing software-defined manufacturing.

5.4. Evaluation of key metrics of the designed hollow glass smart manufacturing system

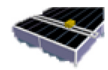
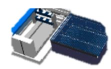
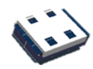
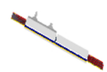
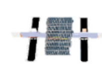
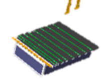
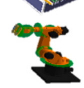
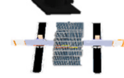
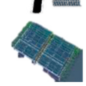
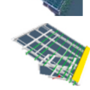
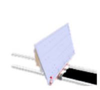
The tempering process of glass is identified as a critical process of hollow glass manufacturing. After the process of heating and blowing in the tempering furnace, the crystal structure inside the glass has changed. The strength and performance of the glass have been greatly improved. Due to the various sizes of tempered glass and the difficulty of loading, the electricity cost of the tempered glass is the most considerable manufacturing cost of hollow glass production. In the case study, there are 15 types of glass specifications in the order batch. Through the digital twin-based design, a total of 6 furnaces need to be loaded on this batch of glass tempering furnaces. As shown in Fig. 14, it can be clearly seen that the utilization rate of the tempering furnace tends to be stable after the number of furnace layers increasing to a specific value. When the maximum difference of the vertical coordinate of the consecutive three points of the curve is not more than 0.5 %, the minimum horizontal coordinate value of the three points is selected as the stable furnace layer number (i.e., 12). The average utilization rate of each furnace reaches 93.60 %, and more than 20 percentage points higher than the average utilization rate of current tempering furnaces at 70 %. This will make the enterprise save the manufacturing cost, and shows that the DTS has great promotion value.

Further, since the loading optimization problem is similar to the three-stage blanking problem of the two-dimensional rectangle, the three-stage blanking test case from Silva et al. [35] was selected for testing the digital twin approach. The testing consists of 10 cases, and the number of small rectangular block types range from 25 to 60. The case test results were compared with the results in Silva et al. [35] and Puchinger et al. [36]. The results were shown in Table 1. The three stages of a two-dimensional rectangular layout can be divided into 3NE and 3E. 3E is a strict (accurate) three-stage blanking layout, belonging to a particular case of 3NE (inexact) layout. Minimizing the number of the tray (a large rectangle-type container for carrying the hollow glass) used in each loading process is the goal of optimization. The used tray number of 3E and 3NE in Silva algorithms are denoted as $M_{Silva(3E)}$ and $M_{Silva(3NE)}$, respectively. The used tray number of 3E in Puchinger algorithm is denoted as $\mathrm{M}_{\mathrm{Puchinger(3E)}}$. "-" represents that the algorithm cannot solve the case within the specified time. In this paper, based on the advantages of dynamically obtaining the online equipment status information from the DTS, a dynamic group matching-based packing algorithm is integrated into DTS to perform the loading optimization. The used tray number of the large rectangle used by the DTS approach is denoted as M_{DTS}.

In all ten cases of Table 1, the number of trays required in the DTS-based packing algorithm is the smallest compared with Silva and Puchinger's algorithm, and the computing time for the DTS approach is less than 1 s, which shows that the DTS approach is feasible and efficient. In practical usage, the load optimization of the furnace should be performed in a real-time manner. Since it is downstream of the caching of toughened glass, the loading optimization needs to be considered with the design of the capacity of the tempering bin. On the one hand, the larger capacity of the tempering bin is, the more glass can be stored to be loaded in the furnace, and the more combinations of glass can be selected in the furnace layout. A better utilization ratio (determines the operation cost) of the loading scheme could be obtained by the loading optimization algorithm. On the other hand, the larger capacity of the tempering bin leads to an increase in the system configuration cost. The DTS could obtain a balance of the configuration cost and theoretical operation cost, which is the advantage of the digital twin approach.

Compared to Industry 3.0, Industry 4.0 implies more intelligent capabilities with extensive adoption of IoT and CPS. The proposed CMCO is adapt to Industry 4.0 because of the following two metrics: 1) in the designing of the manufacturing system in the Industry 4.0 context, more realistic cyber models mirroring the physical system are essential to bridge the gap between design and operation of a manufacturing system. This is why this study proposed the digital twin-based design approach. 2) In the proposed CMCO architecture, the last stage (i.e., Optimization Decoupling) is crucial to achieving "intelligent capabilities" in the manufacturing system. The advantages of using the digital twin approach could be concluded as two aspects: 1) the hardware-in-the-loop simulation enabled by the digital twin could avoid the potential design errors/inefficiency and verify the dynamic execution of a new manufacturing system in its early stage of deployment; 2) the quick-response algorithms integrated into the digital twin could use the online data to perform dynamic optimization to improve the system operation efficiency of the manufacturing system. However, in the presented case study, some decision variables and decision-making processes should be depended on the experience of engineers, and cannot be fully automated under the support of the DTS. More implementation scenarios should be studied to abstract more higher-level design knowledge automation models for guiding the further design of a smart manufacturing system. Future research directions include incorporating open-architecture techniques [37] into the design method. Also, the quality prediction capability [38], reconfigurability [39], robustness [40], and joint optimization capability [41] in manufacturing system design are essential aspects waiting to be addressed. The digital twin is far from realizing the smart design of the manufacturing system, which is a complex system and long-drawn process. Varied types of data from the manufacturing systems should be collected, modeled, merged, and analyzed, which needs intensive study in the future [42].

