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A Digital Twin-Based Approach for Designing and Multi-Objective Optimization of Hollow Glass Production Line

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ABSTRACT Various new national advanced manufacturing strategies, such as Industry 4.0, Industrial Internet, and Made in China 2025, are issued to achieve smart manufacturing, resulting in the increasing number of newly designed production lines in both developed and developing countries. Under the individualized designing demands, more realistic virtual models mirroring the real worlds of production lines are essential to bridge the gap between design and operation. This paper presents a digital twin-based approach for rapid individualized designing of the hollow glass production line. The digital twin merges physics-based system modeling and distributed real-time process data to generate an authoritative digital design of the system at pre-production phase. A digital twin-based analytical decoupling framework is also developed to provide engineering analysis capabilities and support the decision-making over the system designing and solution evaluation. Three key enabling techniques as well as a case study in hollow glass production line are addressed to validate the proposed approach.

INDEX TERMS Digital twin, individualized designing, mass individualization, multi-view synchronization, semi-physical simulation.

I. INTRODUCTION

The mass individualization paradigm as well as service concepts deeply affect design of production line [1], [2]. The individualized design of each production line presents distinctive characteristics due to the personalized needs of system construction, including the diversification of workshop venue, difference of the production capacity, constraint of construction cost, and integration of various legacy equipment [3], [4]. Correspondingly, the manufacturers are in desperate need of two critical abilities. The first ability is quickly translating the end-product information into the production line configurations and machine control schema in a software environment, which will improve the efficiency between R&D and production phase. The second ability is assessing the consequences of system design and servicing decisions through virtual models, which is also an important competitive factor of cutting-down costs for manufacturers.

Designers are usually using and computer-aided simulation and engineering tools to predict performance of various designs earlier in the life cycle, reduce reliance on expensive and various physical testing, optimize design for maximum performance, and cut-down design time and cost. However, conventional simulations of products and production processes are extensively used only to secure superior quality in the final product. The optimization during design and preproduction are limited to factors such as tolerances, locator positions, and clamping strategies, rather than complex coupling relationships among configurations, planning, and scheduling variables [5]. The major issue is how to effectively connect the design and operation of production line.

Driven by the Industry 4.0 vision [6], [7] and the development of big data analytics [8], [9], faster algorithms, increased computation power, and amount of available data enable the simulation with ability of real-time control and optimization of products and production lines, which is referred to as a Digital Twin [10], using a digital copy of the physical system to perform real-time optimization. The breakthrough is achieved from two aspects: 1) Calculation time has gone from hours to minutes, which has made it possible to explore the solution space searching for the global optimum; 2) Increased use of sensors and on-line measuring equipment [11] are making it possible to reuse simulation models during both pre-production and production phases, now with real context data rather than estimated or historical data as input [12], [13]. This will allow for adjustment of machine settings for the work-in-process (WIP) in line based on simulations in the virtual world before the physical changeover, reducing machine setup times and increasing quality. The digital twin's ability to link enormous amounts of data to fast simulation also makes it possible to perform real-time optimization of products and production processes. Particularly in design, realistic product and production process models are essential to allow the early and efficient assessment of the consequences, performance, quality of the design decisions on products and production line.

However, current approaches to implementing the vision of digital twin lack a conceptual basis, evidenced by insufficient possibilities including the real-time synchronization between the digital and the physical world to establish closed control loops at multiple granularity, the absence of high-fidelity models for remote semi-physical simulation and virtual testing, the challenges of mining big data for performance prediction of complex product or production lines, and the lacking of uncertainty quantification methods for established models. Indeed, these challenges can only be settled based on a sound technique basis and a comprehensive model for the digital twin. Also, a mechanism of feedbacking effective information collected in the production of the design phase hinders the applicability of the digital twin vision to design of production line.

To bridge above gaps, a new kind of digital twin-based model for individualized designing of hollow glass production line is proposed, combining the custom design theory, basic synchronization technology, and intelligent multi-objective optimization algorithm. The digital twin model is used for production line design (including functionality and information needed in each phase/step) in the pre-production phase and later inherited for inspection preparation and process control. Finally, a rapid individualized design platform for production line is developed. How the proposed digital twin model enables individualized designing is discussed via a case study of hollow glass production line.

The outline is organized as follows. Based on a review on related works in section 2, the architecture and design logics are presented in section 3. Three key enabling techniques including reference models, distributed integration, multi-objective optimization between static design and dynamic control is detailed in section 4. Section 5 and 6 give an illustrative application and discussions to verify the proposed model, respectively. Section 7 makes the summarization.

II. RELATED WORKS

Aiming at satisfying customers' differentiation demands, the individualized design is a process of designing, selecting, configuring, and transforming based on variant reference models to form a new one [14]. The digital simulation and optimization based design of products and production line has grown extensively the last 20 years.

