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ARTICLE

Digital twin-driven joint optimisation of packing and storage assignment in large-scale automated high-rise warehouse product-service system

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ABSTRACT

Current mass individualisation and service-oriented paradigm calls for high flexibility and agility in the warehouse system to adapt changes in products. This paper proposes a novel digital twin-driven joint optimisation approach for warehousing in large-scale automated high-rise warehouse product-service system. A Digital Twin System is developed to aggregate real-time data from physical warehouse product-service system and then to map it to the cyber model. A joint optimisation model on how to timely optimise stacked packing and storage assignment of warehouse product-service system is integrated to the Digital Twin System. Through perceiving online data from the physical warehouse product-service system, periodical optimal decisions can be obtained via the joint optimisation model and then fed back to the semi-physical simulation engine in the Digital Twin System for verifying the implementation result. A demonstrative prototype is developed and verified with a case study of a tobacco warehouse product-service system. The proposed approach can maximise the utilisation and efficiency of the large-scale automated high-rise warehouse product-service system.

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KEYWORDS
Digital twin; large-scale automated high-rise warehouse; warehouse product-service system; storage assignment; cyber-physical systems

1. Introduction

With the wide application of big data analytics, warehouse system has entered a stage of rapid development towards intelligence. Statistics show that the machining time only accounts for about 5% of the total production time and the warehousing cost in the system accounts for more than 40% of the total production cost. A well-operated warehouse system can not only reduce the cost of the whole supply chain (Qu et al. 2010), but also improve the operation efficiency and the overall service level of the enterprise. Reducing the cost of warehousing has become the top priority of many enterprises to improve economic efficiency.

Conventional warehouse system inside an enterprise is of limited functionality in storage and independent from the packing operation and goods distribution. It is also small in scale and thus usually managed according to periodically statistics, prespecified rules, or artificial experience. As a new kind of inventory service mode appeared in the Industrial Parks under the background of service-oriented manufacturing, large-scale automated high-rise warehouse product-service system integrates multiple functions of packing, stocking, storage, picking, transportation and distribution of goods. It can contain up to tens of thousands of pallets and logical volumes. The daily warehousing volume is large and the available time window for each operation is short (Zhong et al. 2013). Both the in-stocking and out-stocking operation have unpredictable demands and interactions, and consequently, the decisions that need to be made are massive (Alvarez et al. 2001). Driven by the personalised demands, small batches with low volumes have to be delivered more frequently and shorter response time from a significantly wider variety of stock keeping units (SKUs) (Berg and Zijm 1999). Low degree of automation and the lack of efficient management methods make the enterprises face great investment risk. Dealing with the management of warehouse product-service system requires not only an online

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monitoring system as foundation but also a systematic optimisation method. A better insight in the key factors for improving the capacity of warehouse product-service systems may lead to significant reductions in inventory levels and improvement of response time (Huang et al. 2019b).

Conventional warehousing problem includes distribution system decision, inventory management under space restrictions, storage assignment, scheduling of warehouse operations, and order-picking. The final operation, defined as the process of retrieving products from storage in response to a specific demand, is recognised as the costliest activity for most warehouses (Koster, Le-Duc, and Roodbergen 2007). Besides the warehousing, the capability of warehouse product-service systems is also influenced by the efficiency of packing (also mentioned as case-packing) of goods, which is a key process before warehousing. The optimisation of packing can reduce the number of cartons used, reduce the bottleneck warehousing process, and prevent the blockage of logistics. Underperformance in packing system will consequently lead to unsatisfactory service of warehouse product-service system for the whole supply chain. Since there only exists a very short-time interval and limited-buffer space between packing and storage assignment procedures, the closed-coupling relationship between these two operations calls for an efficient decision-support system. Despites the urgent need of a joint modelling between packing and storage assignment management, yet we didn't find research about the joint optimisation model and decision-support tool.

With the rise of Industry 4.0, the new concept of digital twin has attracted more and more attention (Tao et al. 2018a and Tao et al. 2018b). Via the integration of a new generation of information technology and IoT technology, digital twin refers to realising the real-time mapping, interaction, integration and data fusion between the physical and virtual system. It is a new mode of operation to achieve the optimisation of system performance metrics such as design, configuration, control, scheduling and operating (Leng and Jiang 2019).

This paper proposes a novel digital twin-driven joint optimisation approach for packing and storage assignment in large-scale automated high-rise warehouse product-service system. A Digital Twin System is developed to integrate all kinds of real-time data from physical warehouse product-service system and then to map it to the cyber model. A joint optimisation model on how to quick optimise stacked packing and storage assignment of warehouse product-service system to adapt rapidly change of product is integrated to the Digital Twin System. Through perceiving online data from the Digital Twin System of warehouse product-service system, the periodical optimal decision can be obtained via the joint optimisation model and then fed back to semi-physical simulation engine in Digital Twin System for verifying the implementation effect. The iteration between optimisation engine and semi-physical simulation engine in Digital Twin System can maximise the utilisation and efficiency of the large-scale high-rise warehouse product-service system.

The remainder of the paper is organised as follows. After a literature review on recent warehouse system research and digital twin models in industry, section 3 details how to build a Digital Twin System of large-scale automated high-rise warehouse product-service system. Section 4 focuses on the twining data-driven joint optimisation between case-packing and storage assignment problem. Section 5 presents a demonstrative prototype of Digital Twin System as well as a case study in a tobacco warehouse product-service system. Conclusions are addressed in section 6.

2. Related works

Research on optimisation of warehouse system could be categorised into the design stage and the operation stage (Ashayeri and Gelders 1985).

The design optimisation of warehouse system includes overall structure, sizing and dimensioning, department layout, equipment selection and operation strategy (Gu, Goetschalckx, and Mcginnis 2010). The decisions (variables) in this stage involve material flow, department identification, size of the warehouse, pallet block-stacking pattern, aisle orientation, number, length and width of aisle, door locations, storage equipment selection, material handling equipment selection, storage selection and order picking method selection. Önüt, Tuzkaya, and Doğaç (2008) proposed a particle swarm optimisation algorithm for the multiple-level warehouse layout design problem. Horta, Coelho, and Relvas (2016) proposed a mathematical programming approach for optimising layout of a just-in-time cross-docking warehouse. Thomas and Meller (2015) provided a set of guidelines for obtaining a good design configuration for a manual case-picking warehouse on the decisions of size and layout of the forward area, dock door configuration, pallet area shape and pallet rack height. Öztürkoğlu and Hoser (2019) developed new warehouse designs that provide a reduction in travel distance for the order-picking operation, and then developed a harmony search algorithm to find optimal tunnel positions that minimise the average tour length under a randomised storage policy in the order-picking.

The operation optimisation of warehouse system includes receiving and shipping, SKU-department assignment, zoning, storage location assignment, batching, routing and sequencing, and sorting (Gu, Goetschalckx, and Mcginnis 2007). The decisions (variables) involve assignment, space allocation, truck dispatch schedule, batch size, routing and sequencing of order picking tours. Lee and Elsayed (2005) investigated the problem of the determination of the space requirements for warehouse systems operating under a dedicated storage policy. A non-linear programming model and an iterative search procedure is formulated to minimise the total cost of owned and leased storage space. Chow et al. (2006) designed a RFID-based Resource Management System (RFID-RMS) to help users to select the most suitable resource usage packages for handling warehouse operation orders by retrieving and analysing useful knowledge from a case-based data warehouse for solutions in both time saving and cost-effective manner. Dotoli et al. (2015) proposed an integrated framework of Unified Modelling Language, Value Stream Mapping tool, and a mathematical formulation for the analysis and optimisation of production warehouses. Lu et al. (2016) presented an interventionist routing algorithm for both static and heuristic dynamic optimising the order-picking routes in warehouse operations. More realistic and improved order-packing planning models should be developed (Grosse et al. 2016). Chen et al. (2016) proposed an ant colony optimisation-based routing method to find picking routes for multiple-block pickers with nondeterministic time in picker-to-parts warehouses. Yoshitake, Kamoshida, and Nagashima (2019) presented a real-time holonic scheduling method and a robotic system for order picking in logistics warehouses with automated guided vehicles. Weidinger, Boysen, and Schneider (2019) defined the resulting picker-routing problem and provided efficient solution methods of picker routing in the mixed-shelves warehouses of e-commerce.

