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Design of Cargo Sorting and Transmission Scheme based on Digital Twin

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Abstract. Technological advancements are driving the transformation of traditional warehousing logistics towards automation, with sorting being the core of system optimization. To address the challenges of long cycles and low efficiency caused by reliance on physical equipment debugging in current sorting projects, this study proposes a digital sorting and conveying solution based on digital twin technology. For real-time goods arrival sequences, we develop a data-driven virtual modeling method that generates characteristic material profiles, achieving high-fidelity cargo mapping and dynamically configurable routing strategies. Prior to physical system deployment, virtual simulation verifies the feasibility and stability of conveying units, with iterative optimization achieving an average 99.26% (peaking at 100%) cargo transmission success rate. Through parameter optimization experiments, the optimal configuration is determined as 5 conveying units with v_n=0.6m/s speed, enabling efficient coordination among supply rate, conveyor speed, and robotic arm sorting capacity. This configuration balances system stability and space utilization, delivering 59.1s average waiting time and 555.2 units/hour throughput. Scheme is fed back to the real scenario before the actual equipment test.

Keywords: Warehousing Logistics, Digital twin, Cargo Sorting scheme.

1 Introduction

Modern logistics, serving as the backbone connecting production and consumption, integrates transportation, warehousing, distribution, and information services [1]. Warehouse logistics (WL) has evolved from traditional storage to intelligent distribution hubs in the digital era, emphasizing spatiotemporal resource orchestration [2]. Optimized WL systems can accelerate material flow while reducing operational costs[3]. Within Logistics 4.0 frameworks, IoT and AI have enabled automation solutions. However, the existing system mostly stays in the static simulation stage of the real scene and lacks the actual dynamic optimization ability [4]. The concept of Digital Twins (DT) provides a solution.

DT first introduced by Professor Grieves (2003) [5] and formally conceptualized in 2011, is characterized by features a tripartite architecture: physical entities, virtual counterparts, and bidirectional data interfaces [6]. To address evolving industrial demands, Tao expanded this framework into a five-dimensional model integrating data and service layers in 2018[7]. Subsequently, Coelho F further introduced a decision-support dimension in 2021, forming a six-dimensional framework for intralogistics that enables scenario simulation and experimental validation [8]. DT achieves multi-dimensional mapping of physical environments into virtual spaces, employing behavioral emulation through data-driven models to learn digital twins behave under specific scenarios [9]. By enabling optimized decision-making and predictive analytics, it establishes cyber-physical synchronization that facilitates bidirectional feedback loops. On the basis of traditional Simulation models such as Discrete Event Simulation (DES), different dimensions such as fidelity, analyzability and connectivity were expanded [10].

While DT technology has demonstrated value in aerospace, urban planning, and manufacturing sectors [11], its application in warehouse logistics remains underexplored. The digitalization process puts higher demands on the logistics delivery cycle[12], which prompts suppliers to optimize the conveyor path strategy through physical trial and error. However, the current commissioning model based on the static warehouse layout presets the process defects to be discovered only after the infrastructure has been installed and the system is actually tested and operated[13], which leads to a long debugging cycle, large trial and error costs, and at the same time, interruptions in the conveyor line will lead to delivery efficiency. Grieves and Vickers classified DT into two lifecycle phases: Digital Twin Prototypes (DTP) for virtual validation prior to physical implementation and Digital Twin Instances (DTI) for in-service performance monitoring [14]. DTP can highlight possible risks to a physical object before it is operated, and has been applied to achieve better results in issues such as flood evacuation planning [15]. The precision and evaluation of the digital space contributes to the accuracy and safety of the operation of the physical world twin, effectively reducing operational costs and operating time [16].

In this paper, DTP is introduced into the application scenario of real cargo transportation and a digital twin system for cargo sorting (DT-CSs) is designed. Prior to physical deployment, the system constructs virtual work-cell using real-time cargoes arrival sequences and 5 defined sorting categories, enabling: virtual commissioning, iterative optimization, speed matching algorithms. In order to map the real goods with high fidelity, a virtual model method is designed to generate the characteristic materials based on the sequence of incoming boxes. Building working scenarios and conduct feasibility validation and stability testing of conveyor unit sensor layout schemes, and iterative optimization. Conduct rate matching experiments to improve the safety and efficiency of cargo transfer. Finally, feedback the design scheme to the actual scenario to realize the connection between the physical scenario and the digital space.

The structure of this paper: Section 2 proposes the DT-CS framework to map the warehouse picking process; Section 3 designs the picking conveyor system; Section 4 simulates the experiments and realizes the linkage of the virtual and real systems; and finally concludes with the outlook.

2 DT-CSs Framework

This paper designs the digital twin system architecture for goods sorting and delivery according to the needs of goods sorting and delivery, including the system architecture, functional module composition and operation flow.