Scholars conducted a lot of in-depth research on typical product customization design methods, which are adopted at strategic, tactical, and operational level from different functional areas. The conventional product customization design methods usually firstly construct on the modularity to form the configuration space, and then combine reasoning with optimization techniques to meet the personalized needs, which is a kind of static design. However, the individualized design of production line will extend to the dynamic execution system and the operation adaptive correction mechanism, and the key is to perform some optimization problems existing in the process of coupling modeling for achieving higher execution efficiency. A smart production line of highly automated operation for individualized products is a huge investment, and return on investment requires high product quality, factory throughput, equipment utilization, flexibility, as well as low energy consumption. The initial design, resulting in late process organizations and operations, usually constitute a significant part of the system performance [15]. Optimization problems in manufacturing process, however, is a discrete optimization coupling problem. It is different from the multidisciplinary coupling optimization problem from product design area, and its unit optimization characteristics particularly fragmented, rendering distinctive industrial metrics. The most representative instance is the coupling optimization between the process planning and production scheduling scheme [16]–[18], both types of which involves resource assignment and job queue, while they pursuit different optimization objectives. Similarly, coupling optimization problems among production planning and maintenance [19], [20], and main production plan are also complex. Wong *et al.* [21] proposed an integrated ant colony algorithm-based multiagent system to deal with the integrated process planning and scheduling optimization problem. Mohapatra *et al.* [22] established multi-objective optimization model and solved it via modified non-dominated sorting genetic algorithm. The multiple coupling relationship greatly increases difficulty in solving complex optimization problem, and directly restricts the efficiency of related manufacturing process and execution cost. Increased focus on sustainability with reduced waste is also a driver for a more coupling view on optimization of system design [23].

With a rapid development on Internet of Things, data has become more ubiquitous which necessitates the effective mining tools to translate into actionable information. The Digital Twin was proposed and adopted by NASA for monitoring and optimization on safety and reliability optimizations of spacecraft [10], [24]–[27]. The digital twin vision refers to a comprehensive physical and functional description of a component, product or system [28], which includes more or less all information which could be useful in the current and subsequent lifecycle phases [15], [29]. Simulation and seamless transfer of data from one life cycle phase to the subsequent phase is the core of the digital twin vision [30].

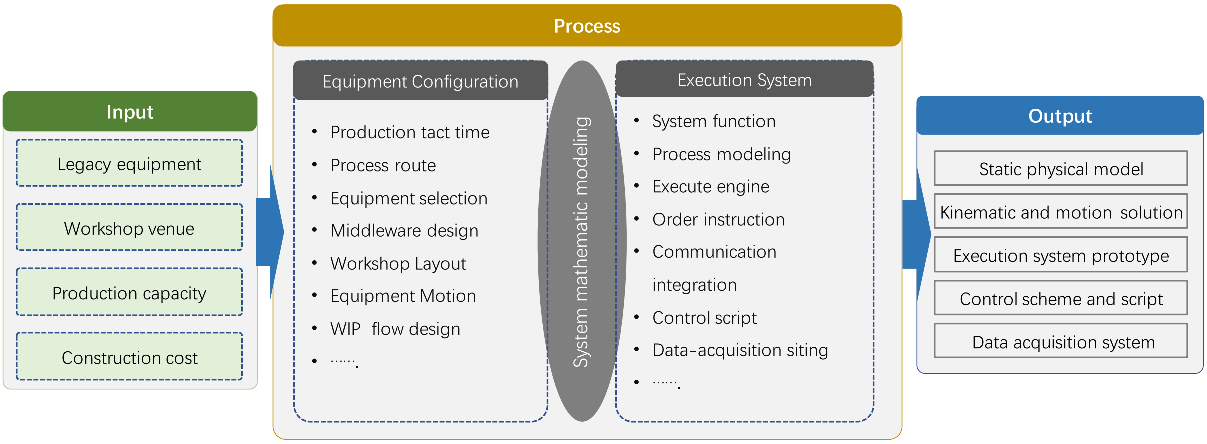

FIGURE 1. An input-process-output view of digital twin-based design system.

Two typical understandings/areas of the digital twin can be observed in industrial practice [31]. In the production design area, companies increasingly use complex product models to boost the immersion in virtual and augmented reality applications [32]. TESLA aims at developing a digital twin for every built car, hence enabling synchronous data transmission between the car and the factory, whereas Dassault strives for the product design performance. In the system management area [33], General Electric emphasizes forecasting the health and performance of their products over lifetime [34], while SIEMENS focuses on establishing a connection between the virtual model and the physical part for improving efficiency and quality in manufacturing.

The rapid individualized design of production line not only includes the geometric structure and function configuration, but also involves the dynamic adaptability of execution system. The improvement on adaptive ability of execution system strictly dependents on the comprehension of key field problems, which requires highly-precise mathematical modeling [35] and the fast algorithm for the coupling optimization problem in the manufacturing execution process. Since the pursuit of systematization modeling exists a lot of difficulty, it is a promising approach by incorporating the special decoupling algorithm into digital twin model of production line.

III. DIGITAL TWIN-BASED DESIGN APPROACH

A. AN INPUT-PROCESS-OUTPUT VIEW OF DIGITAL TWIN-BASED DESIGN

The hollow glass is a manufactured glass product formed by partitioning a space with two or more glass plates arranged in parallel by using a certain width by an aluminium sash having the interior filled with effective molecular sieve as an absorbent. Separating bars are arranged between the edges of the two glass plates, a gas chamber is formed between the two glass plates and the separating bars, and mixed gas composed of air and krypton gas is filled into the gas chamber. Its manufacturing process comprises of operations including cutting, edge grinding, toughen, pairing store, and extrusion. It belongs to the mixed flow production mode, and time series constraint between the parts are so strict that capacity balance and utilization ratio of the bottleneck resources is a key of optimization. The absence or failure of piece part store will easily lead to production chaos, disorder, serious restriction enterprise's production efficiency. The design objective is to reduce the time to production and increase efficiency during the operations.

