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Container Terminal Digital Twin Yard System Construction

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Abstract: New requirements for terminal production and operation have emerged as a result of the increase in container terminal throughput. Traditional terminals' manufacturing capabilities fall short of the expanding service needs. By constructing a digital twin yard for container terminals, the production capacity of terminals can be effectively improved, and the production operation process can be optimized. This paper firstly constructs a digital twin yard system for container terminals, proposing that it is mainly composed of physical space, virtual space, data, services, and intelligent agents. This paper elaborates on the core technologies of digital twin yards and finally takes the container delivery and loading process as an example to solve the production bottlenecks of the yard in the container delivery business by reorganizing the operation process and targeting it, which can improve the terminal production efficiency to a certain extent.

Keywords: digital twin; container terminal; intelligent agents; delivery business; loading business

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1. Introduction

As the global marine sector expands quickly, the increase in throughput necessitates increasing demands for terminal production capacity. As the core production resource of container terminals, there is an urgent need to improve the current operational bottlenecks of yards by enhancing intelligent operation capabilities. The following requirements now exist for container terminal operations:

1. The process of terminal production and operation cannot be analyzed retrospectively;
2. The production and operation of the terminal cannot be visualized;
3. The terminal production and operation process cannot be effectively improved;
4. The level of terminal intelligence cannot be effectively evaluated;
5. The intelligent module of the terminal cannot be effectively iterated;
6. The terminal cannot effectively preview the future time state.

Container terminals are able to visually monitor production issues, evaluate difficulties, and envision solutions in the past. The fundamental phase of terminal process improvement is production process optimization, but it cannot be adjusted immediately during real production, which may easily result in disorganized terminal production activities. Most terminals have begun the process of intelligent transformation, but under the present conditions, it is impossible to evaluate the reliability and effectiveness of the intelligent module; it can only be evaluated through realistic production operations over a long period of time, which can easily lead to production accidents due to the intelligent module. The most important point is that as the terminal operations are increasingly busy, a targeted advanced layout of production operation equipment is an effective way to solve production conflicts. Since most choices are still made manually under the existing structure of terminal production, it is impossible to anticipate and plan ahead for the future tense of terminal production activities.

In order to deal with the present issues with terminal manufacturing, a digital twin system for container terminals is built in this article. It can eventually replace manual decision-making and raise the intelligence of the terminal through the ongoing optimization of the intelligence inside the digital twin architecture.

2. Related Work

The digital twin was first proposed by Michael Grieves in 2003 at a product lifecycle conference, and he pointed out that the digital twin consists of three parts: the physical entity, the virtual space, and the connection between them [1]. Tao Fei first proposed that in industry, the digital twin should consist of five parts, physical, virtual, connected, data, and services, and he described the core digital twin technology [2–4]. Scholars' current research direction is focused on smart manufacturing and Industry 4.0 and less on the application of digital twins in container terminals. Li et al. constructed a digital twin model based on 3D architecture with 3DMAX and U3D technology and used the AdaBoost algorithm to train and optimize the DT mechanism model [5]. Wang et al. focused on the characteristic scenes and key parameters of ship engine systems and ship containers during operation and established a DT-based model and platform based on the basic modeling of Maya and scene rendering of Unity 3D [6]. Jakovlev et al. studied the physical space of digital twins and demonstrated the functionality of the virtual framework from the perspective of cyber–physical security. Additionally, the dynamic changes of both physical and virtual systems were qualitatively presented [7]. Oliveira et al. built a digital twin platform for 3D and real-time geographic reference visualization of container parks, as well as the location of hazardous container cargo. The tool combines different modules, allowing further visualization of information related to containers, their movement, and surrounding areas [8]. Zhao et al. have implemented a microbioreactor digital twin system for cell culture using the open-source digital twin framework, with realizable automated rocking rate and angle control and in-place optical cell density measurement [9]. Li et al. provide an overview of the important manufacturing technologies, production modes, and manufacturing processes based on digital twins in the lifecycle of aeroengine mainshaft bearings, including the metallurgical process, heat treatment process, and grinding process. They present the core technologies and future research directions of the lifecycle of mainshaft bearings based on digital twins and give a defect diagnostic and life analysis of the mainshaft bearings of aeroengines [10]. Kazała et al. present the evolution and role of the digital twin concept as one of the key technologies for implementing the Industry 4.0 paradigm in automation and control and emphasized the importance of integration [11].

In the digital twin of container terminals, Wang et al. established a system framework for intelligent port management based on DT, which is divided into five layers: physical layer, data layer, model layer, service layer, and application layer. Additionally, methods for addressing technical, data security, and management challenges were proposed [12]. Yang et al. comprehensively analyzed the challenges and requirements for the operation of automated container terminals (ACTs) from the perspectives of equipment and operation management and summarized the advantages of digital twins [13]. Wang et al., Yang et al. and Zong et al. analyzed the characteristics of large integrated port operations and proposed a digital twin application system framework. The construction methods and technologies for digital twin modeling, global ubiquitous sensing, data mapping, and model integration were analyzed [14–16].

Some scholars have conducted some applied research on this basis. Koroleva et al. based their work on a high rack container storage system, a marine wireless charging system with automatic ship mooring, drones, automatic cranes, automatic doors, and unmanned transport to build a digital maritime container terminal system [17]. Bielli et al. and Mi et al. simulated the terminal production operations and measured the optimization algorithm strategy to enhance the optimization strategy through the simulation platform [18,19]. Szpytko and Duarte constructed a digital twin model for container terminal cranes by adding transportation and maintenance plans to the digital twin model to ensure stability in the environment and assess the operational risk of the crane through Monte Carlo Markov chains to construct a comprehensive maintenance decision model [20].

Derse and Göçmen calculated the planning model with minimum transportation cost and minimum time consumption at the container terminal through simulation [21]. Gao et al. proposed a digital twin-based method to optimize the energy consumption of automated stacking cranes (ASCs) in handling containers and developed a virtual container yard that was synchronized with the physical container yard in the ACT digital twin system for observation and validation [22]. Ding et al. developed a decision support system (DSS) based on digital twin and big data technologies to provide optimal operational plans and ship delay warnings using a big data engine for real-time monitoring and efficiency analysis, further enabling real-time operational decision-making [23]. Zhao et al. proposed a DT-driven method for energy-saving multi-crane scheduling and crane quantity selection. The approach considers energy consumption and formulates the scheduling problem accordingly [24]. Zhou et al. developed a system that utilizes a digital twin of a port crane as its core combined with multi-sensor data collection methods, OPC UA information models, and plug-in programming to achieve the integration of virtual and real data from multiple heterogeneous sources [25].