Existing studies in warehouse product-service systems mainly focus on storage allocation, assignment and order-picking. Analytical models for dynamic optimising warehouse systems are still lacking. Some scholars focused on storage assignment integrated with other problems. Turki et al. (2017) developed a genetic algorithm-based optimisation program to find the optimal decision variables in a manufacturing–remanufacturing–transport–warehousing closed-loop supply chain. Heide et al. (2018) proposed a discrete-time modelling framework with stochastic demand for capturing an optimal network structure in shared warehouse and transportation networks. Tappia et al. (2019) proposed a queuing network-based analytical model for integrated optimising of storage and order picking systems. The interrelation with other systems such as packing system seems to be largely neglected.

As one of the key enabling technologies to achieve smart manufacturing, the digital twin has broad application prospects in the industry (Nikolakis et al. 2019).

In the design stage of product and manufacturing system, Söderberg et al. (2017) used the digital twin technology to develop the functions needed for real-time geometry assurance and to establish a data model of the product. Schleich et al. (2017) proposed a comprehensive reference model based on the concept of Skin Model Shapes, which serves as a digital twin of the physical product in design and manufacturing. Zhang et al. (2017) presented a digital twin-based approach for designing and multi-objective optimisation of a hollow glass production line. Tao et al. (2018a) proposed a new method of product design, manufacture and service based on digital twin. Liu et al. (2018) presented a digital twin-driven model for rapid individualised designing of an automated flow-shop manufacturing system. Guo et al. (2019) applied digital twin to the design of the factory for supporting designers to evaluate the result, avoiding defects, and thus improving the feasibility. Liu et al. (2019) proposed a new process evaluation method based on the digital twin to evaluate the process plan of Marine diesel engines.

In the operation stage of product and manufacturing system, Alam and El Saddik (2017) proposed a digital twin structure reference model based on cloud computing to analyse the key performance of C2PS. Tao et al. (2018b) proposed a concept of workshop based on the digital twin to achieve the interaction and integration of physical space and virtual space in the intelligent manufacturing paradigm. Urbina Coronado et al. (2018) described a complete digital twin model by combining data with production data collected by operators. Zhuang, Liu, and Xiong (2018) proposed a framework of digital twin-based smart production management and control approach for complex product assembly shop-floors. Leng et al. (2019b) proposed a digital twin-driven manufacturing network physical system for parallel controlling of the intelligent workshop. Zhao et al. (2019) proposed a digital twin-driven cyber-physical system for autonomously controlling of micro punching system.

Digital twin models are increasingly widely used in the industry. However, there exist many problems when adopting it in warehouse product-service system, specific as follows: 1) there is unbearable communication latency between cyber model and physical system due to the lack of highly efficient synchronisation mechanism (Lin et al. 2018) for different sampling cycle or data collection cycle; 2) how to develop a unified event description model for fusion of multi-source data from heterogeneous equipment (Leng et al. 2019a); and, 3) how to develop an optimisation algorithm that adapts the highly frequent dynamic adjustment requirements in the digital twin-based paradigm. This study will try to address the above questions and take the large-scale automated high-rise warehouse product-service system as a research object.

3. Digital twin-oriented semi-physical simulation of LAHW

As shown in Figure 1, the main body of the Large-scale Automated High-rise Warehouse (i.e., LAHW) product-service system consists of shelves, automatic stacking crane, in-out warehouse worktable (includes the bulk stock (reserve area) and the pick stock (forward area)), and automated packing system. Shelves are usually steel structure or reinforced concrete building that of standardised space size. The automatic stacking cranes shuttle the roadway between shelves for loading and unloading goods. The goods are identified by bar code, magnetic label, or RFID technology.

3.1 Semi-physical simulation of warehousing event

Semi-physical simulation (also mentioned as hardware-in-the-loop simulation) refers to the establishment of command channel and information channel (collectively referred to as communication channel) among the execution engine, the simulation model, and the real equipment (or parts of the actual machine), so that the execution engine of the warehouse product-service system can not only control the movement of the simulation model but also drive the action of the physical equipment. Therefore, the simulation model here is called the semi-physical simulation engine, and the establishment of the semi-physical simulation engine is the basis of the development of the Digital Twin System. Built on the 3D engine software for mapping physical equipment, the semi-physical simulation engine of dynamic warehousing event is driven by the data collected from either a communication channel or upper-level optimisation model (which will be detailed in section 4).

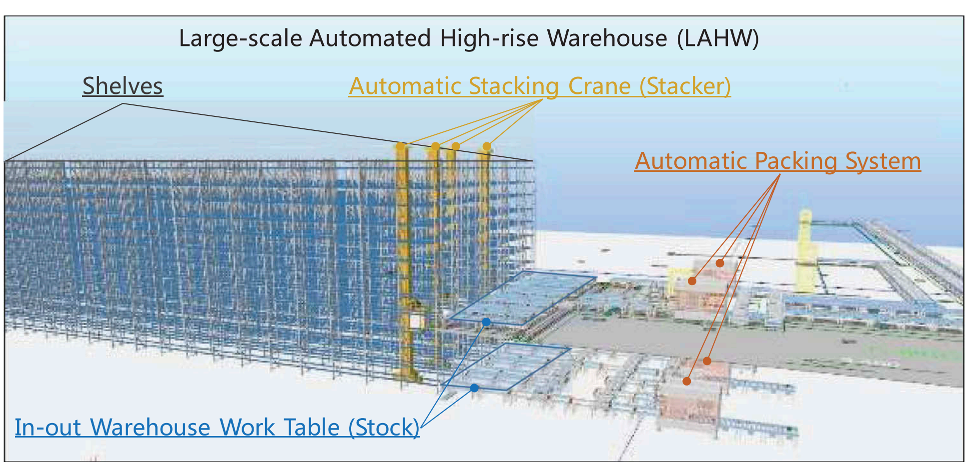

Figure 1. Structure of typical large-scale automated high-rise warehouse (LAHW).

A new kind of semi-physical simulation modelling of dynamic warehousing event is put forward. For any equipment in warehouse product-service system, it can be abstracted by its status, warehousing events, and their relationship. As for the hardware-in-the-loop simulation model of the equipment, the event is generated by the change of the state, and the change of state is driven by the instructions or information in the communication channels. Therefore, a hardware-in-the-loop simulation model of equipment can be abstracted as a triple-tuple of status, events, and instructions. Its formal definition is:

$$SM_i = (SB, E, M) \qquad (3-1)$$

where SB denotes the state block set; E represents the event set; and M refers to the instruction information set of certain equipment.

3.1.1 State block model

The concept of a state block model is introduced here for defining the state information of warehousing equipment simulation. The main body of LAHW is a stacker (i.e., automatic stacking crane). Here, we take the stacker as an example to build an abstract state block model, and then integrate the geometric model into a 3D dynamic semi-physical simulation model. The operating scene of the stacker is shown in the upper part of Figure 2. For example, as shown in the lower part of Figure 2, the state change of the kth stacker in ith warehousing operation is a closed-loop diagram of warehousing process flow, and it can be defined as follows:

$$S_i^k ::= \left\{S_{i,1}^k, S_{i,2}^k, S_{i,3}^k, S_{i,4}^k, S_{i,5}^k\right\} \qquad (3-2)$$

where $S_{i,1}^k$ denotes an idle state of stacker; $S_{i,2}^k$ refers to a state when the stacker is driven to the bulk stock; $S_{i,3}^k$ represents a goods-loading state of stacker; $S_{i,4}^k$ denotes a state of the stacker moving to the shelves; $S_{i,5}^k$ refers to a goods-unloading state of the stacker.