Table A1
Typical equipment in the hollow glass manufacturing system.

Name	Function	Photo
Cutting machine	Used for glass processing and blanking. It includes an air floating feeding table arranged at the end and a double-bridge overpass cutting table.	
Edging machine	Used for edging burr generated after the cutting process, which is prone to breakage when tempered. It composed of a transmission platform, grinding wheel, and fixture.	
Washing machine	Used for cleaning and drying the surface of the glass before making a mirror, vacuum coating, tempering, hot bending, insulating glass, etc.	
Tempering furnace	Used for raising glass intensity by means of physical or chemical methods, to avoid breakage when glass receives external force action.	
Matching machine	Used for pairing two single glass before the pressing process.	
Bar bending machine	A machine capable of bending sheet metal, whose structure consists mainly of a bracket, a table, and a clamping plate.	
Pressing machine	Heats two pre-coated tin-coated glass to form a permanent electro-mechanical connection	
Coating machine	Used for surface coating process production. It is rolled substrate coated with a layer of specific functions of glue or paint.	
Grid Storage	Equipped with an elevated shelf (storing large pieces of glass) and a low shelf. Multiple pieces of glass can be stored in one grid.	
Matched-glass storage system	A grid-frame structure warehouse for storing matched glass	
Gantry	Used for grabbing and transporting glass.	
Transfer station	Used for transporting glass.	
Robot	Used for grabbing and transporting glass.	
Tempering bin	A grid-frame structure warehouse for tempering glass.	
Glass plate arrangement system	Used for automatic plate arrangement of the loading plate of the tempering furnace.	
Flip grid	Composed of the flip table and the flip bracket. It realizes rotation to change the transmission of the glass from horizontal to vertical.	
Transfer vehicle	Consists of glass receiving plate and guide rail. It is a toughened warehouse system and a matching warehouse system.	

6. Conclusion

This paper proposed a digital twin-based CMCO (i.e., Configuration, Motion, Control, and Optimization) design approach for flow-type smart manufacturing systems in Industry 4.0. The iterative design logic of the quad-play CMCO model is detailed. The design methods of flow-type smart manufacturing systems are proposed and discussed, including configuration design, motion planning, control development, and optimization decoupling. Two key enabling technologies for enabling the design of flow-type smart manufacturing systems are presented, including the generalized encapsulation of the quad-play CMCO design model and the digital twin technique. A prototype of a digital twin-based design platform, named Digital Twin System, is presented for rapid customization of flow-type smart manufacturing systems. The digital twin-based CMCO approach could realize the hardware-in-the-loop simulation to avoid the potential design errors/inefficiency and verify the dynamic execution of a new manufacturing system in its early stage of deployment. Quick-response algorithms could be integrated into the digital twin to perform dynamic optimization based on the online data to improve the system operation efficiency of the manufacturing system. Future research directions include incorporating more artificial intelligence techniques with advanced manufacturing technologies in the manufacturing system design.

Table A2
The notations in the formulation of multi-objective optimization.

Notations	Remarks
α_i	The blanking rate
$\overline{\alpha}$	The average blanking rate
C	The operation cost
β_k^i	The loading rate
D_n	The delivery time of nth production batch
b_i	The parts number of ith production batch
O_j	The parts number of jth production order
ω	The weight vector of α, β, D_n
M	The blanking solution
L	The loading solution
$GC(M)$	The group constraint of blanking solution
$GC(L)$	The group constraint of loading solution
$\widetilde{G}(M_k)$	The Guillotine Cutting constraint of blanking solution
$\widetilde{F}(L_k^i)$	The second-order stratification constraint of loading solution
$\widetilde{R}(M,L)$	The correspondence relation between the blanking and loading
μ	The pre-set regulation parameter for $\widetilde{R}(M,L)$
$r(b)$	The minimum deviation of the delivery time of production batch b
ε	The threshold value of deviation $r(b)$

Declaration of Competing Interest

The authors declare that they have no conflict of interest.

Acknowledgments

This work was supported by the Key-Area Research and Development Program of Guangdong Province under Grant No. 2019B090916002; the National Key Research and Development Program of China under Grant No. 2018AAA0101700 and 2019YFB1706200; the Science and Technology Planning Project of Guangdong Province of China under Grant No. 2019A050503010 and 2019A1515011815; the National Natural Science Foundation of China under Grant No. 51675108 and 51705091; the Science and Technology Plan Project of Guangzhou under Grant No. 201804020092; and the Shenzhen Science and Technology Innovation Committee under Grant No. JCY20170818100156260.

Appendix A

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