Although the retrospective analysis and visualization presentation issues can be resolved in terminals using the five-dimensional digital twin framework [2], there are still limitations in terms of optimization iteration, production preview, and the decision-making of intelligent modules in production. In order to make a digital twin yard system applicable to container terminals, this paper primarily enhances the five-dimensional model, highlights the significance of the intelligent body for the first time, and suggests a "decision-simulation-feedback-optimization" interaction between the intelligent agents and the virtual space. This interaction mode enhances the usefulness of the virtual environment while also extending the original three-dimensional display function, which is exclusively available in the virtual space, and encourages the optimization and upgrading of the intelligent agent.

3. Container Terminal Yard Digital Twin Framework

3.1. Architecture System

The digital twin yard (DTY) of container terminals consists of five parts: physical space (PS), virtual space (VS), data (DD), services (SS), and intelligent agents (IAs). The PS is a collection of physical entities. There are more physical entities involved in the yard, including yard bridges, forklifts, internal trucks, external trucks, containers, space resources, etc. The VS is a collection of models formed by modeling the physical space entities, which is a mapping of the physical space and simulates the intelligent agent in response. DD is the foundation that drives the operation of the digital twin yard, which contains the physical space, virtual space, services, and data generated by the intelligent agent, and it drives other components. Services are the various production systems required in the terminal production operation, such as the Container Terminal Operating System (TOS), the Yard Crane Maintenance System (YMS), the Yard Crane Remote Control System (YRCS), the Container Delivery Reservation System (DRS), the License Plate Recognition System (LPRS), and Container Number Identification System (CIS), which control the production operation in the physical space. The IA is a crucial component of the digital twin yard, which directs the production operations of the terminal yard and optimizes itself through the organic integration of physical space, virtual space, data, and services.

$$\mathrm{DTY} = (\mathrm{PS}, \mathrm{VS}, \mathrm{DD}, \mathrm{SS}, \mathrm{IA}) \tag{1}$$

The overall process of digital twin yard operation is shown in Figure 1. The PS is modeled and mapped into the VS. When the state of the PS is changed, the VS is changed correspondingly. At the same time, the SS is targeted to fit the production system according to the production business requirements and issue instructions to the IA. The IA combines the DD with the PS state for calculation and the VS for simulation, and then feeds back to the IA after the simulation is completed, and the IA judges the decision instructions. This process can be repeated several times until a better decision instruction is selected, and feedback is given to the SS, which issues the final decision instruction to the PS. After the physical space completes the instructions, the intelligent agent compares, iterates, and optimizes itself based on the data generated by the physical space, the virtual space, and the service. The process is based on the existing container terminal production, combined with the five-dimensional framework of the digital twin, to achieve a real sense of "virtual to promote the physical".

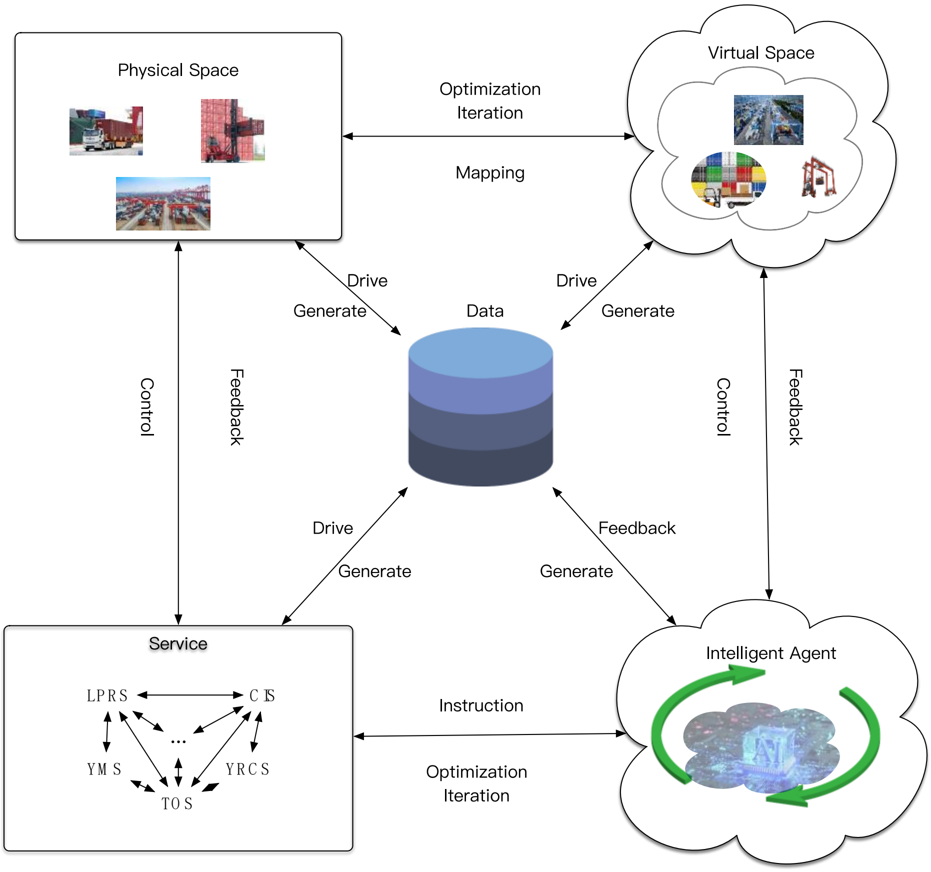

Figure 1. The process of digital twin yard operation.

A container terminal is a typical discrete logistics system with many business types and complex production processes. The terminal production requires manual intervention at the planning level, such as the allocation plan, berth plan, and scheduling level, such as dispatching and unloading. Therefore, the key element of the intelligent decision agent is added to the digital twin yard, which is the biggest difference from the current twin system in Industry 4.0.s

3.2. Core Technology

The digital twin yard system contains five parts: physical space, service, data, intelligent agent, and virtual space. There are further digital twin technologies involved, including spatial model construction, virtual space model iteration and display, service system dynamic fusion, data warehouse, and intelligent agent decision optimization.

3.2.1. Spatial Model Construction

The container terminal yard has many entities such as containers, yard cranes, forklifts, internal trucks, and external trucks. The physical entities in the digital twin yard need sensing modules and network modules in order to passively take the operating instructions while actively sensing the equipment's status. As shown in Figure 2, the various colors represent various ports of discharge and the physical entities can be divided into different types according to the type of equipment.