Similarly, the corresponding position set, trigger time set, and lasting time set can be defined as $L_i^k ::= \left\{L_{i,1}^k, L_{i,2}^k, L_{i,3}^k, L_{i,4}^k, L_{i,5}^k\right\}$, $t_i^k ::= \left\{t_{i,1}^k, t_{i,2}^k, t_{i,3}^k, t_{i,4}^k\right\}$, $T_i^k ::= \left\{T_{i,1}^k, T_{i,2}^k, T_{i,3}^k, T_{i,4}^k, T_{i,5}^k\right\}$, respectively. Thus, on the basis of the above notations, the state block model of the kth stacker in a strictly time-ordered manner is shown below:

$$SB_{i,j}^k ::= \left\langle S_{i,j}^k, S_{i,j+1}^k, L_{i,j}^k, t_{i,1}^k, T_{i,j}^k\right\rangle \qquad (3-3)$$

3.1.2 Event model

Actually, an event is defined as one action or activity that makes the state of the system change from one

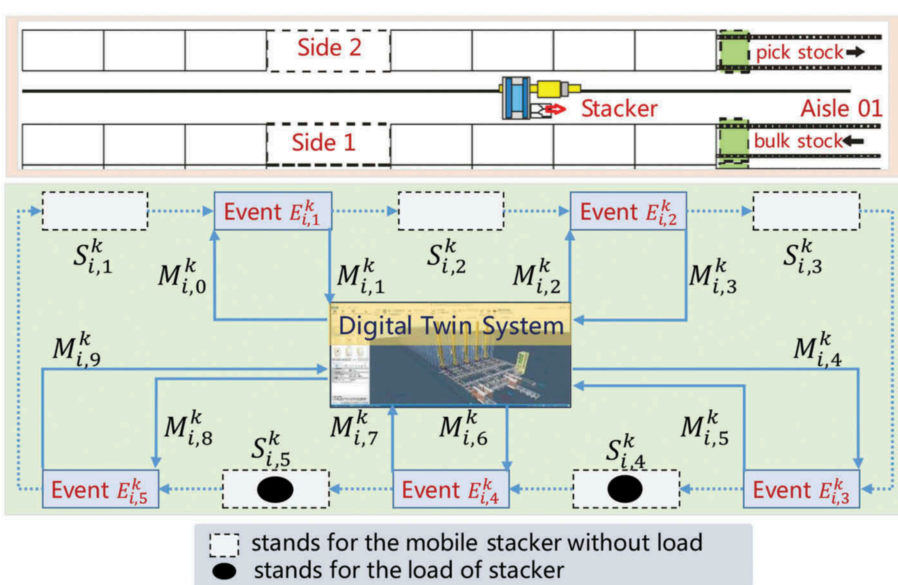

Figure 2. A closed-loop event flow of a stacker in warehousing operation.

to another. An event can be formalised on the basis of a state-pair and thereby modelled as

$$E_{i,j}^{k} = f\left(S_{i,j}^{k}, S_{i,j+1}^{k}\right) \qquad (3-4)$$

where $f()$ refers to the mapping function from a state-pair to an event. Therefore, corresponding to formula (3–2), the event flow of the kth stacker in ith warehousing operation can be defined as follows:

$$E_{i,j}^{k} ::= \left\{E_{i,1}^{k}, E_{i,2}^{k}, E_{i,3}^{k}, E_{i,4}^{k}, E_{i,5}^{k}\right\} \qquad (3-5)$$

where $E_{i,1}^{k}$ denotes that the stacker goes to the bulk stock after receiving an instruction; $E_{i,2}^{k}$ represents that the stacker arrives at the bulk stock and begins to load products; $E_{i,3}^{k}$ represents that the stacker starts to move to the shelves after loading the goods; $E_{i,4}^{k}$ denotes that the stacker arrives at the destination and begins to unload the goods; $E_{i,5}^{k}$ represents that the stacker leaves at the shelves to bulk stock after unloading the goods.

In the Digital Twin System, a communication channel is built between the host computer (i.e., digital model) and equipment (i.e., physical PLC) for enabling the interoperability. We can add an information model to state block model presented in Figure 2 to realise the information uploading and instruction issuing between physical equipment and host computer. In the warehousing operation, the interaction information set between stacker and Digital Twin System can be formalised as follows:

$$M_{i}^{k} ::= \left\{M_{i,0}^{k}, M_{i,1}^{k}, M_{i,2}^{k}, \ldots, M_{i,9}^{k}\right\} \qquad (3-6)$$

where $\left\{M_{i,0}^{k}, M_{i,2}^{k}, M_{i,4}^{k}, M_{i,6}^{k}, M_{i,8}^{k}\right\}$ denote the instructions that the upper Digital Twin System sent to the stacker, respectively; $\left\{M_{i,1}^{k}, M_{i,3}^{k}, M_{i,5}^{k}, M_{i,7}^{k}, M_{i,9}^{k}\right\}$ represent different status that the stacker feedback to the upper Digital Twin System, respectively.

3.1.3 Information model

The information model must be established based on the communication channel to realise the cyber-physical synchronisation in the Digital Twin System. Therefore, the information model can be defined as follows:

$$IM_{i}^{k} ::= \left\{M_{i,j}^{k}, M_{i,j+1}^{k}, C, P\right\} \qquad (3-7)$$

where$C \in \{0,1\}$ denotes whether the communication channel is established; and $P = \{0,1,2,3,4,5,6,7,8,9\}$ denotes specific communication protocols such as OPC, Modbus, Profinet and TwinCAT.

Based on the above definition, we can establish the mathematical model of dynamic semi-physical simulation. The host computer sends instructions to the Digital Twin System through the command channel, thus driving the operation of the semi-physical simulation model. As shown in Figure 3, the above mathematical model of state, event and information channel is expressed by Javascript or C# script on the 3D equipment (e.g., stacker) simulation model in the Digital Twin System to realise the data correlation and interoperability between the physical equipment and the cyber simulation model. According to different interactive instructions, Javascript or C# script can be utilised to drive the dynamic operation of the 3D semi-physical simulation model.

3.2 Information integration and cyber-physical synchronisation

The Digital Twin System consists of two parts: joint optimisation model and semi-physical simulation engine (Figure 4). Through perceiving online data from the physical warehouse product-service system, periodical optimal decisions can be obtained via the joint optimisation model and then fed back to the semi-physical simulation engine in the Digital Twin System for verifying the implementation result. The semi-physical simulation engine can accurately and timely realise the hardware-in-the-loop physical simulation of the warehouse based on optimised results obtained from joint optimisation model, transferred to the control instructions, and then transmitted it to the PLC system on the physical equipment. The key is to synchronise between cyber model and physical system under different sampling cycle or data collection cycle.

Firstly, a communication channel for up-forward information and down-forward instructions among virtual sensor, equipment model, RFID, physical PLC and configuration software, is established firstly. Secondly, based on the command and information channel, a database is built for caching the warehousing instruction, intermediate instruction, machine instruction, field information data, single machine historical data and background data. Then, the communication

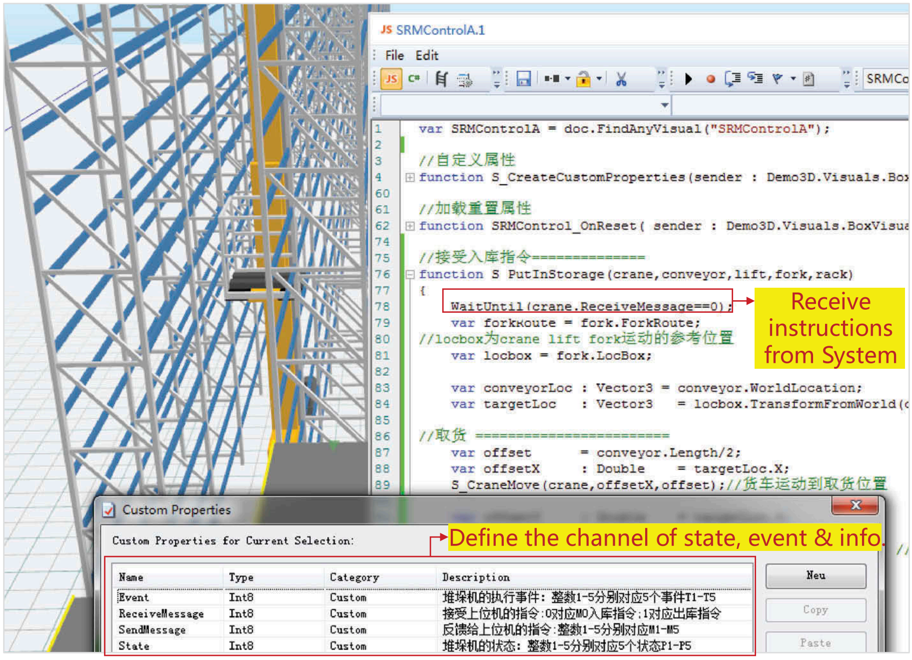

Figure 3. Digital twin-oriented script code on the cyber model of equipment.