The input of design includes individualized parameters and variables. The process of design includes equipment configuration design and execution system design. The final output of design is the whole line model, motion script, control scheme, execution system, and data acquisition system. More detailed design process is shown in Fig. 1. The rapid individualized designing of production line holds two distinctive metrics: the first is reflected in static physical configuration, in which flexibility should be considered on the single equipment type selection, the whole line layout, customized sites, and capacity demand; the second is embodied in the dynamic execution, in which the difference of configuration will cause the fluctuation of manufacturing execution efficiency, and the execution engine must be compatible with this difference to adaptive adjust and optimize.

B. DIGITAL TWIN-BASED DESIGNING AND DECOUPLING LOGIC

A digital twin-based iterative rapid individualized design approach is proposed. As shown in Fig. 2, it consists of three major steps:

1) The rapid individualized design relies on the predefined reference models and interfaces. The overall design solution on the platform can not only be used for quantitative comparison, but also for semi-physical random disturbance and robustness test.

2) The distributed simulation is to customize the whole line based on field and customization capacity via 3D modeling of single equipment, precisely assembling of whole line, performing semi-physical simulation (including

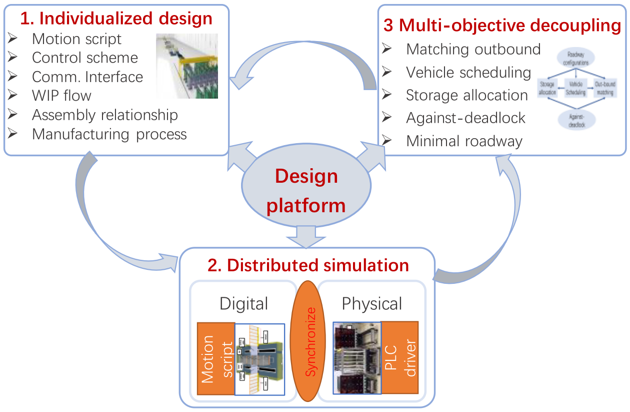

FIGURE 2. **Digital twin-based iterative rapid individualized designing approach.**

physical properties such as friction and gravity) in the model, and evaluating the whole line of execution result. Different from the traditional simulation architecture, the simulation is used as a validation tool for optimization solution, rather than only visual display of simulating random events and overall optimization solution. The virtual twinning based on distributed simulation establishes relations between physical production line and their virtual models, and allows the check for conformance with the design intent and customer requirements.

3) The multi-objective optimization acts various optimizing calculation on schemes and plans, in view of factors such as the optimization mechanism, circumstances of the whole line equipment, current production situation, lower feedback from the whole line execution.

The design platform is to establish communication channel among the designing simulation and optimization. In fact, there exists a closed-loop mechanism between the static design and dynamic execution; in other words, the static design is validated by the dynamic execution simulation results, while the dynamic execution is promoted through the adjustments of static design. In this interaction process, the potential coupling among material optimization, the energy consumption, and resource scheduling restricts the execution efficiency, which is validated by high-level semi-physical simulation.

IV. KEY ENABLING TECHNIQUES

The most challenging aspect for realizing digital twin-based individualized design is the real-time synchronization and decupling of multi-objective optimization problems. This section describes three key enabling techniques.

A. RAPID INDIVIDUALIZED DESIGN BASED ON REFERENCE MODELS

The first step is to rapidly create an initial digital model of physical production line using reference models. Though mass individualization paradigm impels the construction of massive quantities of smart production lines, these instances are mere unrelated copies. In design of digital copies of the physical manufacturing, important model properties such as scalability [36], interoperability, expansibility, and fidelity should be defined. The idea of building reference models [37] is adopted, which refers to producing a copy of a production line and using it for reasoning about other instances of the similar production line, and finally establishing a relation between multiple copies. As enabler of interoperability and integration, a four-tuple semantic data model is established as a reference representation of system design and operations, and it can be formulated as:

$$RefMdl = \{Sta, scp, Ctrl, Intf\} \tag{1}$$

where the four elements denote static attributes, motion script, control scheme, and communication interface, respectively. The XAML form is adopted as a meta model for the exchange of reference models, because it stores engineering information in the object-oriented paradigm and allows the modeling of physical and logical production line components as data objects encapsulating different attributes. Different operations on this reference model along the life-cycle [38] (such as composition, decomposition, conversion, and evaluation) can also be addressed. Based on the reference models, an individualized design of production line can be denoted as:

$$ManuSys = \{WIP, Eqp, Pos, Asm, Pcs\} \tag{2}$$

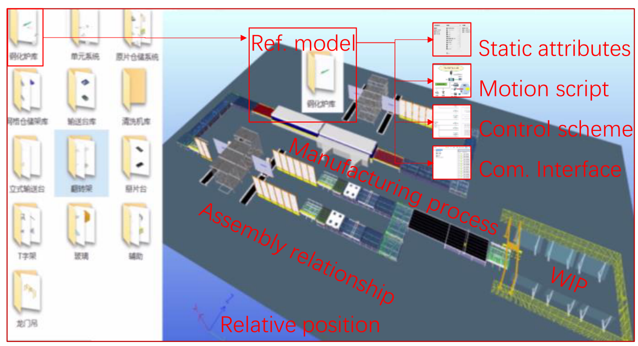

FIGURE 3. **Illustration of various reference models and its elements.**

where the five elements refer to workpiece-in-process, basic equipment node, relative position, assembly relationship, and manufacturing process, respectively. As shown in Fig. 3, this model is used for systems to exchange design information with each other, and thus designers with different technical knowledge will be able to construct physical components via a high-level model, since it serves as a sustainable service blueprint for existing best-practice solutions and can be adapted to fulfill the individualized needs of manufacturers.

Having defined the model, it will enable the exchange of the modeled attributes. In this case, the models can also be available in an open format such as STEP. With the recent technologies for the Internet of Things, the system can also retrieve information from databases in anywhere at any moment. These models allow designers without knowledge about programming to model a digital twin of the production line via operating and creating exchangeable model data.

B. MULTI-VIEW SYNCHRONIZATION AND DISTRIBUTED SEMI-PHYSICAL SIMULATION

A critical gap towards the twinning between the physical world and a virtual model is the real-time monitoring data synchronization for a digital twin in the design [39], which is realized by two major steps: 1) build the real-time communication between equipment through constructing both physical industrial Ethernet and logical PLC, and 2) bridge distributed equipment and conduct semi-physical simulation of the entire production line.

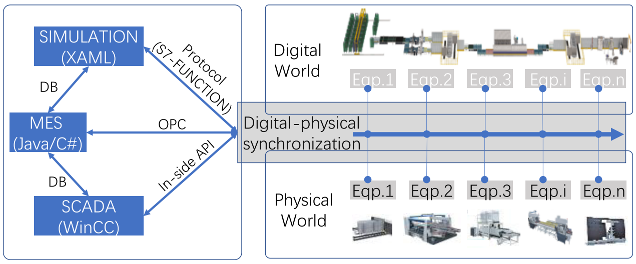

FIGURE 4. Multi-view real-time synchronization logic.

1) DIGITAL-PHYSICAL SYNCHRONIZATION IN EQUIPMENT-LEVEL

The traditional design approach usually realizes electrical control logic validation with software testing after the design of mechanical structure is assembled. As shown in Fig. 4, the real-time data synchronization between physical equipment and digital simulation model is achieved by a multi-view linkage, which is a hybrid method by incorporating Object linking and embedding for Process Control (OPC) into online database, industrial Ethernet protocols, and Application Programming Interface (API). On one hand, by enabling the digital-physical synchronization among Manufacturing Execution System (MES), physical equipment, and simulation, it changes the original serial design for concurrent design. On another hand, by enabling fast and remote test of the system performance in a unit test or distributed hardware-in-the-loop test manner, it avoids the whole line in-situ integration and will greatly reduce the cost of design.

Based on the modular encapsulation of reference model, the input and output information of each equipment is defined, and then the digital-physical synchronization bridge connection is realized through incorporating multi-view linkage technology into PLC. In detail, the digital output signal and switch variables of simulation should be connected to that of physical system, to realize the data transfer and correlation between digital and physical world. With the binding and mapping among PLC I/O point on the simulation model and I/O address on equipment, it guarantees the real-time synchronization of digital twin. The multi-view real-time synchronization serves as a paradigm shift to connect views

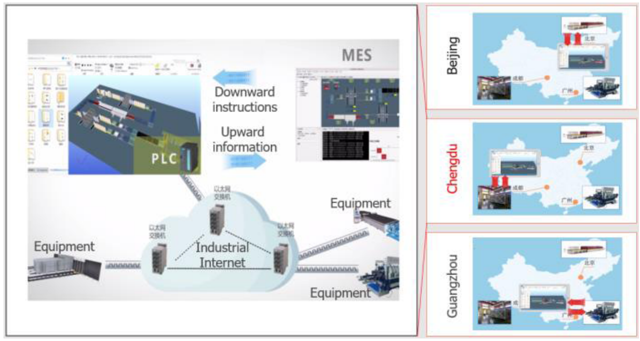

FIGURE 5. Multi-view synchronization-based distributed semi-physical integration.

TABLE 1. Related notations in the decoupling.

Notations	Implications
shp_i	The shape information of the ith model
pos_i	The position information of the ith model
num_i	The number of the models
n_{grid}	The number of the grid frame
n_{bv}	The number of the bottom-vehicle
n_{wv}	The number of the warehouse-vehicle
m	The number of the matching glass
p_{bv}	The motion control parameters of bottom-vehicle
p_{wv}	The motion control parameters of warehouse-vehicle
m_{max}	The maximum number of the matching glass
i_{hybrid}	The flag of whether supporting hybrid storing

and operations in a comprehensive model that incorporates production line layout designing and manufacturing process planning.