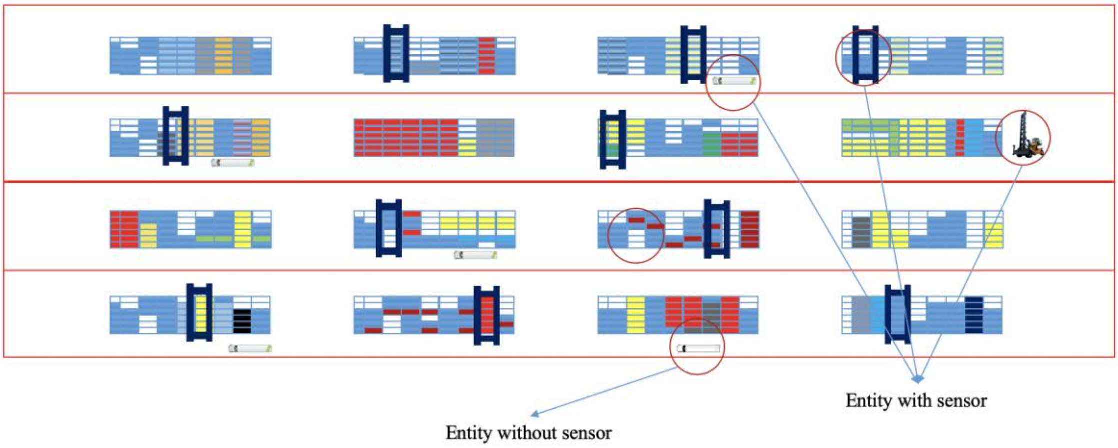

Figure 2. Different types of entities.

The physical space model contains a geometric model (GM), physical model (PM), behavioral model (AM), and rule model (RM), where the geometric model is used to build the contents of the field bridge such as length, width and height, shape, structure, etc. Building the physical model will include factors like engine speed, wear level, engine temperature, steel stress, and tension, among others. The behavioral model is used to explain how the yard crane operates, including how commands are carried out, how the yard bridge is moved around, how it is maintained, etc. The regulations established in the yard operation, such as the span height operation restriction and the speed limit for yard bridge movement, constitute the rule model. In the virtual space, the GM is necessary and the other models depend on it, so the virtual entity (VE) can be expressed as:

$$\mathrm{VE} = \mathrm{GM} + \alpha_1 \mathrm{PM} + \alpha_2 \mathrm{AM} + \alpha_3 \mathrm{RM} \tag{2}$$

where α_i denotes the weights of the four-dimensional model.

Fine granularity modeling is necessary since the forklifts, inner trucks, and yard bridges at container terminals have active perception and passive acceptance. Containers, outer trucks, yard roads, yard ranges, etc., belong to non-active perception entities; hence, only geometric models may be built for them using coarse granularity modeling; let α_1, α_2, α_3 = 0. Industry 4.0 has common digital twins for beat-to-beat manufacturing systems that typically call for an extremely high level of isomorphism between the digital and physical worlds. It is not necessary to require ultra-high isomorphism in various decision-making and simulation processes. Entity models with different granularity can be built under different business types or scenarios, thus reducing energy consumption to a certain extent, speeding up the operation of the digital twin yard, and improving its responsiveness. It is the first instance of a virtual space with configurable isomorphism in the container terminal system.

Thus, the virtual space can be expressed as follows:

$$\mathrm{VS} = \sum_{i=1}^{I} \sum_{j=1}^{J} \mathrm{VE} \tag{3}$$

where i denote the set of types for which modeling needs to be performed and j denotes the number of models that need to be modeled in each type.

The modeling process is shown in Figure 3 and is divided into cell type selection, cell characteristics selection, meshing, model checking, boundary condition definition, and calculation correction. The cell type can be classified according to shape, such as point, line, and surface cells, and according to cell order, such as linear, quadratic, and P cells. After selecting the cell type, it can be corrected according to the solid characteristics. By dividing different numbers of meshes, different accuracy models can be built. After the model is constructed, the model can be calculated, verified, and corrected by a finite element, a higher-order singular value decomposition method, etc., to ensure consistency with the physical space.

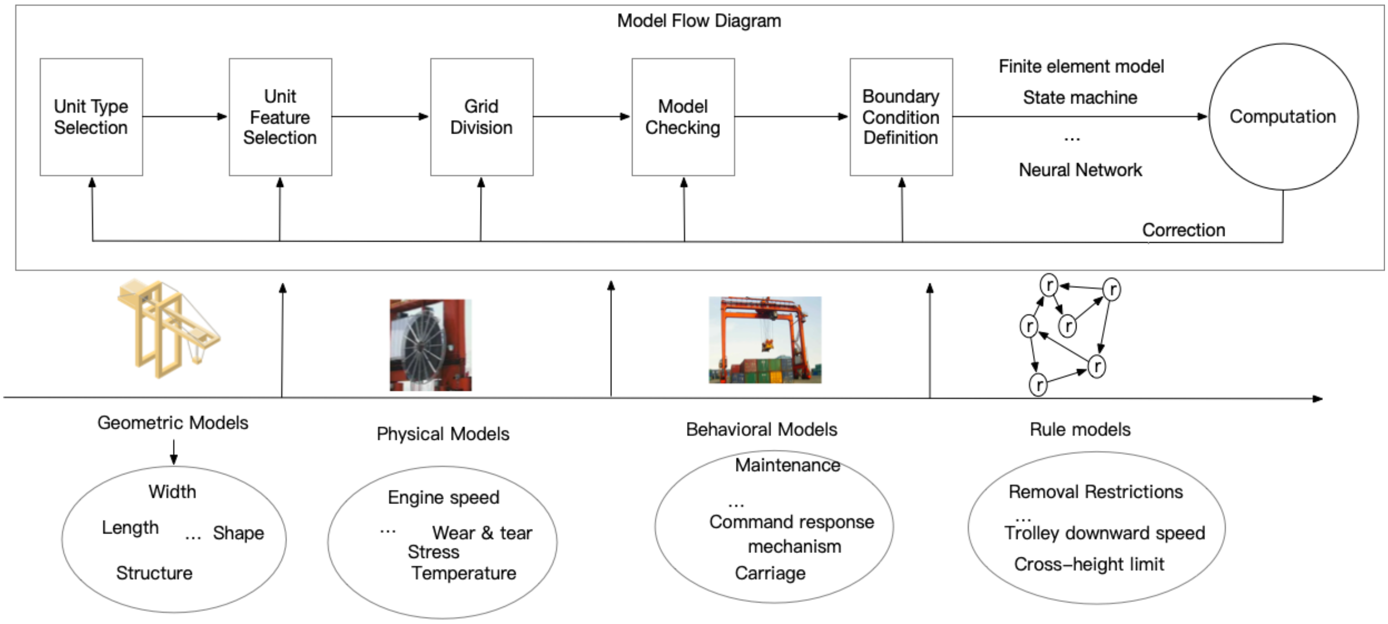

Figure 3. Model flow diagram.