2.1 Requirement Analysis of System

Current sorting systems face dual limitations: Current sorting system digital models are limited to simulating predefined scenarios with latency in responding to real-time order dynamics and lack flexibility. Physical debugging methods only reveal operational defects during post-deployment testing, resulting in inefficient validation with prolonged cycles. To address these issues:

1. The system should dynamically construct digital twins by real-time collection of cargoes sequence data. Cargo data comprises arrival time, velocity, dimensions, and mass 4 kinds of detail sheet paste locations and five configurable routing labels (set by operators as destinations/order types).
2. Based on routing rules, the system simulates sorting logic to design conveyor unit layouts ensuring cargo safety.
3. Dynamic adjustment of conveyor speed(v_n) and palletizing rate(v_2) matches supply rate(v_1), achieving efficient and stable upstream-downstream integration while maintaining minimum inter-cargo distance (L).

The final conveyor solution is fed back into the physical world to reduce the pre-project testing investment time and economic cost.

2.2 System Architecture

It is necessary to design and build a DT architecture applied to a specific service scenario [17]. The paper proposes a digital twin framework for material sorting systems (DT-CSs), structured into five layers in Fig. 1: (1)Physical Layer: the layer includes physical entity (PE) Conveyor rollers, physical cargo, sensors (photoelectric types); (2)Virtual Layer: the layer includes virtual entity (VE), scene and simulation of PE virtual mapping; (3)Data-Driven Layer: acts as the "nervous system" connecting physical and digital domains for closed-loop optimization, including Real-Time data fusion, adaptive control, performance evaluation. (4) Decision Support Layer: accurately monitor the location and status of goods through the reasonable deployment of photoelectric sensors; planning conveyor layout and operation strategy to ensure efficient cargo flow. (5) Service Layer: displays real-time workflows via interfaces; Real-time mapping of physical system operation status (e.g., cargo movement, equipment status); display of key parameters to support real-time operator intervention.The solid line represents the mapping process from physical space to virtual space, and the dashed line represents the optimization feedback process from digital space to physical scenario by simulating the conveyor line according to the actual scenario constraints and designing the scheme.

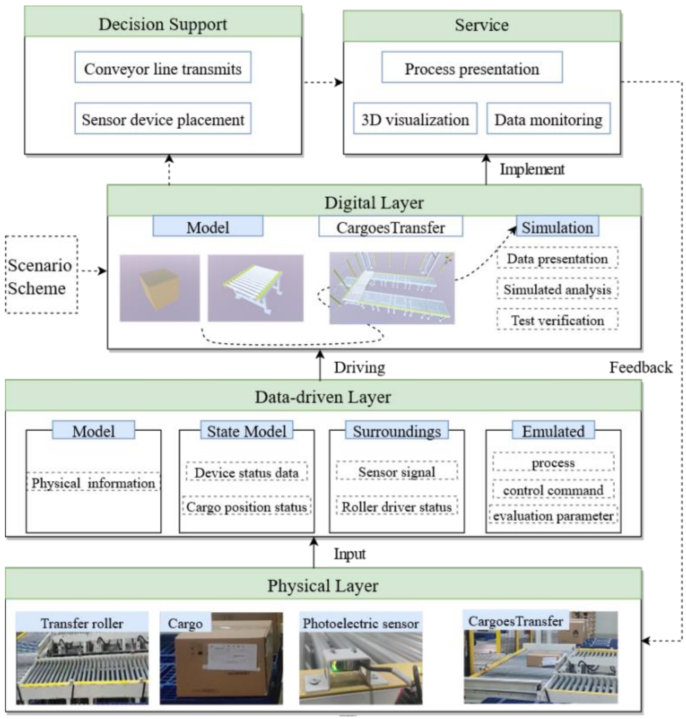


Fig. 1. The DT-CSs network architecture

2.3 System Functional Modules

Based on the framework(Fig. 1), the system is designed with five modules: (1)Digital Cargo Building (DCB): Constructs virtual cargo entities based on received system information;(2)Transport Scheme Design (TSD): Designs conveyor units and transport line layouts for cargo transmission; (3) Sorting Transfer Module (STM): Executes cargo sorting and transportation; (4)Data-Driven Module (DDM): Receives upstream cargo data, stores process data (e.g., cargo positions, conveyor status), transmits palletizing grasp positions, and facilitates inter-layer communication via command storage and dispatch;(5)Aided Visualization Module (AVM): Visualizes cargo sorting and transportation processes.

The specific operation process is shown in Fig. 2. Upstream cargo enters the system, and the system obtains the SPU (Standard Product Unit) information of the incoming cargo. The system senses the SPU information, The DCB constructs digital twins in real-time using list data, incorporating dimensions, mass, 4 label positions and 5 configurable routing tags. The cargo models traverse conveyor lines designed by TSD, while STM-driven routing simulations design layouts ensuring cargo safety (L≥1m), v_n and v_2 synchronize with v_1,achieving scheme simulation. The AVM visualizes workflows in *Digital Space*. DDM enables bidirectional data flow and feedback the scheme in *Physical Space*.

