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Digital Twin-Driven Approach for Process Management and Traceability towards Ship Industry

Kan Wang [1,*], Qianqian Hu [2] and Jialin Liu [1]

[1] College of Ocean Science and Engineering, Shanghai Maritime University, Shanghai 201306, China; liujialin001026@163.com
[2] Marine Public Safety Research Center, Shanghai Maritime University, Shanghai 201306, China; guqinghu@126.com
* Correspondence: wangk@shmtu.edu.cn; Tel.: +86-(021)-38282517

Abstract: The digital twin (DT) approach has risen in popularity for applications in many industrial process managements. By applying the "Shipyard 4.0" digital transformation trend, the ship industry is developing techniques able to reduce risks by improving operation process management. This study proposes a combination of a DT approach and practical experiment as part of a five-tier framework for DT-driven process management in the ship industry. This study focuses on the characteristic scenarios and crucial parameters within the ship engine system and shipping cargo container in operation procedures. DT-based models and platforms are established in this study based on the basic modeling of Maya and scene rendering of Unity 3D. To address the fusion issue of multi-source heterogeneous data in the ship operation process, a Bayesian neural network (BNN) method is introduced into DT's virtual model layer and data support layer. By integrating an improved BNN-based algorithm into DT-based models, the collected data can be extracted and aggregated accordingly. In the ship engine room, the operating temperature is selected as a critical parameter, with the best mean percentage deviation (MPD) between DT-driven predictions and test value of 3.18%. During the shipping cargo container process, the results indicate that DT-based models have acceptable performances under different conditions, with optimal MPDs of 5.22%.

Keywords: digital twin; process management; BNN; DT-driven prediction; ship industry

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1. Introduction

Process management in the ship industry consists of multiple stages (design, construction, operation and maintenance), which should associate multidisciplinary teams with designers, contractors, engineers and safety managers. For the most part, product lifecycle management (PLM) is the business activity of managing a shipbuilding enterprise's products across their entire processes [1]. PLM defines product as the core element of summarizing shipbuilding enterprise information [2], and lifecycle as the new time dimension of information integration and analysis. PLM has attracted a lot of industrial and scholarly attentions [3–6], due to its potential to shorten innovation leading time and reduce costs. However, it can be found that the following remaining gaps exist in the PLM process [7]:

- Heterogeneous tasks at each stage of the ship industry result in a lack of connection and fusion between the data generated in the operation process, forming information islands.
- A large amount of data is collected in the processes of the ship industry, but there is also a lot of repeated and null data. In the general PLM process, these invalid data cannot be autonomously filtered, which compromises data analysis and sharing.
- The applications of process management rely on data analysis of physical entities; there is a lack of data analysis of digital models. Real-time data interaction and optimization between real ship object and its digital model has not been completely realized.

Digital twin (DT) is regarded as an effective and innovative solution to the above problems in the process management of the ship industry. One of the earliest creators and most enduringly iconic virtual scenes was Second Life, which was founded by the former Linden Lab CEO, P. Rosedale. Second Life and its developer Linden Lab explored notions of digital identity, virtual goods, digital economies and online multiplayer ecosystems in the early 2000s [8]. In 2003, M. Greives proposed the DT as a conceptual model of the lifecycle management process [9], and at the same time, he also redefined process management by bringing virtual models under PLM. Over the past decade, since DT models have been introduced, there have been tremendous increases in the amount and richness of information of both physical and virtual things [10]. Table 1 lists typical DT-driven system configurations, basic models and application scenarios used for lifecycle management in different fields. DT provides the fidelity required to realistically predict shipping performance with post-event recovery actions under the various possible disruptive events. It proves that DT-driven management can be extended in several development directions of marine industrial engineering [11]. DT has been applied to polar supply ships and scientific research ships (S. A. Agulhas II) [12]. Through long-term measurements of environmental conditions and ship response, measurement data of polar research present an opportunity to improve the state-of-the-art. It is recognized that real-time analysis and utilization of such measurements could benefit the insightful operation and management of vessels. The measurement, aggregation, analysis, visualization and insight/interpretation of data, and monitoring of data by means of machine learning or multivariate statistical analyses benefits the ship in terms of technical operation and risk management. A competent managing approach can not only prevent mismatches between processes and operations in high quality but also demonstrates how to optimize management, how to track results and how to evolve based on models' analysis, to adjust workflows at all levels of process management in ship industry.