3.2.2. Dynamic Integration of Service Systems

The operation of a container terminal yard requires the support of various service subsystems, as shown in Figure 4.

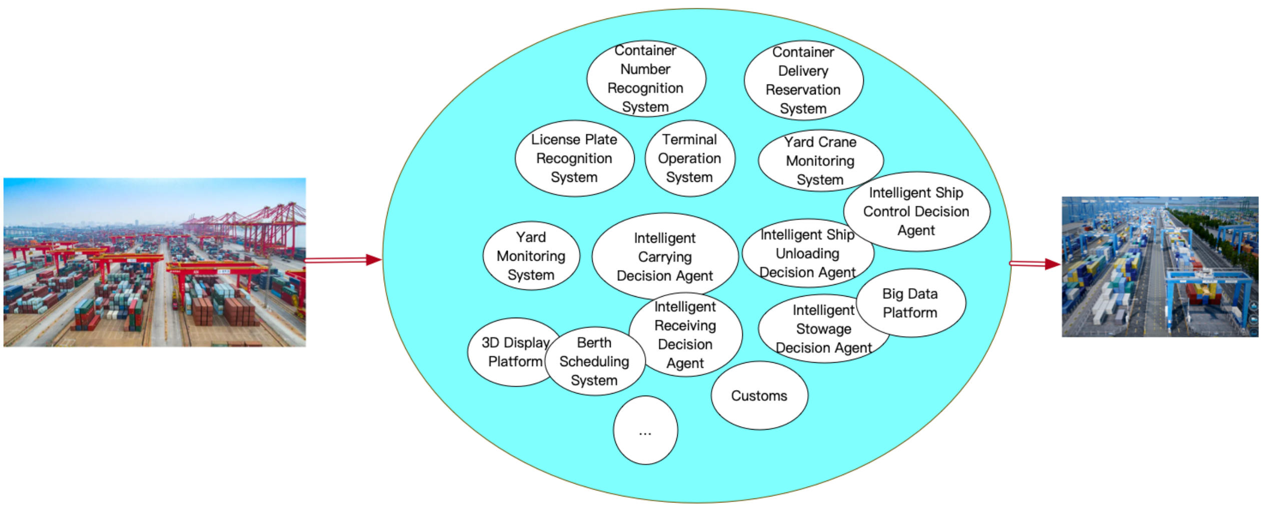

Figure 4. Service integration.

The PS generally requires a command-and-control system, remote control system, identification system, etc. The VS requires a 3D display system, dynamic modeling system, monitoring system, etc. The DD requires a data system conversion system, storage, etc. The SS is a collection of systems that need to be used in the production process of the yard.

$$\mathrm{SS} = \{\mathrm{service}_{\mathrm{PS}}, \mathrm{service}_{\mathrm{VS}}, \mathrm{service}_{\mathrm{DD}}\} \tag{4}$$

Consider a container delivery operation as an example. To complete a container delivery operation, it is necessary for the cooperation of several systems including the container delivery reservation system, the big data platform, the 3D display platform system, the truck number identification system, the container number identification system, the terminal operation system, the field and cranes remote operation system, and the intelligent container delivery agent.

A common data transfer format must be specified since different service systems must communicate with one another when the service platform summons them for varied production needs.

$$\mathrm{Api}_{\mathrm{s}} = (\mathrm{Name}_{\mathrm{s}}, \mathrm{Time}_{\mathrm{s}}, \mathrm{Data}_{\mathrm{s}}, \mathrm{Type}_{\mathrm{s}}) \tag{5}$$

The interface consists of the service system name, time, data, and data type. The service platform needs to unify the management of interfaces for each subsystem and complete data exchange. Dynamic service fusion unifies all of the services in the terminal into a common interface, making it easier to invoke services in different systems and laying the groundwork for IA utilization.

3.2.3. Data Warehouse

The digital twin yard data contains physical data generated by the physical space, simulation data generated by the virtual space, business data generated by the service platform, and simulation data generated by an intelligent agent.

$$\mathrm{DD} = (\mathrm{DD}_{\mathrm{Ps}}, \mathrm{DD}_{\mathrm{Vs}}, \mathrm{DD}_{\mathrm{SS}}, \mathrm{DD}_{\mathrm{IA}}) \tag{6}$$

Physical data ($\mathrm{DD}_{\mathrm{Ps}}$) mainly contains data generated by the production process, including production factors, production process, production environment, production quality, and other data, which are the real results and standard data of production. Simulation data ($\mathrm{DD}_{\mathrm{Vs}}$) contains data simulated in the virtual space after the instructions generated by the intelligent agent, including simulated production factors, simulated production process, simulated production environment, simulated production quality, and the control data generated in the three-dimensional presentation. Operational data ($\mathrm{DD}_{\mathrm{SS}}$) is the data generated in the process of terminal operation, such as the ledger of container delivery records generated in the container delivery reservation system, the instruction dispatch data generated in TOS production, and the box number identification information generated at the gate exit. The simulation data ($\mathrm{DD}_{\mathrm{IA}}$) contains the simulation decision data generated in the intelligent agent in the current situation. The basis for data cleaning and fusion is laid by segmenting the data sources of the digital twin container terminals and identifying disparities in the data.

As shown in Figure 5, cleaning and fusion are necessary when the data are used because of the heterogeneity, scale, real time, and complexity of the data. Data cleaning can be performed by using the Trillium model, the AJAX model, and the Bohn model framework, as well as dirty data pre-processing, the sorting neighbor method, the Lagrange interpolation method, the multiple traversal data cleaning method, cleaning by using domain knowledge, and integrated data cleaning by using a database management system. Data fusion is the organic fusion of $\mathrm{DD}_{\mathrm{PE}}$, $\mathrm{DD}_{\mathrm{VE}}$, $\mathrm{DD}_{\mathrm{SS}}$, and $\mathrm{DD}_{\mathrm{IA}}$ generated from digital twin yards. The least squares unbiased estimate approach can be used to perform data fusion in three different ways: data-level fusion, feature-level fusion, and decision-level fusion.