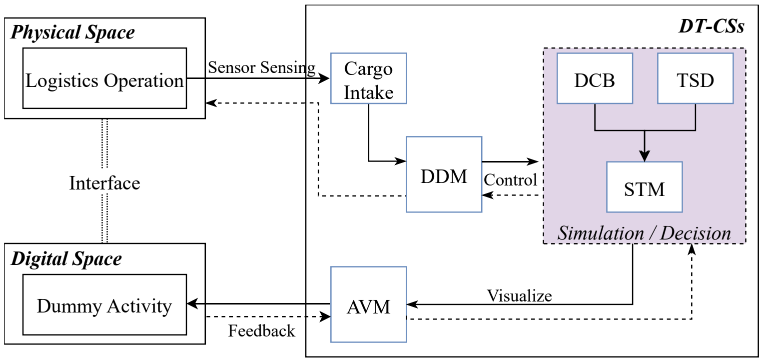


Fig. 2. Operation flow of DT-CSs

3 *DT-CSs* Design

Prior to physical equipment deployment, spatial data (including site area and physical entity positional relationships) is utilized to organize scene parameters and device interconnections within a Unity-constructed virtual environment. A schematic layout is designed for cargo sorting and conveying operations, indicating potential sensor distribution zones (Fig. 3). Key areas are color-coded: blue for conveyor zones, green for palletizing buffer zones, and white for industrial robot mobility zones. T1 (Entry): Interfaces with upstream units, T2 (Sorting): Executes cargo classification, T3 (Conveying): Connects to palletizing units, the others are auxiliary work areas.

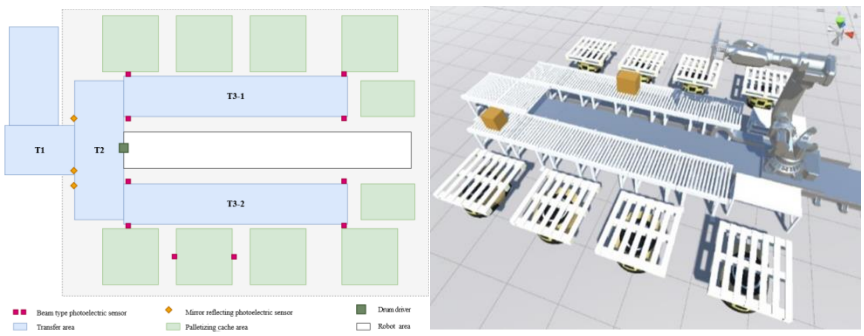


Fig. 3. The 2D warehouse layout design with color-coded zones and 3D virtual scene construction.

Based on the 2D layout, a virtual scene achieves 1:1 PE-VE mapping via precision positioning, integrating cargo systems, rollers, and auxiliary zones. To mirror the real workplace, elements like industrial robots, moving tracks, buffer pallets, buffer tables, and automated guided vehicles (AGV) are added to enrich the surrounding environment. Lightweight modeling of PE, PE include static and dynamic entities.

Static entities. Digital twin static entities are objects with fixed states/positions post-initial configuration, featuring attributes (geometry, density, rigidity) and spatial coordinates to establish environmental frameworks. In material conveying applications, static entities include but are not limited to: Wooden tray (*WTray*), small buffer station (*Buffer*)and Sensor.

$$\begin{cases} WTray = (w_m, w_l, w_w, w_h, w_x, w_y, w_z) \\ Buffer = (b_m, b_l, b_w, b_h, b_x, b_y, b_z) \\ Sensor = (s_m, s_l, s_w, s_h, s_x, s_y, s_z) \end{cases} \tag{1}$$

Static entities are modeled as expressed in Eq. (1), w_m , b_m , s_m denote the corresponding solid model, including model material, texture, color and other information, where the size information is (w_l, w_w, w_h),(b_l, b_w, b_h),(s_l, s_w, s_h).The model is exported in FBX format and imported into Unity(Fig. 5). The world coordinate position of the entity is determined in the virtual space: (w_x, w_y, w_z) , (b_x, b_y, b_z) , (s_x, s_y, s_z) . The distribution of roller drivers and sensors is shown, beam photoelectric sensors in T3.

Dynamic entities. Dynamic digital twin entities demonstrate time-variant states (position, velocity, status), with attributes dynamically adapting to system conditions. Beyond static geometric and physical properties, PE still require real-time modeling of: cargoes, Transfer Roller (*TranN*), industrial robot (*Robot*).

$$\begin{cases} cargoe = (c_m, c_x, c_y, c_z, c_{st}) \\ TranN = (\mathrm{n}_m, n_l, n_w, n_r, n_h, n_x, n_y, n_z, n_v, n_{st}) \\ Robot = (r_m, (r_w, r_p, r_r, r_h, r_x, r_y, r_z), r_{st}) \end{cases} \tag{2}$$

Eq. (2) represents the model of dynamic entities. (c_x, c_y, c_z)is the dynamically changing position. Cargo may be routed through designated areas T1-T3 during operational processes. $(r_w, r_p, r_r, r_h, r_x, r_y, r_z)$ denotes the position of robot. Compared to static entities, they extend behavioral parameters for state transitions (binary state encoding: 0=stopped, 1=running). c_{st} indicates the running state of the material and r_{st} notes the change of the position of the industrial robot.