Table 1. Configuration, model and platform of DT applications for process management.

Configuration	Model	Driving Technology	Proposed Application	Year
Device layer User interface layer Web services layer Query layer Data repository layer	Cyber-physical system model	Web services AR	Visual management of offshore platform in oil/gas exploitation process [13–15].	2016
Design Manufacturing Assembly Inspection	DT-conceptual model	Paradigm shift in computer-aided tolerancing Geometrical variations management	Reference model based on shape concept, skin model is proposed [16].	2017
Process industry space Communication system User space	DT-reference model	IIoTs Machine learning AR and VR Cloud technology	For maintenance process management, to avoid high-risk events [17].	2019
Quality prediction Control system Data	Quality prediction and control model	IoTs XML Machine learning BPNN	Models of group products for assembly and welding production line of shipyard management [18].	2020
Monitoring and control system Remote interface	Electric power model	Open platform Co-simulation functional mock-up interface-standard	Reduce fuel consumption and improve overall ships' performances [19].	2020

Table 1. *Cont.*

Configuration	Model	Driving Technology	Proposed Application	Year
Perception layer Transport layer Service layer Application layer	DT indoor safety model	IoTs BIM SVM	Realize on-site display of operation status, hazards warning, positioning, classification and grade evaluation [20].	2020
Modify parametrization Cost and decision-making Hierarchical structure Modular set-up	Causal dynamic statistical model Economic sub-models	Lightweight Java Monte Carlo method	Identify effective steering inputs and predict influence of potential measures [21].	2021
In-cylinder combustion Energy terms Effective expansion ratio	Atkinson cycle engine model	GT-Power software vSimulink	Simulation-optimization platform for developing process management strategies for hybrid electric vessels [22].	2021
Physical scene IoTs device and service Cyber scene Stakeholders	Radio propagation model Weighted moving average model Log-normal shadowing path loss model	iSafeTrack	DT-enabled tracking solution framework for safety management (Hong Kong cargo terminal) [23].	2021

In this study, a practical DT-enabled platform was presented to manage the potential risks of the ship operation process for the marine industry. Herein, the novel DT-driven applications were performed for synchronization and prediction for operating temperature, products concentration, environment parameters, etc. In order to determine their suitability and traceability as a DT approach, two examples were investigated in terms of accuracy by comparing their history, real-time and DT-driven data. Regarding this DT system, the intelligent mode can enable decision-makers to make advanced response plans for emergencies in the ship operation process.

2. Materials and Methods

2.1. 3D Modeling in Maya

In this study, Autodesk Maya is applied for basic DT modeling, and Unity 3D is used as the virtual render engine of DT real-time scenes. As the initial step of DT visualization in the ship operation scene, basic 3D modeling can set the foundation for data fusion of the subsequent ship operation process. The basic DT modeling is based on building 3D models, and in Maya, the modeling methods include the non-uniform rational B-splines (NURBS), polygons, subdivisions, etc. Among them, the NURBS modeling method [24] uses mathematical functions to describe the curve and surface of models, and controls the models' accuracy by modifying the parameters of curve or surface. In this way, diverse mixing function shapes can be obtained in different intervals. The purpose is to freely control the shape of curve to boost greater freedom. The NURBS modeling method can make the DT models in this work reach the required accuracy. In addition, it allows smooth curves or surfaces to be controlled with fewer points, resulting in streamlined surfaces. The mathematical definition of NURBS is as follows:

$$P(K) = \frac{\sum_{i=0}^{n} N_{i,m}(K) R_i P_i}{\sum_{i=0}^{n} N_{i,m}(K) R_i} \quad (1)$$

where $P(K)$ is the position vector of the curve; $N_{i,m}(K)$ is the cardinal spline by the m time.

The cardinal spline of Equation (1) can be defined by recursive Equation (2).

$$N_{i,0}(K) = \begin{cases} 1, & K_i \le K \le K_{i+1} \\ 0, & Other\ situations \end{cases} \quad (2)$$

$$N_{i,m}(K) = \frac{(K - K_i)N_{i,m-1}(K)}{K_{i+m} - K_i} + \frac{(K_{i+m+1} - K)N_{i+1,m-1}(K)}{K_{i+m+1} - K_{i+1}},\ m \geq 1 \tag{3}$$

where P_i is the control point; R_i is the weight factor; K is the knot vector.