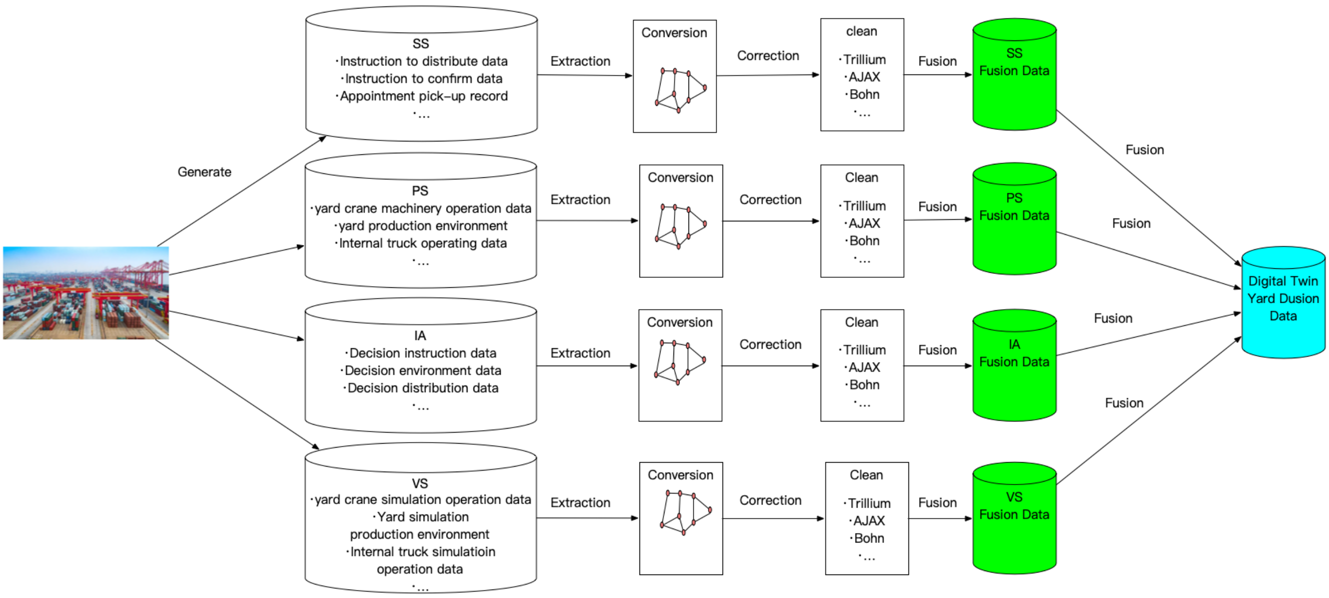

Figure 5. Data cleaning and fusion.

When the intelligent agent command is issued, the command operation data generated by physical space operation and virtual space operation can be fused, so that the difference can be analyzed and compared to enhance the level of assistance to improve the intelligent agent, virtual space model consistency, and stability of physical space equipment operation.

Data cleaning and fusion is a necessary step under big data, which is a prerequisite for decision and data-driven analysis. Through data cleaning and fusion, we need to build a data warehouse to form an integrated, analysis-oriented data environment to better support decision-making analysis.

3.2.4. Intelligent Agent Decision Optimization

The majority of the decision difficulties in the operation of container yards currently rely on manual decision-making. Staff members rely on their work experience for dispatching instructions. Manual decision-making has certain limitations, such as insufficient prediction of site resources, low level of refinement, and no retrospective decision-making. Therefore, in the digital twin yard, intelligent decision-makers are relied on to dispatch instructions. The intelligent agent decision is based on the existing container terminal production base, combined with mathematical algorithms and artificial intelligence, etc., to simulate manual decision-making. The intelligent agent has the ability of self-learning and self-retrospection, and through continuous self-optimization and self-iteration; thus, manual labor is replaced, and manual participation is reduced. An important advancement in the digital twin system of the container terminal is the intelligent body self-optimization, which propels instruction allocation and simulation with the virtual space separately and realizes the intelligent body self-optimization and upgrading through continuing mutual feedback. As shown in Figure 6 below, the delivery decision intelligent agent is developed by the rule sieve algorithm, Monte Carlo tree search algorithm, and neural network. The real-time operation of the yard combines historical data to make command decisions and records environmental data, so as to backtrack, learn, and improve the intelligence level.