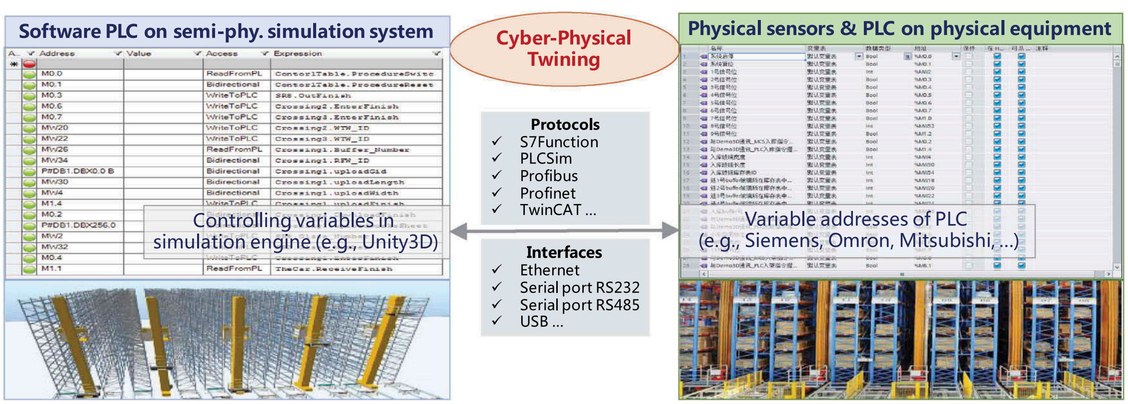

Figure 4. Technical rationale of cyber-physical synchronization.

protocol, instruction format and field information format are defined so as to facilitate timely issuance of instructions and timely upload of in-situ collected from the sensor on the warehouse equipment. As shown in Figure 4, the cyber-physical synchronisation is realised by a middleware for hybrid integrating public protocols (e.g., S7Function, Profinet, TwinCAT and Profibus) and interfaces (e.g., Ethernet, RS232 and RS485) with databases. Finally, the connection and integration between the upper joint optimisation model and controllers inside equipment are realised. Based on the visualisation engine (e.g., open source Unity3D), the performance-related statistical data are visualised, so as to carry out real-time monitoring of the whole warehouse from a multiple granularity.

The function of semi-physical simulation engine presented above includes three aspects: 1) mapping all kinds of data of the cyber models of warehouse product-service system (Zhang et al. 2015), and then providing the data input to the upper-level joint optimisation model; 2) verifying optimised results from the upper-level joint optimisation model; and 3) translating it into instructions, and then distributing the instructions to all controllers in warehouse product-service system. The semi-physical simulation engine is running during the whole process of warehousing to accumulate knowledge and record the statistics of implementation effect, such as operation balance and the bottleneck process. It can verify the optimisation scheme and continuously improve the overall system performance.

4. Twining data-driven joint optimisation model

Besides the semi-physical simulation engine, the Digital Twin System also includes a joint optimisation model. Digital twin-oriented optimisation algorithm has two characteristics: 1) rapidly identifying the optimal or near-optimal solution in a short-time for adapting to the highly frequent dynamic adjustment requirements from both the production system and stochastic delivery demands; and 2) coordination of multiple objectives of coupled optimisation problems.

4.1 Architecture of joint optimisation and its decoupling

By distributing the activities evenly over the warehouse product-service system, congestion may be reduced and activities may be balanced better among subsystems, thus increasing the throughput capacity (Berg and Zijm 1999). A study revealed that order-picking is the most costly among these warehousing activities (Berg and Zijm 1999). However, compared to goods order-picking/ex-warehousing, in-stocking is of much more quantity of flow, which poses a larger scale of optimisation problem as well as a higher response speed. Therefore, planning issues addressed in this paper are packing and storage assignment. Packing decides which parts are to be stored in which package/case and in what quantity. Storage assignment determines where the packages are to be stored. Intelligent packing may result in a reduction of the package numbers and costs of cartons. More importantly, reducing package numbers could not only reduces inventory costs but also simplifies the storage assignment operation within the warehouse (e.g., the travel time for stackers is smaller). It can be inferred out that the optimisation of packing is tightly coupled with the warehousing optimisation.

Figure 5 illustrates the operation rational of Joint Optimisation Model and Semi-physical Simulation Engine in the proposed Digital Twin System, which has been discussed at the beginning of section 3.2. The joint optimisation model is split into three sub-modules: 3D packing optimisation module, storage assignment module and heuristic bi-level programming coordinator module. The goal of the packing module is to stack a set of goods for maximising the utilisation rate of space in each package. The storage assignment module is a set of rules which can be used to assign packages to storage locations (Koster, Le-Duc, and Roodbergen 2007). This module prunes out unused resources and performs an assignment that attempts to balance the load across the available areas and equipment.

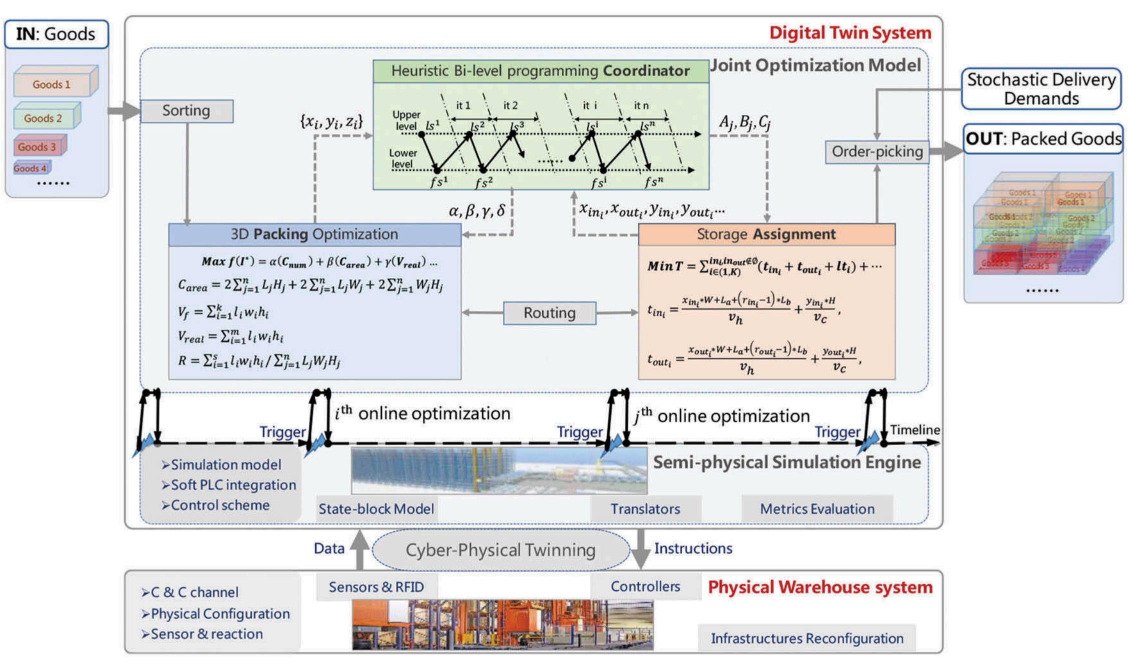

Figure 5. Architecture and rational of joint optimization in the Digital Twin System.