The conveyor system incorporates two distinct roller types: linear conveyor rollers and diverting transfer modules. Through geometric simplification while preserving essential mechanical functions—including load-bearing capacity and variable-speed operation. The roller is set up physical and behavioral models, $(\mathrm{n}_m, n_l, n_w, n_r)$ is the dimension information of the transfer roller, the world coordinate of the nth roller is (n_x, n_y, n_z) . *Rigidbody* components are implemented on rollers with calibrated centers of gravity, while goods-contact surfaces are configured as colliders to enable physics-compliant interactions. Combined with sensor model, n_v is set and controlled roller speeds, n_{st} is the state of the conveyor roller. In digital space, the position of VE is denoted by *P*, static entity remains unchanged after environment setup, dynamic entities are recorded according to the work process.

3.1 Digital Cargo Modeling (DCM)

In real-world logistics, cargo boxes exhibit significant dimensional variability and random arrival patterns, causing mismatches between upstream cargo sizes and pre-built virtual models. To address this, dynamic model adaptation based on real-time cargo sequences is essential. Building on Eq. (2), this study proposes a feature-cargo generation algorithm for scenarios with unknown cargo specifications. By synchronizing real-time sequence data, the method constructs digital twin cargo models, enabling adaptive alignment between physical and virtual sorting systems, which is implemented through the following process:

Step1. Construct a standard virtual cargo model. Build a standardized model in Cinema 4D and render each of the six sides of the cargo. Box's lateral surfaces are labeled 0, 1, 2, and 3, corresponding to four potential locations for attaching cargo detail sheets. This step streamlines the instancing process for variably sized cargo, enabling efficient adaptation to diverse physical dimensions while maintaining parametric consistency across digital models.

Step 2. Acquire cargo information. Upstream cargo info received by the system is randomly generated. Based on Eq. (2), the information geometric model of the cargo *Cm* shows as follows：

$$C_{\mathrm{m}} = (c_l, c_w, c_h, c_{ms}, c_t, c_{la}) \tag{3}$$

In Eq. (3), the system facilitates real-time cargo sizing with scriptable parameters (c_l, c_w, c_h) based on step 1. c_{ms} denotes mass, c_t denotes five configurable routing labels, and c_{la} denotes detail sheet paste locations.

$$\begin{gathered} c_l, c_w < n_l, n_w \\ c_{ms} < 25kg \\ C_t \in \{c_t, t = 1,2,3,4,5\} \subset S \end{gathered} \tag{4}$$

In Eq. (4), setting constraints on cargo information. length and width must be less than the conveyor roller's, and mass must be under the roller's max load (mass:0-25kg). *S* represents the set of actual routing info, set by operators based on entry conditions. c_t is a subset (routing priority:1-5) of *S*, allowing operators to flexibly set sorting conditions. To simulate a large number of cargoes in virtual space, a cargo info database needs to be added. First, system data exports to UTF-8 CSV for SPU recognition. Second, cargo attributes are parsed into typed BoxOrder variables via structured parsing, enabling queue access. Finally, digital cargo info is generated; exceeding set limits triggers "Error".

Step 3. Cargo spatial instantiation. After the system determines cargo information, it defines the world coordinate position $P_c = (c_{x0}, c_{y0}, c_{z0})$ and instantiates C_m. Cargo in the T1 area is marked as part of the Loader group, with a *Rigidbody* component added for physical properties. The weight status is set ***true*** to incorporate physical attributes, and a Cargo *Collider* component ensures model authenticity. To facilitate smooth cargo transportation by rollers, the center and size of the Cargo Collider are dynamically updated to fit the new model.

Step 4. Complete cargo transportation info. The first three steps solve the information problem of random goods, and this step is to solve T2 dynamic material diversion. c_t is defined as courier company or destination area, which determines the diversion direction. Digital cargo construction is complete in T1(Fig. 4). It includes Min (260×175×55), Max (940×575×480), and Mode (395×395×185) cargo sizes in orders.

Algorithm Digital cargo construction algorithm

Input: Data (Characteristic information of the Cargo)

Output: Model (Digital Model with cargo information)

function CreateCargo (Data)
  Instantiate in Map
  Bornpoint.position
  GetConfigData (D)
  New Vector3(C_l,C_w,C_h) using Eq.(3)
  AddComponent<Rigidbody,BoxCollider>
  Add (C_{ms},C_t,C_d) using Eq.(3)
  Add(materials[label]. mainTexture = sideImage)
  return Model
end function

a) Min(260*175*55)　b) Mode(395*395*185)　c) Max(940*575*480)

Fig. 4. Cargo sizes

3.2 Transport Scheme Design (TSD)

For the goods to reach the gripping point of the robot arm smoothly, the design of the conveyor unit for the delivery of goods is crucial. The real goods are carried in cartons (Fig. 4), and the rigid constraints of the cartons require that the length of the rollers be 50-150mm wider than the width of the goods, so the width of the rollers is 900mm, and the length is 1000mm. Order pre-processing aligns cargo with unit specifications.