Based on the polygon modeling method in Maya, the 3D model of the ship can be created by controlling the position and parameters of point, line and surface. A polygon is a straight-sided shape (three or more sides) defined by 3D vertices and the edges connecting them, whose internal areas are called surfaces. Vertices, edges, and surfaces are the basic components, and the 3D basic model for DT is composed of individual polygons that are combined to form a polygon mesh. The polygon mesh shares common vertices and edges between ship-based entities' surfaces, which are called shared vertices and shared edges. The polygon modeling method creates polygon surfaces according to some discrete points contained in the 3D space of the ship and combines polygon surfaces to form polygon models. Then, the polygon object with a spatial structure is formed by combining several polygon surfaces together and creating a common edge between two adjacent polygon surfaces. There are essential differences between the methods of polygon and NURBS, which have been both used in 3D modeling in our study. A NURBS object is a parameterized surface with strict UV direction. Only four sides can appear, except the shear surface, when using NURBS to create 3D models. We can create the polygon by converting existing NURBS, so that it can be edited and modified easily in the modeling process. In this work, according to the attributes of all ship elements, the minimum size unit is set as 0.1 m. When the ship models are refined, the number of planes of individual parts are controlled under 5000 to ensure the smoother operation of Maya. When the combination of each individual model is completed, it will be imported into the real-time render engine.

2.2. Real-Time Rendering in Unity 3D

This study creates an interactive virtual scene based on Unity 3D, which can continuously support the testing of DT system. Unity 3D is a render engine that has gained popularity within research, as virtual 3D environments, objects and their interactions can be created within [25]. Developed by Unity 3D, it allows one to create integrated virtual scene render engines for types such as real-time 3D ship-based visualizations and animations. In this study, Unity 3D is used to realize DT for the process of ship operation, adopting a way to realize communication between data service and Unity 3D. Basically, the workflow of the real-time rendering engine is divided into three aspects, including data collection and processing, scene building and visual output. Data collection and processing contain the 3D ship model, texture, components, etc. Scene construction involved in ship operation is essentially a processing plant of resources, and the scene elements and editing are covered. Scene elements are for objects (ships, containers, engine room, etc.), scripts, components, lights, etc. Scene editing is a further refinement of the scene, such as modifying the parameters of the ship engine room in the properties panel or adding a component to the shipping container. The specific process can be observed in Figure 1 and the sensors are set in the ship engine room, container and other positions to collect the data of the environment parameters (i.e., ambient temperature, wind velocity). The programmable logic controller (PLC) data can be collected from IoT devices on the ship's critical components and upload them in real-time with the JavaScript object notation (JSON) format. It is integrated with the Mono Developer compilation platform and supports C#, JavaScript and Boo scripting languages [26]. In our study, C# is used in Unity 3D as the scripting language in the development of DT's rendering scenarios. There is a receiving server (a data receiving back-end service), which is configured to receive the data uploaded by IoTs devices in the ship industry. Based on Unity 3D's support for 3D Maya formats, its visualization mode allows us to change the parameter values in real-time while the scripts are running, making it convenient to develop DT-based platforms. Unity 3D can be used for real-time transmission and rendering data of the virtual model, sensors or point-clouds. In Unity 3D, it can obtain data from the server in real-time via HTTP or Socket. Then, we implement it to drive the mapped virtual equipment in real-time in Unity 3D through real-time data acquisition. After adding physical properties and behavioral logic, the models and data can be processed into real-time rendering effects. Unity 3D issues commands, the service receives commands, IoTs and sensors acquire commands and send them to PLC, resulting in the control relevant equipment in the ship operation process. It can also be interacted with on multiple platforms in the form of AR, VR, and mix reality (MR), realizing the DT-driven process management in the ship industry.

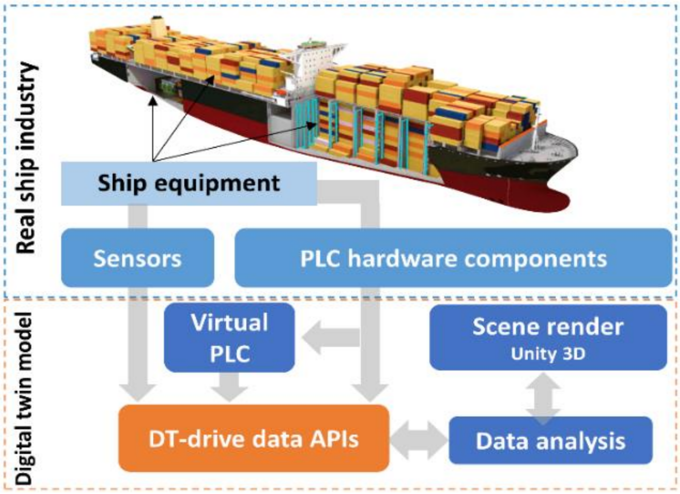


Figure 1. Specific process of data communication between the real scene and DT model.