In the coordinator module, the heuristic bi-level programming approach of decoupling model is presented to make the overall search coordinated and feasible. The solutions can be negotiated and coordinated by weighted utility equation (*i.e.*, coordinator) as

$$\theta(\alpha, \beta, \gamma, \delta, A_i, B_i, C_i) = 0. \qquad (3-8)$$

The decision variables (i.e., $\alpha, \beta, \gamma, \delta, A_i, B_i, C_i$) will be detailed in following sub-sections. By relying on the decisions from the sub-modules of fine-grained granularity (Leng et al. 2018; Leng and Jiang 2017a), iterative heuristics can cut-down the solution space to manageable proportions. The optimisation initialises with a guess of the optimal upper-level decision values on 3D Packing Optimisation and moves this initial decision via a heuristic process to achieve a new decision. By solving the lower-level Storage Assignment problem, the optimal reaction is obtained and returned to the upper-level for each iteration. Finally, the coordinator will find optimal or near-optimal values with the extremum sequence, while the key constraint can implicitly characterise the underlying relationship between packing and storage assignment.

The iteration time cycle between packing and storage assignment can be identified by evaluating the inflow scale of goods. Here, the joint optimisation model is triggered by the metric evaluation on the system performance, namely, inbound and outbound flow. Once the metrics are higher than a pre-specified value, it will perform the optimisation rapidly and send the results to the semi-physical simulation engine for verification and generation of instructions before distributing to the physical system. The inbound flow is the number of goods stored in the warehouse through the stacker every hour and can be obtained according to the following formula

$$Q_{In} = \frac{\mu * N_{In} * p}{D_w * d_n * b} \qquad (3-9)$$

where N_{In} denotes the receipt of warehouse product-service system in a specified time interval, μ represents the comprehensive unbalanced coefficient of system, p refers to the consumption number of cases, D_w denotes the total working time during the inspection, d_n denotes the effective working time for warehouse product-service system, and b stands for the weight of a package. Similarly, the outbound flow refers to the hourly removal of the goods stored in the warehouse through the stacker, which can be denoted as Q_{Out}.

4.2 Optimisation model of 3D packing

4.2.1 Modelling of 3D packing

The packing of goods (Figure 6) is a key process before storing goods into a warehouse. The optimisation of goods packing can reduce the use of cartons, ensure the balance of loading, reduce the bottleneck warehousing process, and prevent the blockage of logistics. It is affected by many constraints, which requires an automated scheme to complete sorting and packaging efficiently under these conditions. Table 1 offers an overview of the notations. Considering the constraints of goods packing, its mathematical model is established as follows

$$C_{area} = 2\sum_{j=1}^{n} L_j H_j + 2\sum_{j=1}^{n} L_j W_j + 2\sum_{j=1}^{n} W_j H_j \qquad (4-1)$$

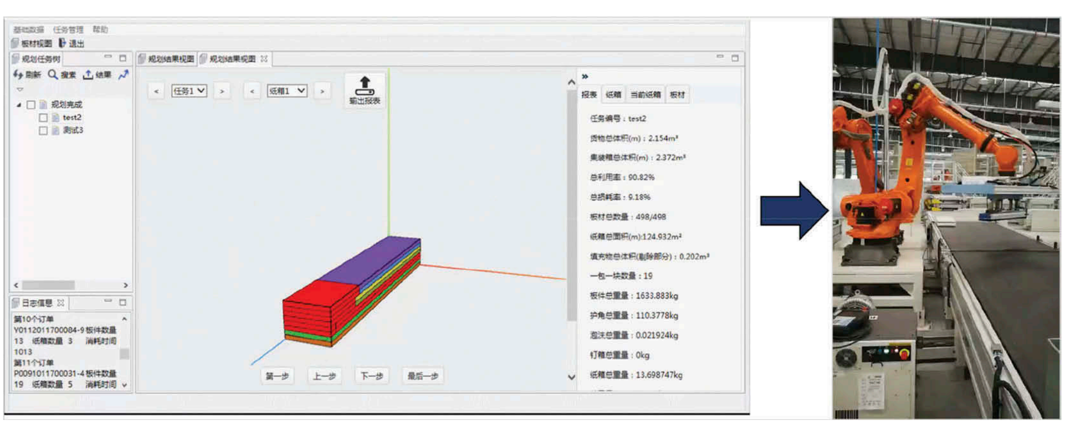

Figure 6. The 3D packing model and its physical twin.

Table 1. The notations used in storage assignment modelling.

Notations	Remarks
l_i, w_i, h_i	The length, width, and height of the *i*th goods
x_i, y_i, z_i	The coordinates of the *i*th goods in the case
m, n	The layer index in the case
C_{num}	The total number of goods in set *containerList*
C_{area}	The total surface area of the goods
V_f	The total volume of filling goods
V_{real}	The actual volume of the fill block
R	The total utilisation rate of cases
$\alpha, \beta, \gamma, \delta$	The weights among four factors

$$V_f = \sum\nolimits_{i=1}^{k} l_i w_i h_i \tag{4 – 2}$$

$$V_{real} = \sum\nolimits_{i=1}^{m} l_i w_i h_i \tag{4 – 3}$$

$$R = \sum\nolimits_{i=1}^{s} l_i w_i h_i / \sum\nolimits_{j=1}^{n} L_j W_j H_j \tag{4 – 4}$$

Therefore, the optimal scheme I^* of 3D packing is determined by four sections:

$$Max\ f(I^*) = \alpha(C_{num}) + \beta(C_{area}) + \gamma(V_{real}) + \delta(R) \tag{4 – 5}$$

The constraints in the packing process are:

(1) Items cannot overlap in the same layer of the package, that is, for any two items in the package in the same layer of S_m, S_n should meet the following requirements:

$$\begin{cases} y_m \geq y_n + w_n \\ x_n \geq x_n + l_n \end{cases} \tag{4 – 6}$$

(2) Items in different layers of the same package cannot overlap, that is, for any two items in the package in the same layer S_m, S_n should meet the following requirements:

$$z_m \geq z_n + h_n \tag{4 – 7}$$

3) The position of all items in the packages is within the allowed range and cannot exceed the permitted range. It is assumed that the item S_i is on the package C_j, and the long side is in the X-axis direction:

$$\begin{cases} max\{x_i + l_i\} \leq L_j - minL \\ max\{y_i + w_i\} \leq w_j - minW \\ max\{z_i + h_i\} \leq H_j \end{cases} \tag{4 – 8}$$

4.2.2 Optimisation algorithm for the 3D packing

To optimise the packing model proposed above, this paper proposes an optimisation algorithm of packing based on utility-layering technique. The flow of algorithm is shown in Figure 7. By adopting hierarchical optimisation strategy, suitable packages are selected for the length, width and size of goods. In the stacking process of a certain layer, the stack position of goods in the cases and its discharge sequence is determined firstly. The layered stacking of a single package is started from the lowest level. When using the single-layer packages stacking algorithm, the optimal solution is selected within a limited time via adopting the first-fit strategy, which is suitable for the rapid optimisation goal of Digital Twin System. Then, the stacked packages are mixed packing to reduce the use of cartons. Finally, for the rest empty space in the packages, a foam filling block is generated by a filling scheme. The design of this layered strategy has the characteristics of low computational complexity, which is suitable for the online optimisation demands in the Digital Twin System, and it can find a suitable optimisation scheme within a specified time.

4.3 Optimisation model of storage assignment

Packages need to be put into storage locations before they are picked to fulfill customer orders. The assignment of packages to the most convenient storage locations (i.e., SKUs) involves reducing both order-picking time and costs. An effective storage assignment policy may reduce the mean travel times of retrieval and order-picking.