To monitor the status of goods and rollers, sensors are used to detect the passage of goods. The time intervals between cargoes passing through drums can be recorded by means of sensor detection times between the conveyor units. The reflective photoelectric sensor (RPS) operates by emitting a light beam from one end and detecting it at the other. If the beam is interrupted (no signal received), it confirms the cargo has reached the designated position. While end and mid-section sensors enable detection, positioning within the conveyor system design remains essential to ensure uninterrupted multi-cargo transfer.

Setting the conveyor unit as Ni that implement three sensor layout schemes (S1-S3) as detailed in Table. Sensor configuration and location: S1 only places sensors on the rollers for docking palletizing; Sensors placed at mid-sections of all Ni units in T3 for intermediate monitoring in S2; S3 sets up sensors at ends of all Ni units in T3, with detection on the end of the rollers. The evaluation indexes for the success of the scheme include:

E_1 (Successful delivery to gripping point)
E_2 (Collision-free transport)
E_3 (Stable transmission)

Key parameters include:

Cargo ID**:** Unique sequence identifier
Roller State (n_{st} **):** T (loaded) / F (unloaded)
Sensor State (Sr**):** 0 (detected) / 1 (undetected)

where mapping of the roller status corresponds and the sensor status ensures real-time status synchronization.

Table Scheme designed sensor position scheme content and index in the unit

S	Sensor Configuration and location	Sensor	Parameter	E_1	E_2	E_3
S1	End of conveyor line	RPS		√	×	×
S2	Middle position of N_i	RPS	ID、Sr、n_{st}	√	√	×
S3	End position of N_i	RPS		√	√	√

Given site constraints (11800*6800mm), the conveyor system's unit count (N) and speed (v_n) are designed through rate-matching optimization to ensure collision-free cargo transfer to palletizing zones. Key factors include: Inbound speed (**v_1**), $\boldsymbol{v_n}$, Safety distance (**L**), Palletizing speed (**v_2**). A discrete-event simulation algorithm evaluates system performance by analyzing throughput, average waiting time, and blocking rate. Input parameters (v_1, v_n, v_2, L) are tested under varying configurations, with experimental results and site constraint, demonstrating optimal balance at N=5 and v_n=0.6m/s.

3.3 Transport Scheme Design (TSM)

The STM module integrates sorting and conveying functions. Under the TSD framework, each conveyor line contains 5 transfer units (N=5 per line), establishing a theoretical maximum capacity of 10 temporarily stored goods system-wide. When either line reaches its 5-unit capacity, the system blocks upstream cargo intake. Corresponding to Figure 6, T2 Features three alignment markers ($P_{2\text{-}0}$ to $P_{2\text{-}2}$) for sorting and alignment of goods; Each line comprises five N_i (N_1: Interfaces with palletizing systems) in T3, sensors monitor positions $P_{3\text{-}1}$ to $P_{3\text{-}5}$, enabling real-time cargo tracking. The system monitors the sorting and transfer process of digital goods in real time as follows:

Step 1. Cargo enters the system through the T1. T1 connects to the upstream system, receiving cargo information C_m. The digital cargo model is instantiated, and the roller drive is set to ensure cargo reaches the $P_{1\text{-}1}$.

Step 2. Cargo enters the T2, which is conveyed to designated positions $P_{2\text{-}0}$, $P_{2\text{-}1}$, and $P_{2\text{-}2}$ for sorting and Diverting. System sets and adjusts the drive n_v and operation status of the conveyor rollers. T2 specific process is as follows:

- Intake: Convey the cargo to the alignment position $P_{2\text{-}0}$
- Safety stop time t_1.
- Sort: Convey the cargo to the corresponding position $P_{2\text{-}1}$($P_{2\text{-}2}$) based on c_t .
- Safety stop time t_2.
- Convey: Redirect the cargo towards T3 and convey it.

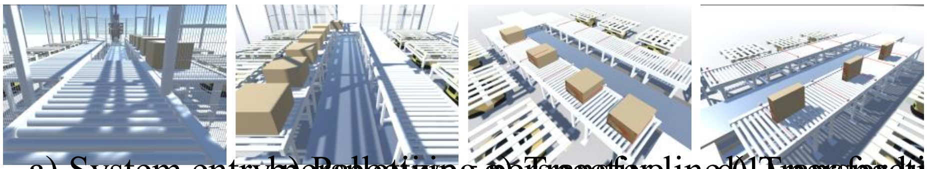
Step 3. The T3 module receives cargo from T2 and transports it along predefined routes via straight conveyor segments. Upon entering T3, system dynamically adjusts movements based on real-time feedback from the TSD-designed N_i. Cargo transitions from T2 exit points $P_{2\text{-}1}$($P_{2\text{-}2}$) to T3 conveyor, progressing from N_5 to N_1 in reverse indexing sequence. Final positioning at station $P_{3\text{-}1}$ triggers a palletizing-ready state, where industrial robots initiate pickup protocols.