2) DISTRIBUTED SEMI-PHYSICAL SIMULATION AND INTEGRATION

The digital twin can use data from individual equipment to perform on-line adjustments or data from machining parts to wisely make adjustment batch number. However, individual adjustment means new challenges related to scan speed and analysis speed inside the digital twin. It is necessary to tackle the kinetic motion planning, control logic design, and then execution logic validation in the digital model rather than wait for physical model built to test.

After distributed testing of equipment, the next step is to integrate unit equipment into the entire line. Since the full-physical simulation of whole production line will take up a lot of time, space and cost, a semi-physical simulation idea is preferred to shorten the alignment test cycle and reduce the repeated work in the test development process. As shown in Fig. 5, it avoids multiple vendors do the in-situ assembly. These distributed tests in the digital model can quickly locate the malfunction reason, rule out the design mistakes, inspect the system whether can meet the practical production requirement, and test the actual production practicability and stability of physical system in advance.

C. MULTI-OBJECTIVE OPTIMIZATION IN DESIGN

The significance of digital twin-based design is to joint optimize the performance of physical system in a digital context before deployment, which varies by industry [19]. Therefore, this sub-section takes the hollow glass production line as example to discuss the multi-objective optimization problem in a digital twin manner.

1) MODELING OF MULTI-OBJECTIVE OPTIMIZATION PROBLEM

The hollow glass storage system is a key link in the process of hollow glass production line, and has strong proactive intelligent requirements. The major operation in the hollow glass production line is to match diverse types of glasses, which must consider multiple factors including production planning, warehouse pairing efficiency, inventory capacity, equipment operation efficiency, and order delivery time. Isolated or one-sided pursuit of these optimization goals will easily result in production imbalance, rising energy costs, and decrement capacity fell.

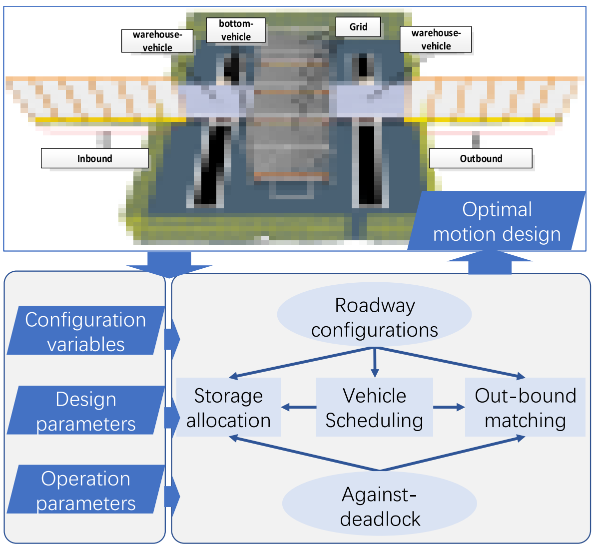

FIGURE 6. **Coupling relationship of multi-objective optimization design.**

The coupling among multi-objective optimization problems in the process of design is shown in Fig. 6. It comprises of three problems including storage allocation optimization (maximize the use of storage space as the goal), vehicle scheduling (minimize waiting time and delivery distance as the goal), and outbound matching optimization (get reasonable matching order and improve the efficiency of outbound as the goal). The coupling submits to two constraints, i.e., roadway configuration rule and warehousing against deadlocks rule. The first is to guarantee the same roadway can only be dynamic stored with the glass of same type, and the second represents all outbound glass can be matched ahead the dynamic storage allocation process. Table 1 details related notations in the decoupling.

2) SOLVING OF MULTI-OBJECTIVE OPTIMIZATION PROBLEM

The design goals of hollow glass production line include load balancing in insulating glass production process, fast response, high efficiency, low energy consumption, and enough capacity. Considering the complex coupling relationship among three optimization problems, a decoupling strategy together with the multi-objective optimization calculation flow chart is proposed in Fig. 7. By adopting a hierarchical optimization strategy, the algorithm gives the highest priority to configuration rules of roadway and storage allocation for outbound deadlock avoidance, then performs rapid matching dispatch optimization according to the real-time inventory storing status, and finally schedules the bottom-vehicle and warehouse-vehicle according to the task priority and the real-time storing status. This hierarchical multi-objective optimization algorithm has a characteristic of low computation complexity and can quickly response to various events within a specified time. This metric makes the algorithm qualified in the digital-twin context, since it can realize the dynamic real-time scheduling.

3) KEY COMPONENTS OF DECOUPLING ALGORITHM

There exist three sub-processes in the proposed algorithm, namely, storage allocation optimization, vehicle scheduling, and outbound matching optimization.

The storage allocation optimization should avoid deadlock ahead to enable that the glass can match outbound from the right end. According to the configuration rules, the glasses with of the same thickness store on the same roadway, and each type of glass has a corresponding ID according to the incoming order. If the ID of glass to be put in storage is less than that has been put in storage, a new roadway storage of the same type should be open to avoid deadlock. Fig. 8 shows a situation of ten pairs of glass storage that will not be deadlocked, and there are also other 207 species of outbound order available (*e.g.*, 1-2-3-4-5-6-4-5-6-10 or 1-2-3-7-10-3-7-10-3-9.).