There are numerous ways to assign goods/packages to storage locations (Koster, Le-Duc, and Roodbergen 2007). The conventional study on storage assignment consists of the development of a programming model and a solving heuristic procedure. However, this type of model suffers from strict hypotheses and constraints that significantly affect the feasibility of real industrial cases. Moreover, the relatively slow computing makes it unsuitable for the online optimisation goal in the Digital Twin System. This section presents a hybrid strategy of storage assignment to serve the rapid response to the material demand and production continuity (Qu et al. 2012) in the Digital Twin System.

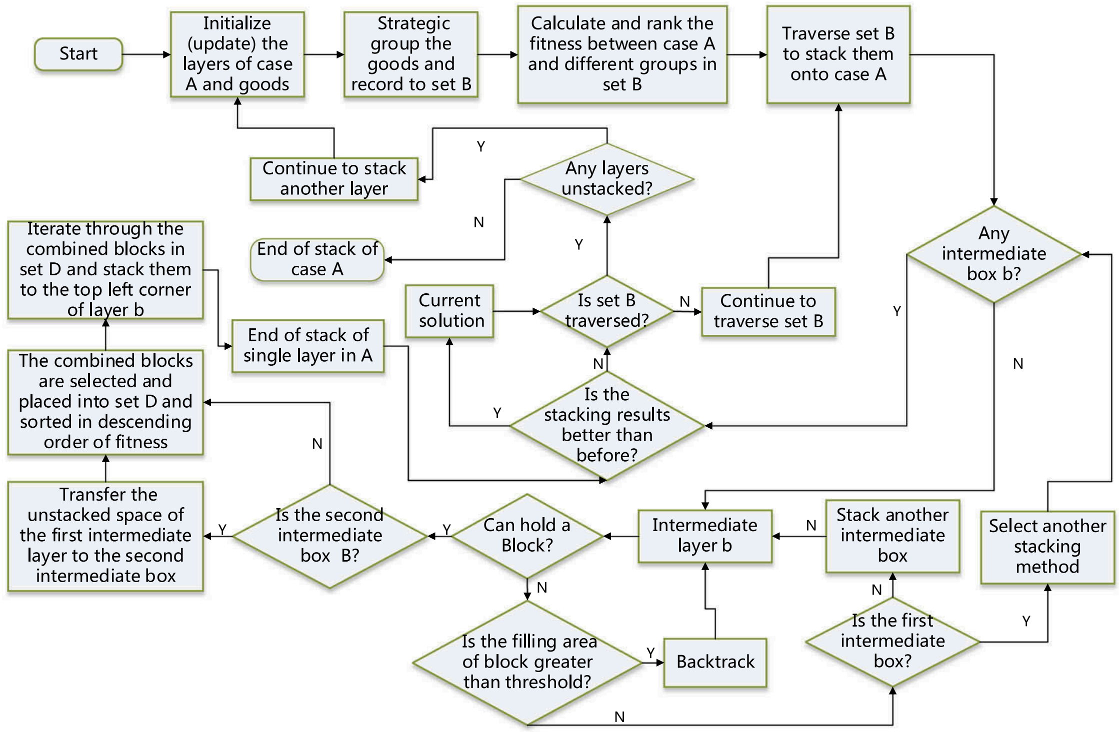

Figure 7. The logic flow of optimisation algorithm for the 3D packing.

4.3.1 Principles for storage allocation

The distribution of packages in the warehouse is mainly divided into outbound, inbound, and re-stocking. Since re-stocking is an adjustment of the inventory that can be completed when the warehousing task is less, it will not have a great impact on just-in-time production. This paper focuses on the first two kinds of storage assignment, namely, outbound and inbound.

According to the online optimisation goal in the Digital Twin System and the characteristics of the large-scale automated high-rise warehouse, the following distribution principles are adopted for the warehousing optimisation model:

- *Allocation of urgent task*: the priority shall be given to the tasks with a high degree of urgency. Under the circumstance of meeting in material requirements, when the outbound and inbound tasks occur at the same time, the outbound tasks are given higher priority.
- *Time order*: on the premise of meeting the first principle, the task is allocated according to the time generated, that is, first-come-first-served.
- *Light SKUs on top and heavy SKUs on bottom*: to reduce the difficulty of operating stacker and its energy consumption, the packages with larger weight is located at the bottom of shelves, while the packages with smaller weight are situated at the top.
- *Proximity distribution*: all packages should be assigned to available spaces that closed to the warehouse entrance (bulk dock). It can not only improve the operating efficiency but also reduce the overall energy consumption.
- *Uniform distribution*: when performing the assignment of same type of packages (there are more than one to delivery simultaneously), try to choose the shelves with more available channels, so as to avoid the stacker blocking in the same channel during the delivery, and thereby to improve the order-picking efficiency.
- *Compound allocation*: when both the outbound and inbound tasks happen in the same channel, the stacker can execute the outbound tasks after the completion of the inbound tasks in the channel, which will reduce the operation time and improve the operation efficiency of stackers.

4.3.2 Improved ABC classification method

Proper storage allocation method can effectively improve the efficiency of warehouse operation. There are several common methods for storage of packages, namely, fixed storage, random storage, classified storage and random classified storage. Considering the stability of warehousing capacity, this paper presents an improved ABC classification method for storage assignment. COI (i.e., Cube-Per-Order) is used as the basis for sorting the packages:

$$COI(i) = \frac{C_i}{f_i} \quad (4-9)$$

where C_i denotes the inventory capacity of ith class of packages; f_i refers to the outbound frequency of ith class of packages. The smaller the metric is, the higher the turnover rate of ith class of packages is, and correspondingly its location to the inbound and outbound port closer is.

As shown in Figure 8, the typical layout of shelves in a large-scale automated high-rise warehouse usually includes the vertical arrangement of shelves and the horizontal arrangement of shelves. In the first type, the operation channel between the shelves is unidirectional arrangement, and there is only one direction of entrance and exit. For the later type, the operation channel between the shelves is bidirectional for entrancing and exiting. In the layout of an actual warehouse, there may be only one type or a combination of two types. For these two basic layouts, ABC classification is adopted to carry out partitioning of goods location.

In consideration of the uniform distribution principle of channel allocation, the storage space is divided into three partitions according to the order from small to large. Conventionally, Area A accounts for 20% of the space capacity and stores the smallest packages; Area B accounts for 30% of the space capacity and stores larger packages; Area C accounts for 50% of the space capacity and holds the largest number of packages. This paper makes an improvement on the dynamic adjustment on the original fixed proportion among three classes. The weights among three classes are periodic adjusted based on the statistics data obtained from the Digital Twin System. A transaction area is reserved between two classes of partitions for adapting the dynamic adjustment on weights.

Using improved ABC classification method to manage inventory can not only facilitate the scheduling of inbound and outbound tasks but also adopt different management methods according to the classification of packages. Inventory management of high frequency can be adopted for class-A packages to ensure timely and accurate supply of production materials. For class-C packages, a long period of spot inspection is adopted to avoid the waste of manpower and material resources.