2.3. DT Data Processing Method

Currently, built-in sensors of IoT devices have the function of real-time perception and interconnection with DT platform. During process management, real-time data of multi-stage can be collected by data acquisition. Combined with historical data, the prediction model associated with it can be further obtained. Due to the large amount of multi-source data, it needs to extract and transform the time and sensor position, respectively, then to conduct the preliminary filtering of environmental information. The organization of multi-source data in the process provides the basis for realization of intelligent management. In this study, the data deduction method adopted is based on the Bayesian neural network (BNN), which is a mathematical model that relies on probabilistic inference. Probabilistic inference is the process of obtaining other probabilistic information through the information of some variables. BNN has a probability layer in addition to the regular three-layer structure. BNN's weight parameter is not a definite value but a random variable, and it is subject to a certain probability distribution. BNN can not only give the predicted value, but also provide the uncertainty of forecast, so it is an important tool to deal with uncertain information. On the basis of the BNN model, an algorithm for multi-source data fusion in the ship industry is proposed. The analysis method used in the present study is based on a mathematical model of Bayes' theorem, which relies on real-time information and experiment data. As shown in Equation (4), when the child node of variable X_i's value is given with μ_i, Bayes' theorem can be used to calculate the posterior probability distribution of variable X_i.

$$P(X_i|\mu_i) = \frac{P(X_i|\mu_i)\cdot P(X_i)}{P(\mu_i)} \tag{4}$$

where the prior probability $P(X_i)$ of X_i is the state (x_i,1, … , x_i, r_i) known as probability distribution; $P(\mu_i \mid X_i)$ is the likelihood function, which contains the variate of instantiation conditional probability.

When all the instantiation variables $\mu_i(j)$ are obtained, the relationship can be understood using the following equation:

$$P(\mu_i|X_i) = \prod_{j=1}^{p} P\left(\mu_{i(j)}\middle|X_i\right) \tag{5}$$

By marginalizing the observed variables, the relationship between the instantiated variables and all possible states of X_i is shown in Equation (6).

$$P(\mu_i) = \sum_{k=1}^{r_i} P(X_i = x_{i,k}) \prod_{j=1}^{p} P\left(\mu_{i(j)}\middle|X_i\right) \tag{6}$$

where $\mu_{i(j)}$ is the instantiation value of variate X_i, which is based on all the P child nodes and the J^{th} variate.

X_i equals the posterior probability of $x_{i,k}$, by $P(X_i=x_{i,k} \mid \mu_i)$ characterization. The marginal probability, also known as $x_{i,k}$, represents its confidence as a probability of occurrence given real-time information. Finally, X_i can be obtained by inference from Equation (5). For a BNN, the calculation of marginal probability is large. Therefore, by constructing a BNN inference engine, a more manageable process can be obtained to deal with the marginal probability calculation. With a more efficient inference engine, the conditional independence between variables in the system can be identified to simplify the computation. A significant characteristic of the condition independence is Markov property. The variable condition of a given parent node is independent of its non-child node.

$$\text{Pred}\left(x_j\right) = x_j,\ j = 1, 2, \cdots i-1 \tag{7}$$

where Pred (x_j) is the parent node of x_j node.

The abovementioned attribute can simplify the inference procedure. It can be applied to simplify the structural learning process to obtain an improved K_2 algorithm. The improved algorithm contributes to the identification of data inconsistencies or uncertainties, so as to more accurately represent the operation process status of the related devices in the ship industry.