3.4 Aided Visualization (AVM)

Visualization serves as the critical interface between human operators and machine intelligence in digital twin systems[18]. This framework integrates three core auxiliary visualization functions, including viewpoint monitoring, collision detection (CD) and simulation.

The auxiliary visualization can show the PE position and the operation status of dynamic entities in the real scene through intuitive 3D models. The system visualizes the cargo generation and transfer process from different perspectives (Fig. 5), operators can intuitively track label placements and monitor real-time logistics status, enabling rapid identification of routing anomalies. The process of sensor detection of goods can also be seen in the c) and d).

The system uses CD to simulate the physical properties of PE and detects the behavioral interactions between entities, such as goods -Ni and cargo-cargo. Real-time collision data is visualized through an interactive interface, enabling scenario simulation and testing to identify potential issues during the design phase. AVM achieves digital mapping of physical scenarios and dynamic simulation of entity work about TSM.



a) System entry perspective b) Palletizing perspective c) Transfer line (1) perspective d) Transfer li

Fig. 5. Visual field of view in different directions

4 Experiment and system implementation

4.1 Experimental Preparation

The system data comes from the actual project to ensure simulation validity and applicability. This study employs Unity3D (2021.3.33f) as the core simulation platform for digital twin implementation. Reference [19] conducts a comparative analysis between Unity and mainstream simulation platforms, demonstrating Unity's technical superiority in parametric flexibility and physics-based rendering fidelity. VE is constructed by SolidWorks with Cinema 4D software for lightweight processing and rendering. The processed models are exported in FBX format and integrated into Unity 3D to construct an interactive digital twin environment, enabling real-time synchronization between physical and virtual systems. On the hardware side, a Siemens S7-1200 PLC controller is used to control the operation and interact with the Unity virtual system.

4.2 Transport unit experiment

The experiment leverages DTP to validate the Ni sensor layout design scheme in TSD. A unidirectional sorting conveyor line was configured, the number of goods is Q. The size model includes single size (395*395*185) and 11 typical multi-sizes. Based on simulation results, feasibility and stability assessment of schemes S1-S3 are carried out to determine the final conveyor unit scheme. During simulation, events such as cargo overturning, collision between cargoes, cargo overflow beyond conveyor boundaries, and insufficient inter-cargo spacing (below L) will be regarded as the critical failure of transferring cargoes. The possible failure accident events are set as F, and the above events correspond to F_1-F_4, respectively. S1 scheme does not consider the influence of F_4. The success rate is defined as the ratio of digital goods that reach the N_1 gripping point from the origin without triggering F_1-F errors to the total experimental trials.

In the single-size model experiments (Fig. 6 a), S1 scheme exhibits growth in F-type events as cargo volume escalates, leading to progressive cargo congestion (Fig. 7 a). This results in robotic arm misalignment during grasping. After Q>100, the success rate is lower than 50% (c), and failure is declared when Q=200. Schemes S2 and S3 achieve zero F-events and 100% success rates under increasing cargo volumes. Sensor-equipped conveyor unit design significantly reduces F1 incidents in high-volume S1 scenarios while maintaining comparable experimental completion times to S1. This validates the feasibility of both S2 and S3 conveyor schemes, demonstrating their operational viability under tested conditions.

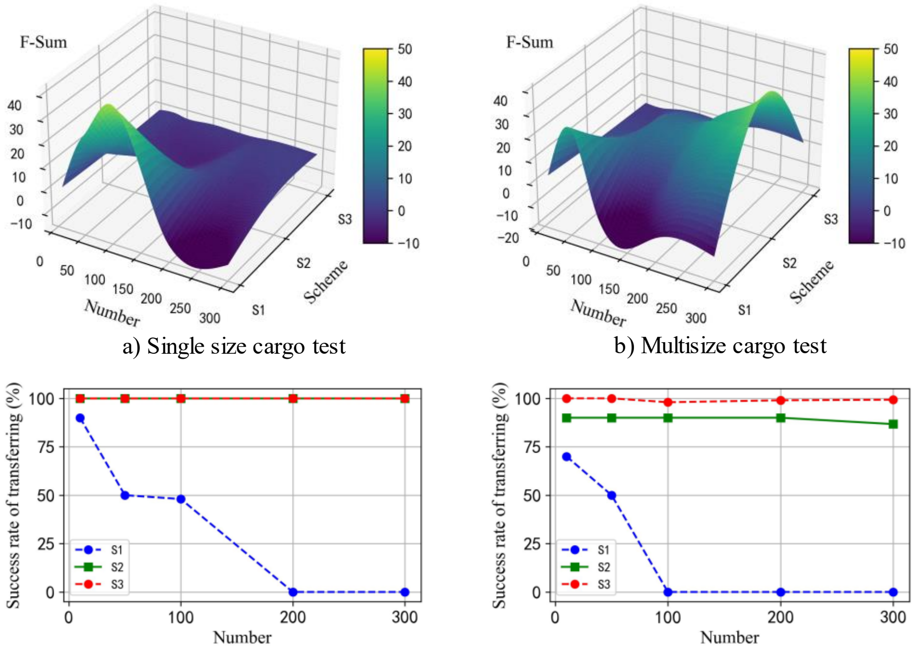
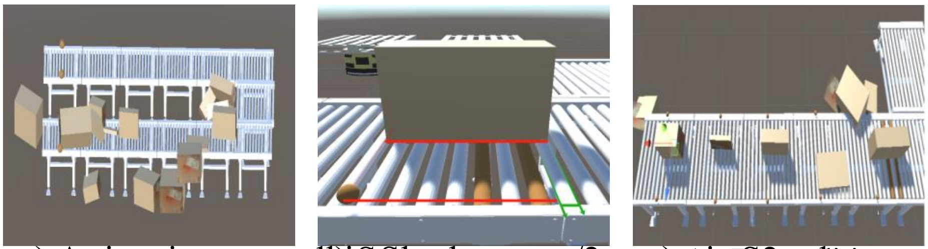