As for the vehicle scheduling, on one hand, reasonable scheduling at the bottom-vehicle according to the task priority reduce waiting time and improve the efficiency of vehicle motion. This paper integrates three strategies including partition principle, nearby principle, and outbound priority principle. On another hand, the first-fit intake strategy is adopted scheduling at the warehouse-vehicle for avoiding deadlock. It can accommodate glass to existing roadways and avoiding open new roadway, which can improve the throughput efficiency of grid frame.

With respect to outbound matching optimization, the goal is to quickly find glass stored in the current road way that can be matched outbound. The matching for glass in the right side of roadway is valid only if its matching glass are on the right end of roadway. When storage is large, the glasses are matched outbound according to first-in-first-out rule and order priority.

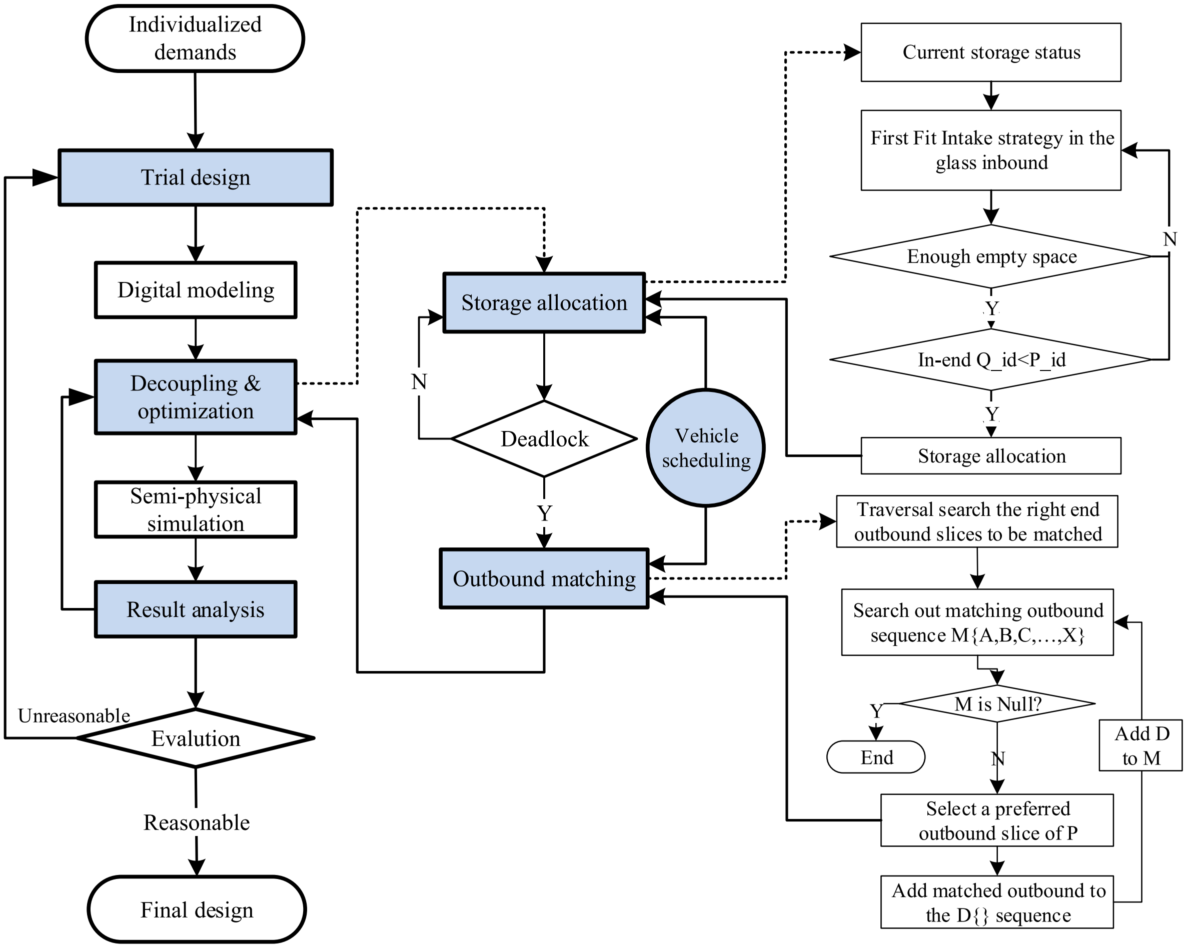

FIGURE 7. Decoupling of multi-objective optimization problems.

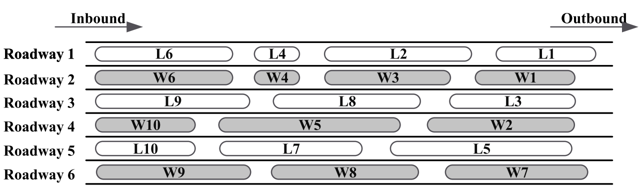

FIGURE 8. An illustration of storage allocation of ten pairs glass.

V. CASE STUDY AND EXPERIMENTS

A. INDIVIDUALIZED DEMANDS

The design of the hollow glass production line is suffered from the multiple constraints of capacity, layout, and process route. It should be compatible with different number of matching, the reservoir distribution, deadlock prevention mechanism, and vehicle scheduling in the matching. A flexible control system exists significant difference and is also the new form of requirements.