3. Results and Discussion

3.1. Holistic DT-Driven Framework for Process Management

According to the basic characteristics and processes of each stage in process management, this study proposes a five-tier framework integrated with DT models and technologies, including physical entity layer (PEL), virtual model layer (VML), data support layer (DSL), analytical computing layer (ACL) and system application layer (SAL), which can be observed in Figure 2. PEL is the "digital twin" of the physical entities involved in process management of the ship industry. With the increase in the scale and professional degree of the ship industry, the ship and its related operating personnel, manufacturing equipment, processing materials, environment and other factors have become more diverse and complex. Physical entity reflects the collection of real objects in real scenario of ship operation process. It should include the environmental objects in the ship operation process, such as site layout of ship construction, operation environment, equipment in ship, and storage state of goods, etc. PEL, which is the fundamental element in the DT system, embodies the cooperation of various elements to complete process management. A virtual model of the ship industry is the core to create and operate a DT model, in order to ensure the effective closed-loop between DT and physical entity. A DT-based model is not only the replica of the physical entity in the ship industry, but also collects the real-time information for driving process management synchronously and predictively. Testing, operation and maintenance of process management based on DT are strongly dependent on data support and integration. Driven by data, the DT model can realize design preview, visual monitoring, operation preview, fault diagnosis, historical state backtracking and in-depth mining of process management. DT of a ship is a key enabler for end-to-end digital workflows in ship certification and inspection. As a critical support of the entire upper system, DSL is composed of data acquisition, data transmission and data management. The data types involve the geometric model data (e.g., size of data, data structure, the location data, style), physical model data (e.g., materials, equipment data, process data, material data), response model data (e.g., operating data, data, load data), and logical data model (e.g., operating characteristics and historical records). ACL addresses the needs of data access, field equipment and monitoring in the process management of the ship industry. "Cloud-Fog-Edge" three-end collaborative work has become a new approach for DT data analysis. Taking the ship engine room as an example, the initial step is to extract the large data of the host system operation, combine the original DT model and resource requirements. It provides the edge AI model intelligent deployment function, and realizes the state detection of the host. The second step is to update the DT model of the ship engine room by the "Cloud-Fog-Edge" collaboration and lightweight deep learning of the mainframe big data. The third step is to use DT model splitting technology to mitigate the intelligent balance communication delay and computing delay, and minimize the AI service delay. The final step is to conduct model training and feedback correction through scenarios such as internal equipment inspection. SAL includes the description of running equipment, diagnosis of running status, prediction of faults and risks, and decision of emergency treatment in process management. SAL provides intelligent manufacturing, real-time monitoring, optimized management, reliable operation, guidance and prediction by DT-drive platform.

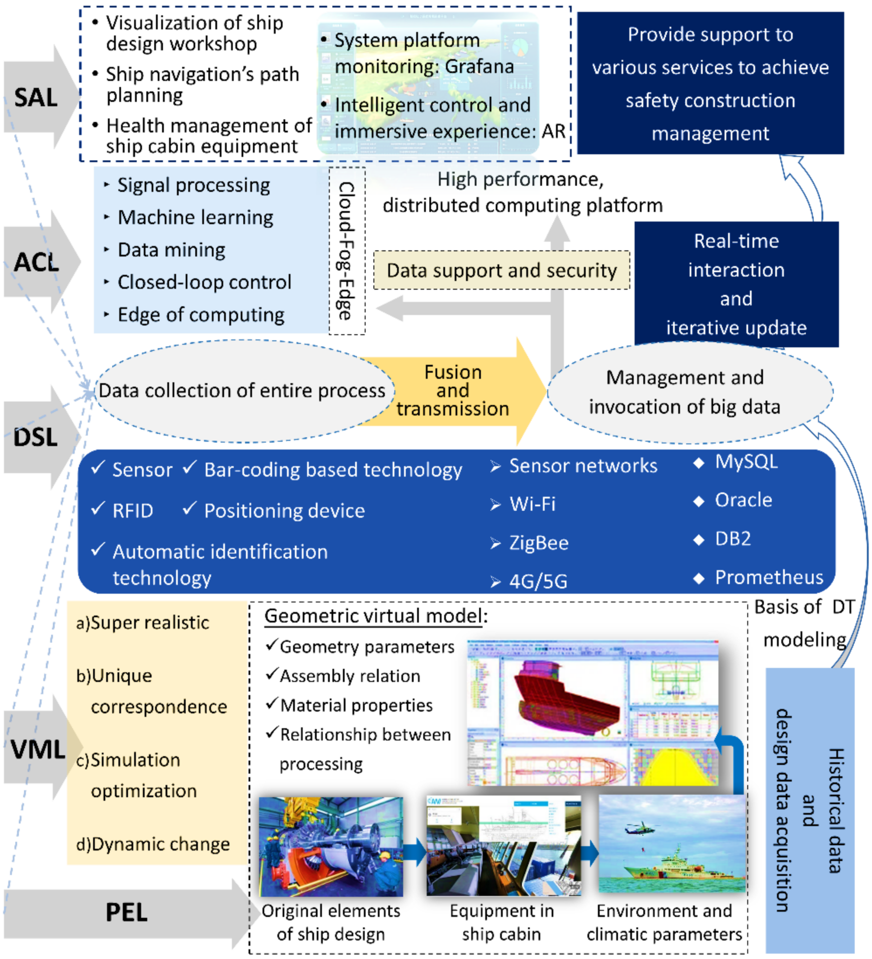


Figure 2. Five-tier framework of process management based on DT-enabled system.