Fig. 6. It demonstrates the correlation between F-event frequency (subfigures a-b) and success rate (subfigures c-d) with experimental cargo volume for Ni units across schemes S1-S3. Setting the experimental failure corresponds to F-Sum value of -10.

In the multi-size experiment (Fig. 6b), S1 shows sharp growth of the cargo F at Q=100, resulting in complete system blockage and operational termination. In the S2 scheme, rising cargo volumes makes the proliferation of F, performance degrades significantly. Due to variations in cargo dimensions, when $c_l > n_l / 2$ (Fig. 7 b) the great static friction between the goods and the roller will cause the originally accelerated goods to roll over and collide with the goods behind them (Fig. 7 c). Experimental results reveal the flaws of the S2 scheme, the success rate reaches the best of 90% (Fig. 6d) and gradually decreases, demonstrating instability in sustained operations. S3 scheme places sensors at conveyor roller ends and enhances collision detection through dynamic bounding box. Improves the existing bounding box system to dynamically adapt to cargo dimensions, reducing roller-cargo collisions. Another key modification is adding a secondary collider to the cargo generation setup, enabling real-time size adjustments for precise spatial awareness. Results shows that S3 simulation F events are maintained near 0, and the success rates are all greater than 98%. Furthermore, sensor placement at the terminal positions exhibits superior stability compared to intermediate configurations.



a) A situation occured in S1 scheme b) Symptom $n_l > n_l/2$ occurs in S2 scheme c) An FS condition oc

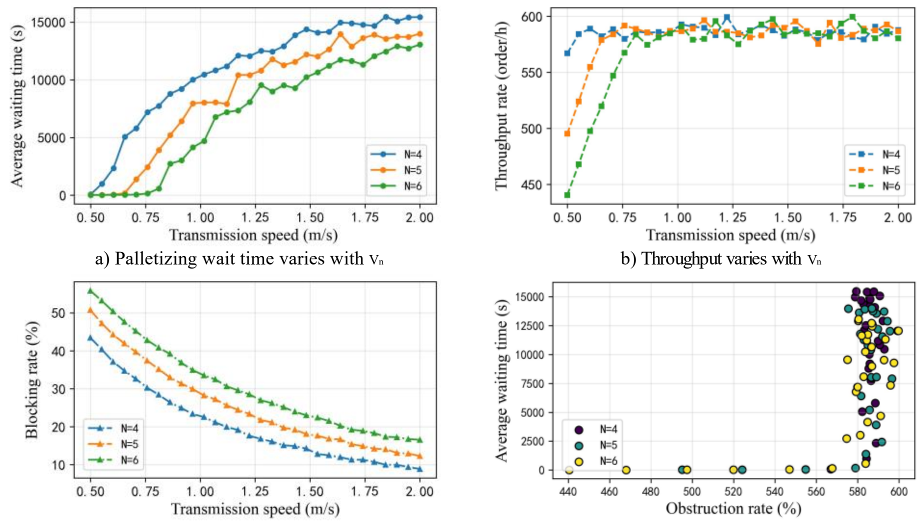
Fig. 7. Simulate the condition of goods in the scheme

Fig. 6 demonstrates the progressive improvement of the DTP-based conveyor system. Both S2 and S3 schemes achieve 100% success rates in single-size cargo experiments, validating the feasibility of N_i-embedded sensor designs. The S3 configuration exhibits superior stability, attaining an average 99.26% success rate (peaking at 100%) in multi-size model tests. The optimized scheme of N_i is finally determined through simulation, and the conveying unit N_i in the T3 area of the conveyor line is equipped with opposing photoelectric sensors, which are set at the end of each N_i. The sensors are used to detect whether the goods arrive or not, and at the same time, ensure that there is no collision between the goods during the conveyance.