The individualized parameters can be categorized into four major types namely, capacity variables (*e.g.*, inventory capacity, throughput, and largest matching number), configuration parameters (*e.g.*, grid frame, roadway, vehicle, and layout), control schemes (*e.g.*, motion planning, control logic, sensor layout, convey instructions, and information collection) and the execution parameters (*e.g.*, inventory management, distribution of roadway, vehicle scheduling, and deadlock avoidance). The final output are assembly model, control scheme, and execution system.

Although the design variables is quantitative parameters, but it does not directly input as the technical parameters of system, its reasons include: 1) the inventory capacity is closely related to maximum matching number and order specifications, and thus the final design of capacity will be a conditional-precise variable; 2) allowing input and output at the same time results in adding to uncertainty and nonlinear relations of inventory throughput; and 3) the vehicle performance is closely related to inventory capacity, throughput, and storage allocation.

B. DIGITAL TWIN-BASED DESIGN PROCESS

Based on the proposed three key enabling techniques, a digital twin-based rapid individualized designing platform for hollow glass production line is presented in Fig. 9. The proposed design platform includes upper-level calculation

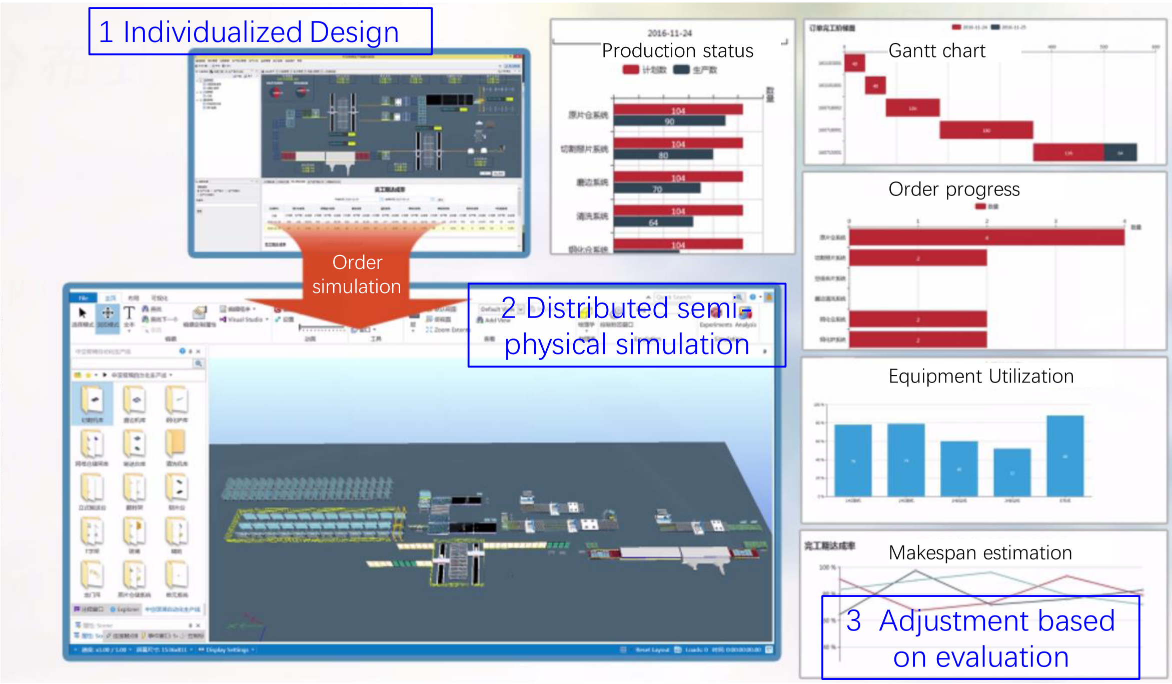

FIGURE 9. **Digital twin-based design of hollow glass production line.**

system and lower-level simulation platform. The control system is developed with J2EE programing architecture and integrated with intelligent multi-objective optimization algorithm. The simulation platform is established through secondary development on the command and information channel based on database and a 3D engine. The calculation system executes the optimization kernel and then transmits the optimization result to simulation platform in the form of a production order. The simulation platform feedback design information from the field to the control system. The simulation platform has real physical properties (*e.g.,* gravity, friction, speed, impact, and inertia.) to depict the real logistics and manufacturing process. As shown in Fig. 9, the individualized design is conducted as following three specific steps:

Step 1. Initial individualized design. The setting up of automatic production line requires special equipment, transmission equipment, storage equipment, robots and other equipment. Based on a series of predefined three-dimensional reference models and the modular encapsulation, the designer can do quick assembly and operation of production line. The function and efficiency of equipment based on the actual action mode and control mode are encapsulated, and the standardized data interface and information interface are defined.

Step 2: Distributed semi-physical simulation. According to the requirements on workshop venue, capacity, process, takt, equipment, plan, a quick layout planning and model assembling are conducted on the simulation platform in a distributed semi-physical manner. The motion design, control scheme design, execution engine design, and simulation of dynamic operation for every link in the whole line are finished, and finally formed a set of initial whole line custom design and intelligent execution kernel (including mathematical modeling, unit algorithm, and the whole line scheduling algorithm).