3.2. DT-Drive Process Management in Ship Engine Room

The ship engine room is the heart of the whole ship during navigation, integrating a large number of important marine equipment. The diesel engine system is the core device in the ship engine room, which provides the power source for ship sailing. The ship cannot survive without the control support of the ship power when carrying out transportation activities. As the power control core of the ship navigation propulsion system, the diesel engine is also the power device with the most failures. The diesel engine system has always been an important guarantee to ensure safe and stable ship operation. The stability of the safe ship operation state is not only related to the temperature of the main engine, the consumption rate of fuel, the power of ship shaft, but also directly affects the safety and reliability of the operation process. The process management of the diesel engine system by DT can ensure proper state monitoring and fault prejudgment. This study focuses on a large container ship, which can carry 19,000 TEU of hazardous cargo containers. The DT modeling object is the diesel engine system in this ship engine room, which includes 15 cylinders, each with a diameter of 0.9 m and a rated power of 56,800 kW. The diesel engine system consists of an air cooler, cylinder, scavenge box, exhaust pipe, exhaust turbocharger and governor modules. The ship engine room includes the entire cabin, engine room floor, ventilation system and surrounding enclosures. On top of that, Maya is applied to build the basic DT model, as shown in Figure 3. The DT technology is integrated into the condition monitoring and fault diagnosis system by means of a mapping model. The DT platform of the ship engine room consists of the physical entity of the diesel engine, virtual model of the engine room, sensor and data acquisition system, optimization algorithm and DT display. In this study, the physical entities focus on the engine system and environment. In the process management of ship operation, it is a prerequisite to ensure that the DT mapping model can monitor the operating state and environmental factors of the engine room. By means of data acquisition, the actual operation data of the ship engine room is collected, which lays a foundation for the mapping between virtual and real models. According to the physical entity of the diesel engine system and environment, the modeling function is used to realize the DT model of real entity mapping. Figure 3 shows that the virtual model constructed is consistent with the real engine room interior in terms of geometric size, shape, material, position and color. In addition, it is necessary to analyze the operation data to ensure that the evolution process of the devices and environment is consistent with the virtual model.

According to the PEL of the real scene, the task of constructing the DT model in VML can be completed. Then, the data support system needs to be built for the DT model. Previous studies have shown that the turbocharger of the diesel engine system is one of the main accidental sources. The reason for turbocharger failure is that the temperature of the internal vessel lubricating oil exceeds the rated range, or the temperature of cooling water in turbocharger is too high. These reasons will induce abnormal operation of the turbocharger, which then increase the accident risks in the ship engine room. Based on this, the internal temperature of the turbocharger is selected as important data from the source of accident prevention. Meanwhile, the environmental parameters of the ship engine room, such as ventilation condition, cabin temperature and cabin pressure, will also be displayed on the DT platform in real-time. Figure 4 presents the interface of the DT platform designed for the ship engine room. By clicking the button above the interface, users can query the operating status of the devices in the ship engine room. At present, this interface can view the running status of the components related to the diesel engine system. The second button above the interface can query the parameters related to the environment, such as wind speed, temperature inside engine room, etc. The last two buttons at the top of the interface can query real-time data and historical data, respectively, and can also access the database through links to extract the relevant data within the time range. Data visualization on the left side of the DT platform is designed in this study. The idea for the column design was inspired by Grafana, which allows DT data to be presented to users as an open source analytics and monitoring solution. In this work, DT-driven platform can be used as a visualized tool with a dashboard, which provides graphs to understand the performance of ship operation with historical data and predicted results. The database can be connected to the DT platform, and the decision-maker can use these data to build dashboards in it to analyze the behaviors of process management metrics that use the DT platform. As shown in Figure 4, the lower right corner of the interface is the surveillance video box, and the images in this box are collected by the surveillance camera connected to the ship engine room. When using the DT platform, users can observe both the DT model and actual entities. In addition, the DT platform provides wireless connection and Bluetooth connection. By logging in to the DT system interface through authorization, the users can conduct management through the mobile devices.