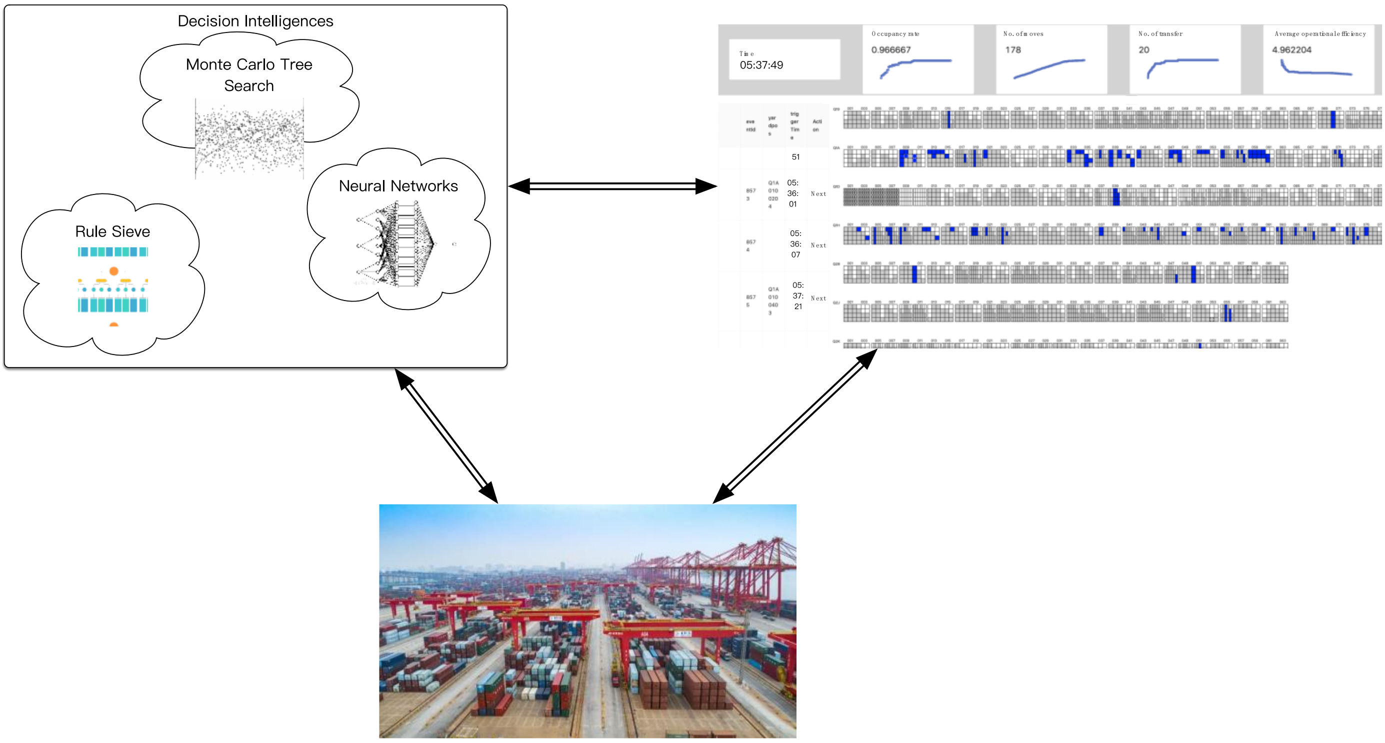

Figure 6. The delivery decision intelligent agent.

4. Optimization of the Production Process

4.1. Optimization of the Container Delivery Operation Process

Container terminal delivery operation refers to the process in which the customer puts the specified container into the yard after the customer's cargo arrives at the terminal through shipping.

4.1.1. Existing Container Delivery Process

The workflow for the container delivery industry is comparatively simple at this stage in the development of container terminals. The existing delivery process is shown in Figure 7. Typically, the customer makes a delivery reservation through the delivery reservation platform and selects the delivery time on their own, with a 2 h window for the reservation. When the user arrives at the terminal gate, the incoming truck will be checked using either an appointment form or license plate recognition. If the audit is successful, it will determine if the truck can enter the yard to deliver the container operation based on the arrival time and the reservation time. The terminal typically decides to let the user wait in the buffer zone for a while as a punishment mechanism if the arrival time is later than the reservation time. The site scheduler will then set up the yard crane to execute the container delivery operation in accordance with the yard's actual operational status.

From the viewpoint of the current container delivery operation process, the entire workflow has been initially computerized, and the data can be connected through the terminal service system. However, there are still certain areas that can be improved. When a customer makes an appointment to deliver a container, the terminal service decision-making intelligence can determine the best time to deliver the container and can send feedback to the customer for confirmation. It can reduce the waiting time for the outer container truck by analyzing the operation of the terminal through the terminal service when a container truck enters the gate and arrange the operation of the yard and bridge through decision-making intelligence in accordance with the actual operation situation. When outbound trucks leave the gates, an analysis of customer delivery business data is performed to update customer data and assist in optimizing the decision-making intelligence.

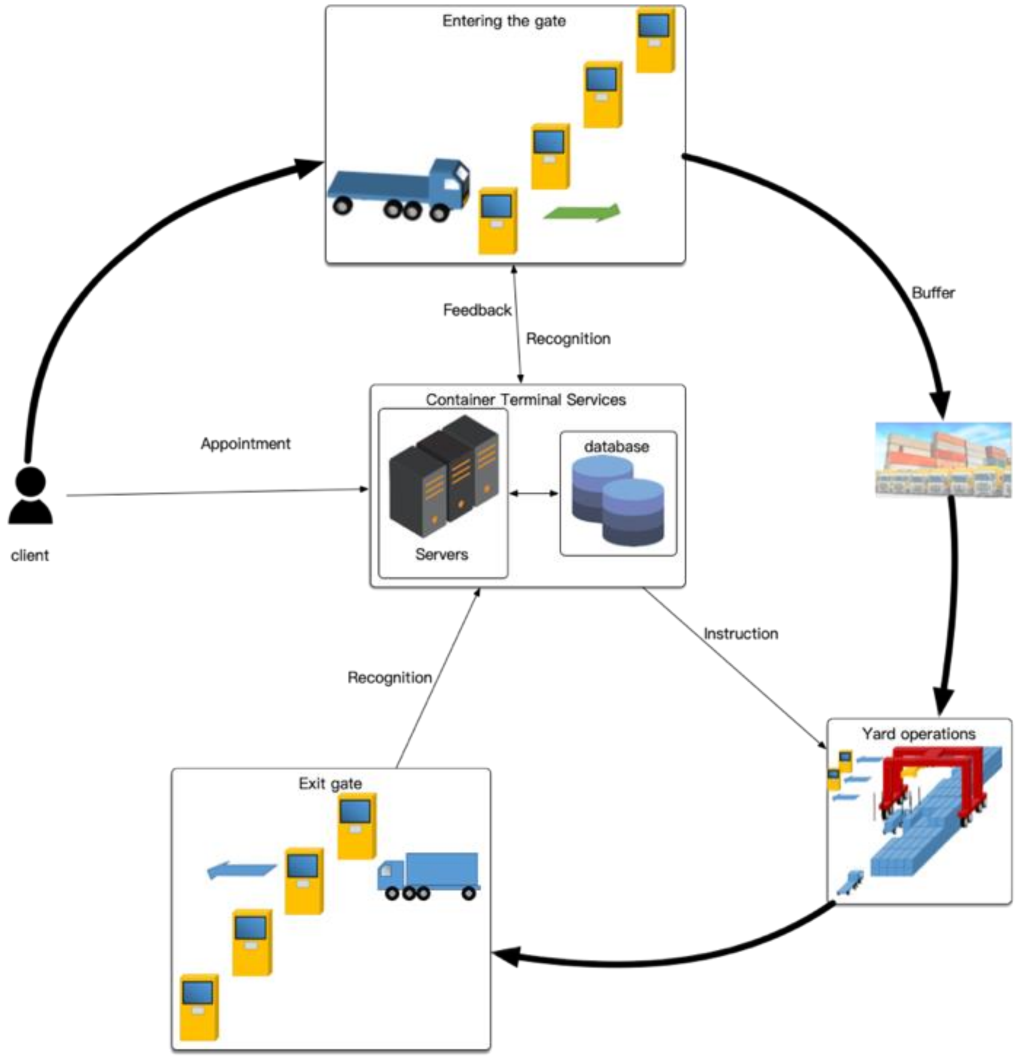

Figure 7. General delivery process.