4.3.3 Storage assignment model

Over a period of time of in-out warehousing tasks, a stacker carries one pallet each time according to the time sequence and the priority of urgent task. The problem of storage assignment can be described as follows: in the execution of a period of time of in-out warehousing tasks, packages are allocated to the available space to minimise the time spent in completing all the tasks. Table 2 offers an overview of the related notations. Considering

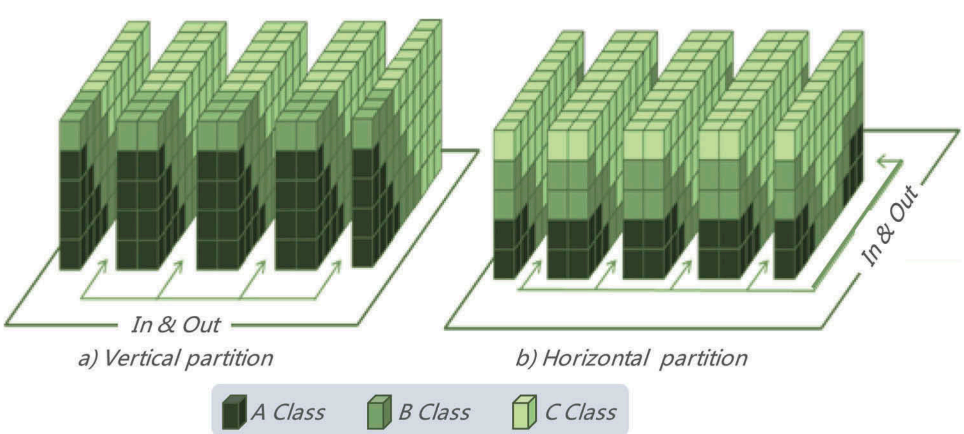

Figure 8. The ABC classification of two typical shelves.

the compound operation strategy of inbound and outbound, the objective function is established as follows:

$$MinT = \sum_{i\in(1,K)}^{in_i,in_{out}\notin\emptyset}(t_{in_i}+t_{out_i}+lt_i)+\sum_{i\in(1,K)}^{in_i\notin\emptyset,in_{out}\in\emptyset}2*t_{in_i}+\sum_{i\in(1,K)}^{in_i\in\emptyset,in_{out}\notin\emptyset}2*t_{out_i} \quad (4-10)$$

$$lt_i=\begin{cases}\frac{(x_{in_i}+x_{out_i})*W+|r_{in_i}-r_{out_i}|*L_b}{v_h}+\frac{(y_{in_i}+y_{out_i})*H}{v_c}, & r_{in_i}\neq r_{out_i}\\ \frac{(x_{in_i}-x_{out_i})*W}{v_h}+\frac{(y_{in_i}-y_{out_i})*H}{v_c}, & r_{in_i}=r_{out_i}\end{cases} \quad (4-11)$$

$$t_{in_i}=\frac{x_{in_i}*W+L_a+(r_{in_i}-1)*L_b}{v_h}+\frac{y_{in_i}*H}{v_c}, \quad (4-12)$$

$$t_{out_i}=\frac{x_{out_i}*W+L_a+(r_{out_i}-1)*L_b}{v_h}+\frac{y_{out_i}*H}{v_c}, \quad (4-13)$$

$s.t.\ 1\le i\le K, 1\le r_i\le R, 1\le x_i\le P, 1\le y_i\le Q.$

The storage assignment has been identified as a non-polynomial (NP) hard problem. Hence, to obtain effective solutions in a reasonable time, various policies have been developed, such as metaheuristic, heuristic (e.g., randomised storage strategy, class-based storage rule, ranked index-based rules and correlated policy), clustering and stochastic methods (Accorsi, Manzini, and Bortolini 2012).

Considering the diversity of the shapes of the packages, this paper presents a packages-location matching method. The actual volume of the packages should be less than or equal to its external cuboid volume to stock. The general idea of the matching is: through the elimination and the comparative analysis method, the target storage location with the highest matching degree is selected layer by layer to store the current packages, and the matching degree is expressed by the maximum space utilisation rate of the storage location. The flow of the algorithm for matching storage location and packages is detailed in Table 3.

Table 2. The notations used in storage assignment modelling.

Notations	Remarks
R	The number of channels in the warehouse
P, Q	The number of columns and layers of the shelf
W, H	The width and height of each location
v_h, v_v	The horizontal and vertical speed of stacker
L_a	The distance between the entrance and the closest channel
L_b	The distance between channels
K	The number of tasks assigned
T	The operation time for stacker
lt_i,t_{in_i},t_{out_i}	The driving, entry, and exit time of ith warehousing
x_{in_i}, x_{out_i}	The column location of ith entry and exit
y_{in_i}, y_{out_i}	The layer location of ith entry and exit
r_{in_i}, r_{out_i}	The channel location of ith entry and exit

Table 3. The detailed pseudocode of packages-location matching.

```
BEGIN
 Step 1:
      Initialise GaN,A_j,B_j,C_j
Step 2://Update the size(a_i, b_i, c_i) and quantity (n_i) of the goods
Step 3://Calculate the capacity of each kind of location (GaV_j)
      v_i = a_i * b_i * c_i
      V_i = n_i * v_i
      GaV_j = A_j * B_j * C_j - ∑^{v_i}
Step 4://Compare single volume with maximum capacity
      MaxGaV = 0
      for j: = 1 to size(GaN)
         if GaV_j ≥ MaxGaV
            MaxGaV = GaV_j
         end if
      end for
      if v_i > MaxGaV
         goto Step 7
      end if
         goto Step 5
Step 5://Find out the maximum space utilisation of the goods
      MaxU = 0
      for j: = 1 to size(GaN)
         u_j = v_i/GaV_j
         if u_j ≥ MaxU
            MaxU = u_j
         end if
      end for
Step 6://Output result
Step 7://Abnormal output
END
```

After the storage assignment, there exists a problem of routing order pickers to ensure a good route through the warehouse, which is actually a Travelling Salesman Problem. It can be solved by many heuristics such as largest gap and traversal heuristic (de Koster, Le-Duc, and Roodbergen 2007), which are omitted here for concise reason. Finally, the packing and storage assignment are jointly and rapidly optimised before the commands are distributed to controllers.

5 A demonstrative prototype and case study

5.1 A prototype of digital twin system

A prototype of Digital Twin System (DTS) is developed based on an open source visualisation engine named Unity3D. As shown in Figure 9, the prototype includes four modules, namely, basic DTS, 3D semi-physical simulation, multi-view synchronisation (with other systems) and performance analysation. Based on the proposed key enabling techniques, the module of performance

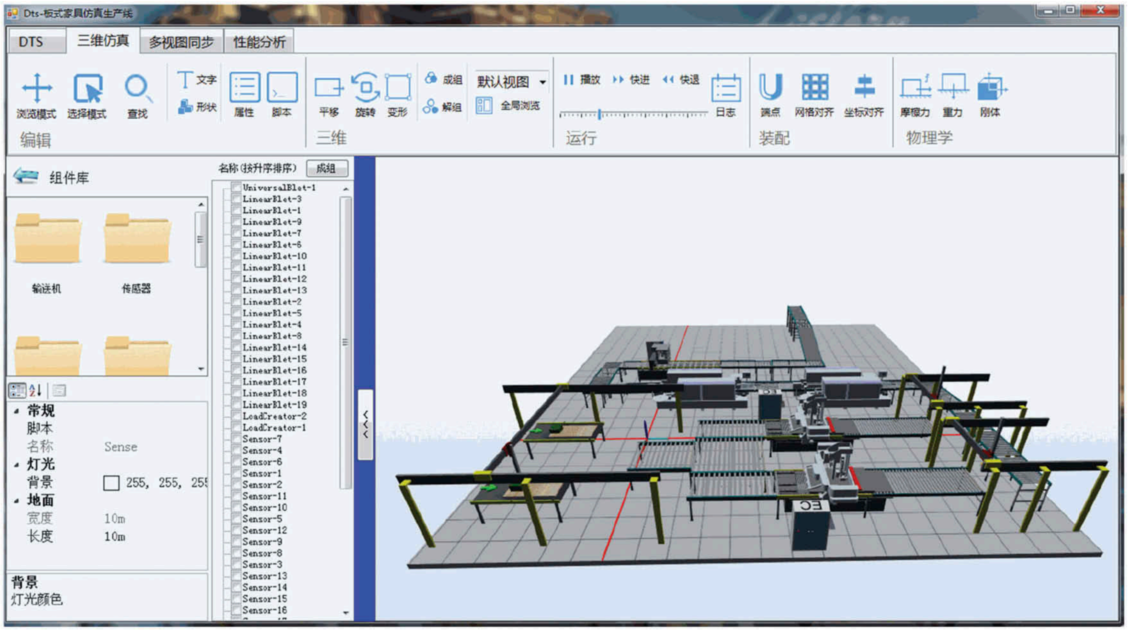

Figure 9. An open source unity3D-based digital twin system prototype.

analysation is developed with J2EE programming architecture and integrated with joint optimisation model. The joint optimisation model is triggered by the metric evaluation on the system performance, namely, inbound and outbound flow. Once the metrics are higher than pre-specified value, it will perform the optimisation rapidly. The module of performance analysation executes the optimisation kernel and then transmits optimal results to the semi-physical simulation module for verification and generation of instructions before distributing to the physical system. The 3D semi-physical simulation module has real physical properties (e.g., gravity, friction, speed, impact and inertia) to depict the actual logistics and stocking processes. The 3D semi-physical simulation module feedbacks in-situ data from the physical system to the multi-view synchronisation module for coordinating with other systems.