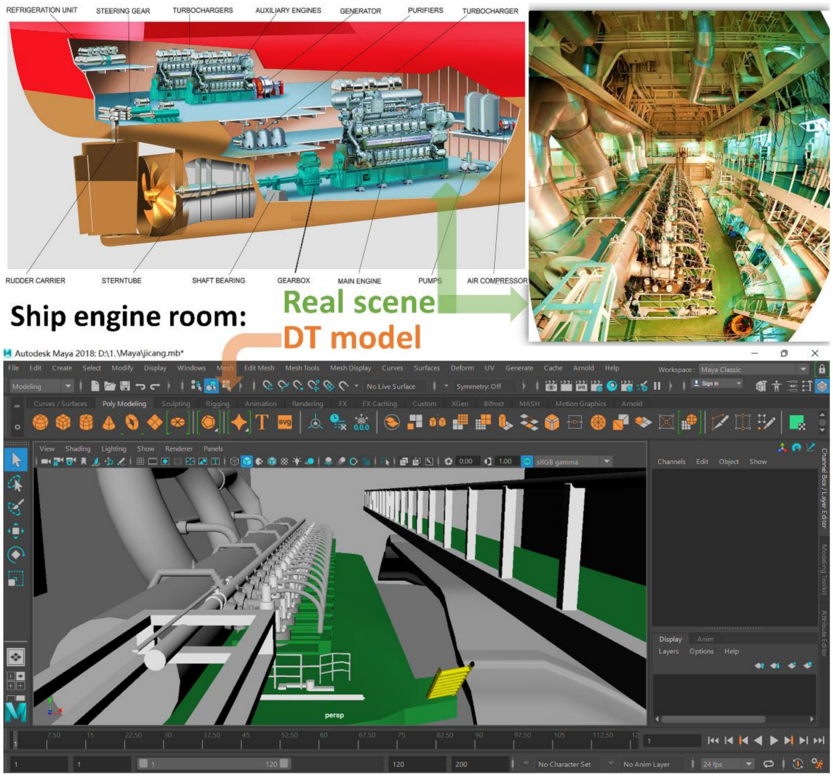


Figure 3. DT modeling for ship engine room.

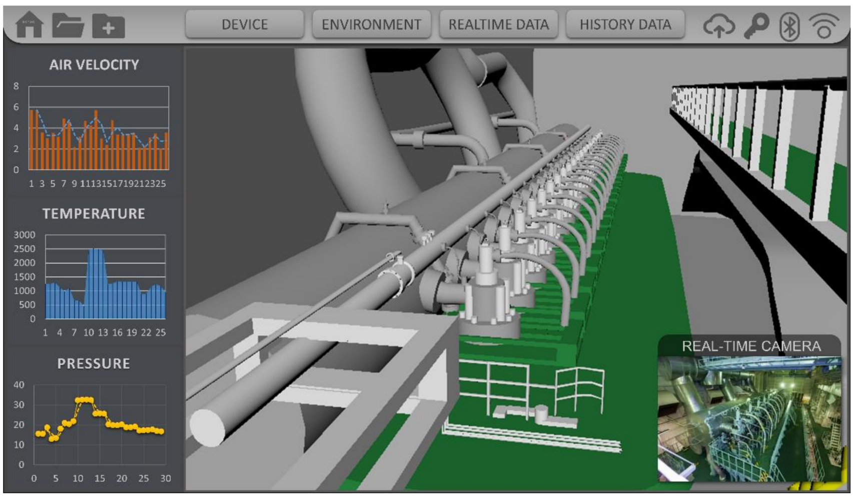


Figure 4. DT-driven platform for process management in ship engine room.