4.1.2. Delivery Operation under a Digital Twin Yard

Based on the digital twin yard system, the container delivery business can have a new operation mode. As shown in Figure 8, during the delivery reservation stage, the customer makes a reservation through the DRS system and submits the relevant container information and external collector card information to the DRS system. The DRS system generates the reservation result by interfacing with the TOS system, and the TOS system issues a decision instruction to the delivery decision intelligent agent based on the operation of the yard and bridge entity in the yard and bridge system. The intelligent agent calculates the delivery time of this reservation order. The intelligent agent simulates the gate, yard, and bridge operations in the virtual space by extracting the yard model data, unloading operations, allocation plan, container history data, loading operations, and other business data. After the virtual space simulation, the simulation process and simulation results are saved, and the results are fed back to the intelligent agent. The intelligent agent judges whether the simulation data is feasible; if not, the intelligent agent recalculates and simulates; if feasible, it feeds back to the TOS system and DRS system and finally feeds back to the customer.

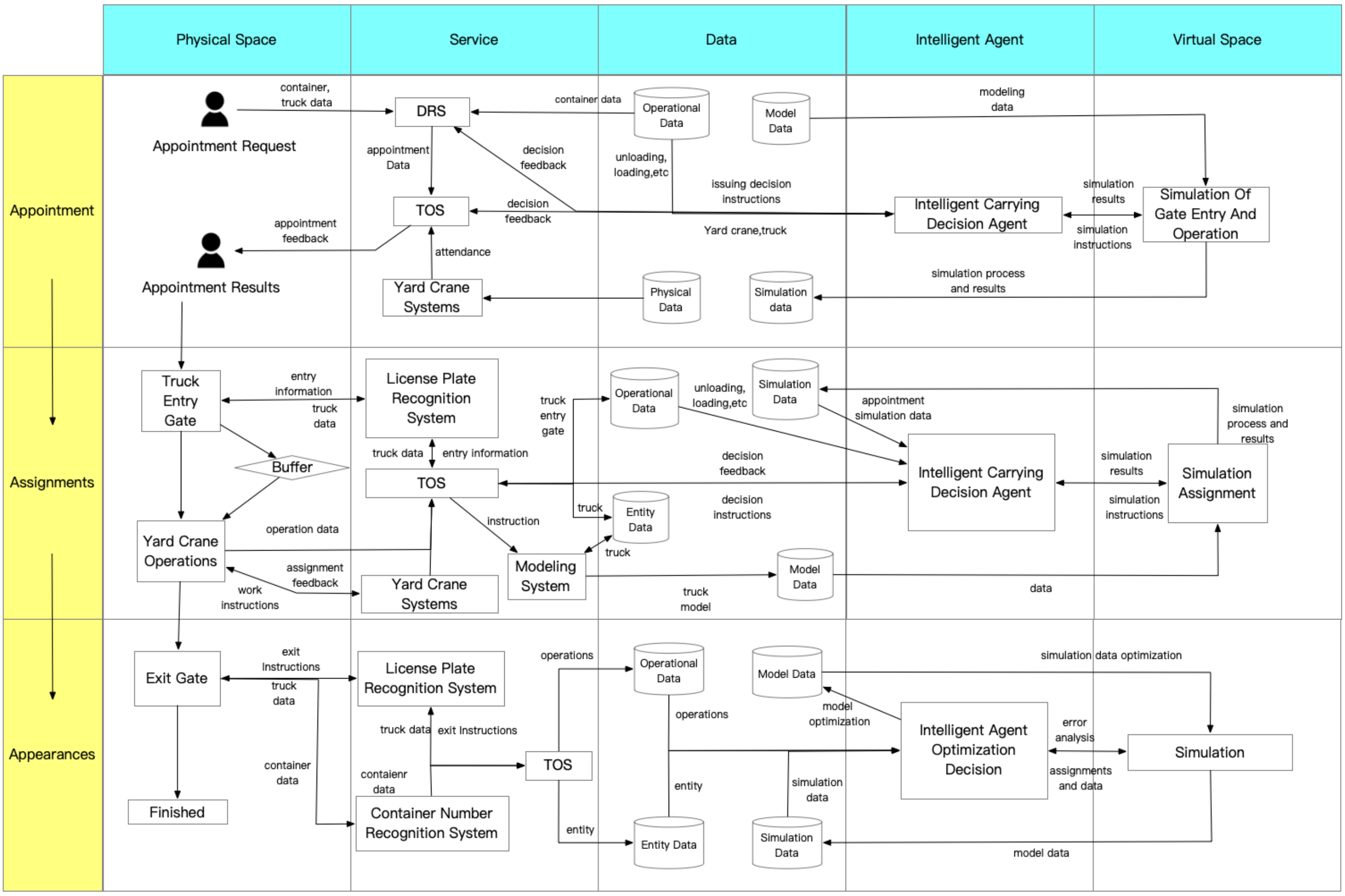

Figure 8. Digital twin yard delivery process.

In the operation stage, the external collector vehicle booked by the customer enters the gate. At this time, the vehicle identification system identifies the data provided by the gate and provides the vehicle data to the modeling system, and the modeling system performs dynamic modeling. At the same time, the vehicle information is provided to the TOS system, and the TOS system gives instructions to the intelligent decision-making agent, which makes decisions and carries out simulation operations in the virtual space and stores the simulation process and results. After the simulation is completed, the intelligent agent provides the field and bridge operation instructions to the TOS system. The TOS system assigns instructions to the field and bridge system and carries out the operation. When the vehicle enters the gate, due to the high randomness of the customer's arrival time, it can enter the buffer zone first and wait to see if the operation conditions are not met through the TOS system instruction assignment.

In the departing stage, after the yard operation is completed, the outer truck loads the container to the gate, and the license plate recognition system and the container number recognition system carry out recognition at the same time and provide the result to the TOS system, which will confirm whether to release the container. The intelligent agent reconfigures and simulates in the virtual space after the overall operation process is complete by fusing and uniting the physical data, business data, and model data. The simulation space then updates the simulation data of the operation process and operation result. The virtual space considers the error factor by judging the difference between the actual data and the simulated data at the beginning of the job process and the end of the process and carries out model iteration optimization if it is due to model error, and strategy optimization by the decision agent if it is due to business error.

4.2. Digital Twin Loading Operation Process

Based on the digital twin yard, the container terminal has a new operation mode for container dispatching.