5.2 Case study

The demonstrative prototype is verified with case study of a Large-scale Automated High-rise Warehouse (LAHW) system for storing and distributing tobacco,

Table 4. Parameters of the warehouse under study.

Column	Channel	Layer	Locations	Avg. Delivery Cycle	Stackers	Bearing
10	21	13	8190	5.82 days	5	300kg

which is constructed by a comprehensive automated logistics solution provider in the Pearl River delta of China. With a length of 158.85 metres, a width of 117.65 metres and a height of 19.19 metres, it houses 8190 storage locations and five lanes with storage and retrieval cranes/stackers. Parameters of the LAHW under study are detailed in Table 4.

It is designed for fully automatic tobacco transport using robust conveying systems, the LAHW system accepts the goods from production, stores them and makes them available again in time for delivery to a number of customers (Berg and Zijm 1999). An order to delivery cycle of average 5.82 days imposes a significant pressure on the configuration and operation of this high-rise warehouse.

The main equipment (i.e., Clip-holder, Tray-discharger, Stacker, Straight Shuttle and Vertical Elevator) of warehouse under study not only determines the transport storage capacity of the whole system but also plays a key role for in the achievement of the system requirements for maximum flow. Therefore, the utilisation rate of the equipment, which is the ratio between the maximum demand of the system and the maximum capacity of the equipment, is necessary to be analysed. As shown in Table 5, this section contrasts the warehouse managed by the DTS prototype with that managed by the original Oracle® ERP used in the factory. We have anonymised part of data due to the confidentiality reason.

Table 5. Comparison on system performance and major equipment of warehouse.

Type	Metrics	Capacity	Utilisation (Rate) 1X (ERP)	Utilisation (Rate) 1.5X (DTS)	Gap
System	Q_{In}	240	201(83.4%)	252(105%)	+25.9%
	Q_{out}	180	95(52.8%)	168(93.3%)	+76.8%
Equipment	Clip-holder (pcs/h)	240	201 (83.8%)	236 (98.3%)	+17.4%
	Tray-discharger (pcs/h)	400	201 (50.3%)	258 (64.5%)	+28.4%
	Stacker (opt/h)	325	314 (96.6%)	264 (81.2%)	−15.9%
	Straight Shuttle (pcs/h)	140	111 (79.3%)	90 (64.3%)	−18.9%
	Vertical Elevator (pcs/h)	50	16 (32%)	12 (24%)	−25.0%

The warehouse managed by the original Oracle® ERP can smoothly operate under normal loading pressure. The inbound demand of inventory is 168 cases/hour, while the outbound demand is 80 cases/hour. However, the warehouse managed by the DTS prototype can smoothly operate under 1.5 times (i.e., 1.5X) loading pressure than original one. After an hour of actual utilisation, the inbound demand is 252 cases/hour, while the outbound demand is 168 cases/hour. Other improvements are gathered in the last row of Table 5. Moreover, the whole system of warehousing operation doesn't exist deadlock and still runs stably without any bottleneck, indicating that the system is stable and reliable.

In the simulation of the maximum loading pressure, the utilisation rate of some equipment is relatively low. For instance, the utilisation rate of stacker based on DTS is about 81.2% on average and decreases by 15.9% compared with the original results 96.6%. The reasons are as follows: 1) the temporary storage station for pallet group is not enough, leading to a shortage on pallet supply; 2) unreasonable transportation line layout and goods sorting strategy; 3) the emergency supplementary scheme for fault detection still needs to be improved; and 4) unstable information feedback and instruction issuing process, and thus the communication mechanism needs to be improved.

From another perspective on the utilisation of packages and cartons in the packing process, mass individualisation paradigm requires a satisfactory solution on packing goods of different sizes. It depends on the utilisation rate, the carton quantity, surface area and filler volume. Table 6 gives the comparison on the utilisation of cases and cartons in the packing process. The results show that the DTS prototype significantly saves the resources. Compared with ERP, the total utilisation of cartons achieved by DTS is improved by 17.49% and the computing time is significantly shortened by 83.83%, which is helpful for achieving the online optimisation goal of Digital Twin System.

6 Discussions

The proposed digital twin system could feedback the real-time data and document the results via the semi-physical simulation of a batch of warehousing orders. With the help of powerful data analysis of simulation engine and optimisation algorithm on the digital twin system, it can not only generate warehousing plan for quantitative comparison but also can be used to optimise the packing solution for saving carton resources. Finally, intelligent control could be realised, and the efficiency of the warehouse product-service system can be continuously improved. The proposed approach can be reproduced for the implementers who want to introduce digital twin technology into the warehouse product-service system. Firstly, they could do the interconnection and software development work referring to the proposed approach. Secondly, they could also introduce the proposed iterative optimisation approach for highly efficient balancing the key overall bottleneck resources between packing and warehousing. It can also realise the validating and on-line testing of decisions/solutions.

Table 6. Comparison on the utilisation of cases and carton in the packing process.

Task	Total Utilisation	Cases	Area	Filler	Time(ms)	Layer Utilisation
DTS (Sim. 1)	91.73	117037	159332.10	274.06	1054783	≥0%
DTS (Sim. 2)	94.58	127753	162724	170.12	1658817	≥60%
DTS (Sim. 3)	100.00	218795	216819.05	0.02	1416350	= 100%
DTS (Avg.)	95.44	154528	179625.05	148.07	1376650	-
ERP	81.23	155333	None	None	8514355	≥0%
Gap	+17.49%	−0.5%	-	-	−83.83%	-

However, the proposed digital twin system lacks an analysis of the physical random disturbance on system robustness. Practice shows that frequent in-stocking of warehouse product-service systems and short debugging time usually lead to prominent reliability problems. Failure of a station not only leads to the warehousing stagnation at this stage but also propagates even to the entire warehouse product-service system. The fault-propagation effect is not conducive to release the capacity and guarantee delivery time. Therefore, it is necessary to conduct rapid optimisation so as to avoid the extreme situation of system dead-locking in the warehousing progress. It is actually a kind of in-line control decision problem considering the spatiotemporal brittleness effect of faults. Also, the bottleneck prediction and reduction model (Huang et al. 2019a) of the warehouse product-service system should be established based on the deep learning (Leng and Jiang 2016) and data mining (Leng and Jiang 2017b) analysis of the operating efficiency, and then various indicators of the warehouse product-service system can be further adjusted and optimised iteratively.

7 Conclusions

This paper developed a Digital Twin System to integrate real-time data from physical warehouse product-service system and then to map it to the cyber model. A novel digital twin-driven joint optimisation model on how to quickly optimise stacked packing and storage assignment of warehouse is integrated into the Digital Twin System. Through perceiving online data from the physical warehouse product-service system, periodical optimal decisions can be obtained via the optimisation engine and feedbacked to the semi-physical simulation for verifying the implementation effect. The proposed approach can maximise the utilisation and efficiency of the large-scale automated high-rise warehouse. However, the proposed digital twin system lacks an analysis of the physical random disturbance on system robustness. It is necessary to conduct rapid optimisation in avoiding the extreme situation of system dead-locking in the warehousing progress. Also, based on the analysis of the system's overall operating efficiency, the bottleneck reduction model of the warehouse product-service system should be established in future.

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Disclosure statement

No potential conflict of interest was reported by the authors.

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