4.3 Rate-matching optimization

To ensure the safety and high efficiency of the conveyor line transmission of cargoes, the experiment simulates a dual-line parallel transmission process. Orders are dynamically routed to available lines based on real-time data, with each order sequentially passing through N conveyor units before entering the palletizing queue. When a conveyor line is N, the order generation is suspended. Under S3, the time interval Δt for cargo traversal through a conveyor unit is obtained and set as the safe distance time according to L. The parameter scanning method systematically explores combinations of N (4-7) and v_n (0.5-2.0m/s) under a supply rate of 1000 orders/hour. By simulating 24-hour operational data, calculate performance metrics the throughput, average waiting time, and the blocking rate for each configuration. Finally determine the theoretically optimal parameter configuration.

Experimental analysis reveals a coupled impact of conveyor unit count (N) and speed (v_n) on system performance. While theoretical optimization suggests N=7 and vn=0.5m/s yield minimal waiting time for palletizing goods (12.2s) and 392 units/hour throughput, physical constraints (site dimensions, robot glide time) render this configuration impractical. Further, comparative analysis N range from 4 to 6 (Fig. 8a-c), which reveals critical performance trade-offs:



a) Palletizing wait time varies with V_n b) Throughput varies with V_n

c) Blocking rate varies with V_n d) The relationship between blocking rate and waiting tir

Fig. 8 Coupling of N (4-6) and vn Spaces with system performance**.**

Average Wait Time for Palletizing. N exhibits progressive escalation with vn increments, for N=5-6, wait time stabilizes at ≤59s within v_n =0.5–0.7m/s.

Throughput. Averages at 555 units/hour for N=4-5 at $v_n \geq$ 0.7m/s, yet with diminishing stability returns.

blocking rate. blocking rate inversely correlates with system robustness, with n=5 exhibiting a median blocking rate, Minimizes at N=4.

Combined with Fig. 8d, the relationship between blocking rate and palletizing waiting time further affects the palletizing waiting events, While N=4 achieves nominal throughput superiority, its operational instability renders it suboptimal for sustained logistics workflows. In the supply range of 500-570 Order/hour, there is very little time for goods to wait for palletizing in N=5.

Comprehensive analysis identifies N=5 and v_n =0.6 m/s as the optimal parameter configuration, achieving reduced palletizing wait times (59.1s) and meeting throughput demands (555.2 orders/h), while resolving the stability deficiencies observed at N=4. Excessive transfer speeds compromise system coordination efficiency without improving throughput.

4.4 System communication implementation

This study implemented a digital space communication simulation framework, resolving synchronization mapping between digital and physical workflows.In digital Space, sensor-conveyor collaborationoperates via event triggering: photoelectric sensors initiate signals, and roller drivers execute actions upon reception. The actual scenario uses Siemens S7-1200 PLC controller to record the data, in order to realize the complete operating data of the conveyor equipment from the controller, as well as to avoid the system latency problem of a large amount of data transmission, Unity and PLC communication using S7.Net protocol.

A visual comparison of the virtual simulation of the experimental system movements (Fig. 9b) and the equipment movements of the automated logistics system (Fig. 9a) was visualized and synchronized mapping was achieved, also validated through operational scenario simulations (Fig. 9c).

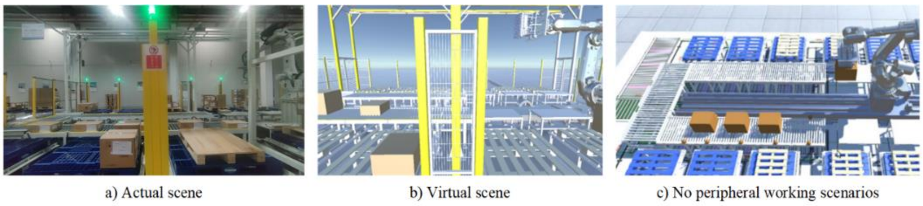


Fig. 9. Compare the field work scene with the digital space transfer virtual scene

5 Conclusion

This study addresses high-cost physical testing in cargo sorting by proposing a Digital Twin Prototype (DTP)-based pre-validation framework. The DCM and TSD modules design digital cargo models and conveying logic, while DDM and STM modules co-ordinate sorting processes, with AVM enabling real-time simulation visualization. A dynamic cargo modeling method ensures high-fidelity mapping for unpredictable real-world sequences, supporting configurable routing for increasing the flexibility. Simulation validates a sensor-deployed N_i-end scheme in T3 (safety distance L$\geqslant$1m), success rate of the conveyor is average 99.26%, which greatly reduces the number of times of equipment dismantling and installation in the actual process, improves the construction efficiency, and reduces the time and economic costs invested. Building upon the optimized Ni configuration, the conveyor line's sorting and conveying scheme is engineered with precise length specifications and synchronized velocity parameters (conveyor speed, inbound order rate, robotic palletizing speed) to ensure operational efficiency and safety. Through systematic analysis, the parameters N=5 and vn=0.6 m/s are established as optimal configurations. Future work focuses on bidirectional cyber-physical communication and data-driven predictive optimization toward Kritzinger’s Level-3 Digital Twin.

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