As Shown in Figure 9, when a ship berths, berthing information is transmitted to the Berth Plan System (BPS). The BPS transmits the corresponding data to the TOS system. The TOS pushes the acquired ship data to the Crane Assignment Intelligent Agent (CAIA), which calculates the splitting plan by collecting data in DD and sends the decision result to a simulation in virtual space. Before the loading operation starts, the TOS system issues the instruction for the CAIA to calculate the work block and verify it by the virtual space simulation. When the loading operation is carried out, the TOS issues instructions, the Instruction Delivery Intelligent Agent (IDIA) calculates the specific instructions, and the Yard Crane Delivery Intelligent Agent (YCDIA) calculates the specific execution of the instructions, which is verified by simulation and then fed back to the TOS. After verification by simulation, it is sent back to the TOS and finally released to the crane system, yard crane system, and truck system for its execution. After the execution, the system will record the current yard time state and operation process and feedback to the intelligent agent and virtual space to achieve self-feedback. After the execution, the system will record the current yard time state and operation process and provide feedback to the intelligent agent and virtual space to achieve self-feedback.

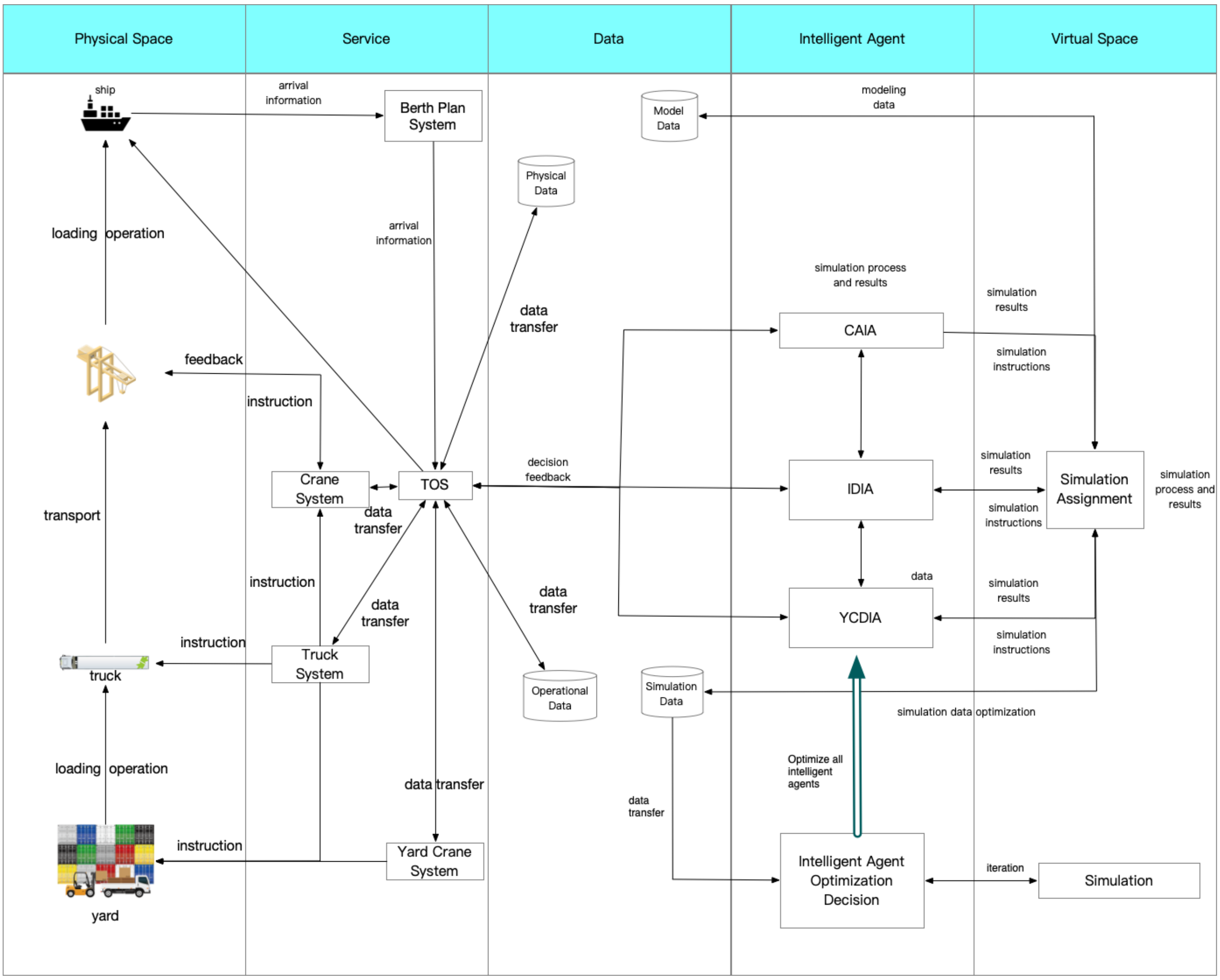

Figure 9. The digital twin loading operation process.

For the above production process, after data tracking in a terminal in Shanghai port, the vehicle reservation rate increased by 27%. In the original process, the customer's delivery time was uncertain when he arrived at the yard after making a reservation, and the terminal would carry out the delivery operation when it did not affect the operation of the yard. However, in the current production process, the intelligent agent judged the suitable delivery time and the customer carried out the delivery according to that time, and the waiting time was greatly reduced from the original average waiting time of 27 min to 19 min. In the case of other production processes, such as loading and discharging, the rate of overturned containers in the yard decreased by 1.28%, which also shows that the digital twin yard is beneficial to the production operation of container terminals.

5. Conclusions

Container terminals lack intelligence, and the impact of intelligent modules is frequently restricted to the professional experiences of staff members who share a certain personal inclination. While reducing errors caused by manual skill, the digital twin yard can aid in the advancement of terminal intelligence. The digital twin yard can simultaneously identify the production operation bottleneck in the yard and promote the terminal to increase production effectiveness. The digital twin yard of the container terminal is an essential pathway for improving terminal intelligence and an essential tool for supporting terminal transformation and modernization. The construction of a framework for a digital twin yard, the development of implementation strategies, and the analysis of the terminal's common container delivery and loading operations all serve to demonstrate the paper's scientific approach to the design of digital twin architecture for container terminals. Access to more capable decision-making agents may be advantageous for future terminal manufacturing. Additionally, it may be considered linked to auxiliary systems that can follow the movements of departing container truck vehicles in real-time, such as a highway inspection system. This will make it possible to schedule container delivery operations in advance, reducing outgoing truck waiting times and improving terminal service efficiency.

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