Step 3: Design adjustment based on performance evaluation. Based on the preliminary design scheme, the production process is verified with the help of simulation platform for dynamic simulation. According to the operation efficiency and load analysis for design modifications, a new set of the most suitable design for the whole line of custom and intelligent implement kernel is formed.

C. COMPARATIVE EXPERIMENTS AND ANALYSIS

At present, this system has been successfully applied to a hollow glass processing enterprise in Chengdu, China. According to the latest statics from this enterprise, the fastest rhythm of hollow hot line pressing is about 16s per piece. The system can help enterprises to save artificial cost more than two workers in each stage. By using random order generator to simulate a batch of order, a series of simulation on design of production line is conducted. After the performing of in the kernel optimization engine and scheduling rules, the results about grid frame matching storage system simulation are obtained in Table 2 based on a statistical eight days processing of different batch numbers. The total length of WIP glass (*i.e., Lth_{wip}*) ranges 73258 from to 63748.

The results show that the proposed algorithm significant improves performance metrics such as the roadway utilization rate and throughput efficiency, which apparently exceeds the engineering requirements threshold (*i.e.*, roadway utilization rate is beyond 85%). Therefore, the proposed system meets the goal of improving the efficiency of the hollow

TABLE 2. Results on the system simulation.

No.	Batch	Lth_{wip}	Frc_{rw}	Frc_{bv}	Ulz_{rw}	Ulz_{bv}
1	744	73258	237	229	70.2	69.5
2	932	71292	224	217	72.3	71.4
3	462	60492	199	195	69.1	67.4
4	606	61324	200	219	69.7	60.9
5	394	58732	198	173	67.4	73.8
6	1040	64136	200	181	73.1	78.1
7	782	66112	225	201	66.8	71.5
8	372	63748	216	179	67.1	77.4
Avg	666.5	64887	212.4	199.2	69.5	71.3

glass storage and matching. The roadway utilization rate (*i.e.,* Ulz_{rw}) is about 69.5% on average, and the major resistance factors are glass storage disorder and the ascending rules of roadway storage distribution. The outbound high-speed vehicles utilization rate (*i.e.,* Ulz_{bv}) is about 71.3%, which is hindered by that glass is a unit with the outbound matching. In conclusion, the proposed digital twin-based design and decoupling system significant improves the performance of the production line, and of course, the decoupling algorithm needs to be improved in the later research.

VI. DISCUSSIONS

A. THE BENEFITS

The benefits and contributions of this paper can be concluded as three points. Firstly, this paper presents an innovative rapid individualized design platform, which covers both static configuration design and execution system design. With the aid of the massive reference models, the designer can quickly complete the production line layout design, equipment configuration, and the virtual assembly of model. According to our statistics, it takes average a day to satisfy customers individualized requirements, a week to enable the motion of whole production line, and a month to integrate the whole equipment including the products, equipment, and execution system. Secondly, the digital twin-based platform can simulate production order and accurate predict the order delivery time, through collecting production takt and calculating production load. The production performance of the whole line can be analyzed and feedback to the initial design. Once a deficient performance, the virtual design can be adjusted and iterated until find the optimal design of the whole line. Thirdly, this digital twin-based model is promising for in-line inspection and may well be combined with real-time process adjustment. Through the real-time feedback to the digital model, it can realize full view and transparent monitoring of the production line, and provide data support to optimize the production line.

B. THE CHALLENGES

The first challenge is to build a digital twin model combining product lifecycle management, manufacturing execution system, and operations management system [40], [41]. After releasing process plans to the manufacturing execution system, using digital twin model in the cloud server [23] to generate detailed work instructions, associated with the production process design. Therefore, if there is any change from a production environment, the entire process will be updated accordingly in the design and plan.

The second challenge is how to incorporate the big data analytics [42] into digital twin model. When directly collect real-time data from the production equipment, it will cover the information on the digital twin model. When compared the design with actual manufacturing result, the big data analytics are supposed to identify whether there is a difference, and find out the cause of the differences [43], [44]. Also, intelligent decoupling of combined problems is desirable.

The third challenge is to build a more comprehensive digital twin driven physical-cyber-social connected production line [45]–[47]. The preliminary function of digital twin model is to help enterprises to design and manufacture of excellent products. However, meaning more profound is that digital twin model can continue to accumulate the knowledge of the design and manufacturing, which can be reused and improved continuously. The implementation of digital twin is toward smart manufacturing system [48].

VII. CONCLUSIONS

The individualized design plays a significant role in the cost and performance of hollow glass production line. This paper proposed digital twin-based rapid individualized designing of production line. Through the analysis of configuration variables in the design of production line, as well as the design of running process need to meet process constraints and the coupled optimization problems, this paper proposed an idea of "iterative optimization between static design and dynamic execution". The proposed digital twin model enhances the ability to digitally simulate how the production line will perform in the real world. Evidenced by a successful design application in hollow glass matching warehouse system, the proposed decoupling algorithm can provide design with an optimization guide. Actually, the proposed digital twin-based model can be applied into many automated flow-type manufacturing systems, such as custom-made furniture production line and 3C product manufacturing line. Future work will be conducted in incorporating the big data analytics into digital twin model for both design and operating of production line.

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