In this study, the data for the DT model of the ship engine room provides the support for effective operation of the whole DT system. The protection of DT data consists of data acquisition, transmission, processing, management and optimization. During the process management, DT data is generated in the engine room, as well as in VML, ACL and SAL. The DT platform is updated with real-time data with front-end data collected by sensors, while the predictive data generated by ACL and historical data stored in the database are driving engines. At present, relying on advanced data transmission technology, the information island in the ship engine room has been gradually eliminated, which provides a strong guarantee for the comprehensive realization of intelligent process management. In this study, an AMETEK 2101 sensor is pre-installed in the turbochargers of the diesel engine system. The sensors are widely used to measure the real-time temperature data of diesel engines, turbochargers, compressors and other equipment of large offshore ships. A temperature sensor consists of the thermocouple, resistive thermometer assemblies classed to be suitable for installation in ships to monitor engines, bearings, cooling systems and cargo with a maximum temperature of 1380 K. It is designed to meet the requirements of IEC68-2-6 with high vibration resistance and is certified by Lloyd's Register and Norske Veritas. The parameters of the data acquisition device contain sensor parameter information and data acquisition frequency. For the various types of data, the storage methods are diversified. The MBD model is used as the information carrier for the parameters of sensors, and different MBD models are established for diverse sensors. In this work, a distributed remote National Instruments (NI) data acquisition module is used to convert signals into digital quantities in the ship engine room and transmit data to a computer through a wireless network. The computer database is selected with MySQL, which can be used to manage the data of ship engine room and realize data storage, query, backup, security guarantee. The turbocharger is set with sensors, and connected with the data transfer unit (DTU) communication. DTU and the server are communicated through wireless network communication and protocol communication. The server has built a relational database and in-memory database, and uses multi-thread concurrent server framework. The relational database is used to store DTU and sensor data of the turbocharger, and the in-memory database is used to cache temporary data. The environment data of the ship engine room is collected by the monitoring system, including the temperature, humidity, pressure and ventilation conditions.

Based on the real-time and historical data of the turbocharger operating temperature of an actual ship engine system, data fusion and deep learning are carried out by BNN. BNN's unique probability layer enables the network to express uncertainty, with different possible outcomes of output under a given input. BNN can be considered a fusion of infinite subnetworks, similar to BPNN. However, the difference is that in the training process, BNN can optimize all the subnetworks in each training round. During the prediction process, BNN can propagate forward multiple times on the same test set, so that the predicted results come from multiple different subnetworks. Based on this, the BNN model has good regularization effects and better suppression of overfitting than traditional ANNs. In this study, the operating temperature data of the turbocharger have been specifically collected in DSL, which is used as the special input characteristic data of process management. Therefore, the characteristic data can be preprocessed to remove invalid data, before the BNN is embedded to temperature data feature mining. The purpose is to fully extract the associated information of series data, and learn the operation trend of the turbocharger. The previous record of turbocharger operation history data is input into the BNN probability layer. Thus, the characteristic data input of the turbocharger operation prediction of the DT model is summarized and connected to the BNN probability layer, and the BNN structure can also be optimized. This study takes hour as the time scale for data sampling. Figure 5 shows the variation trend of the turbocharger operating temperature obtained at four sampling points. Among them, the condition 1 represents the temperatures of the sampling point at the turbine inlet, the condition 2 and condition 3 represent the temperatures inside the turbine, and the condition 4 represents the temperatures at the turbine outlet. The black data points represent historical data, the blue data points represent real-time data, and the red data points represent the DT-driven predictions. The turbocharger in the ship engine room is connected to the cylinder of the diesel engine, and the exhaust gas step is carried out first after starting up for a period of time. The cooling air is introduced for testing and exhaust. Since this process lasts for a long time, it can be observed from Figure 5 that the temperature curve displays a stable change and a trend of decline in a period of time. When the diesel engine starts running, it quickly generates hot gas, which passes through the turbocharger and turns its turbines, and the temperature curve begins to rise. Moreover, the rotation of the turbine generates heat, and the air is compressed by a compressor impeller to raise the temperature, causing the temperature to rise rapidly in a short time. In this study, the mean percentage deviation (MPD) and coefficient of determination R^2 are applied for evaluating the accuracy of DT model prediction. The equations for MPD and R^2 can be calculated in Equations (8) and (9), respectively.

$$\mathrm{MPD} = \frac{100\%}{n}\sum_{i=1}^{n}\frac{\left|D_{pred} - D_{real}\right|}{\left|D_{real}\right|},\ n = 1, 2, \cdots \quad (8)$$

$$R^2 = 1 - \frac{\sum\left(D_{real} - D_{pred}\right)^2}{\sum\left(D_{real} - D_{mean}\right)^2} \quad (9)$$

where D_{pred} is the predicted data obtained by the DT-driven model; D_{real} is actual value of real-time data or historical data; D_{mean} is mean value of the actual data; n is the data number.

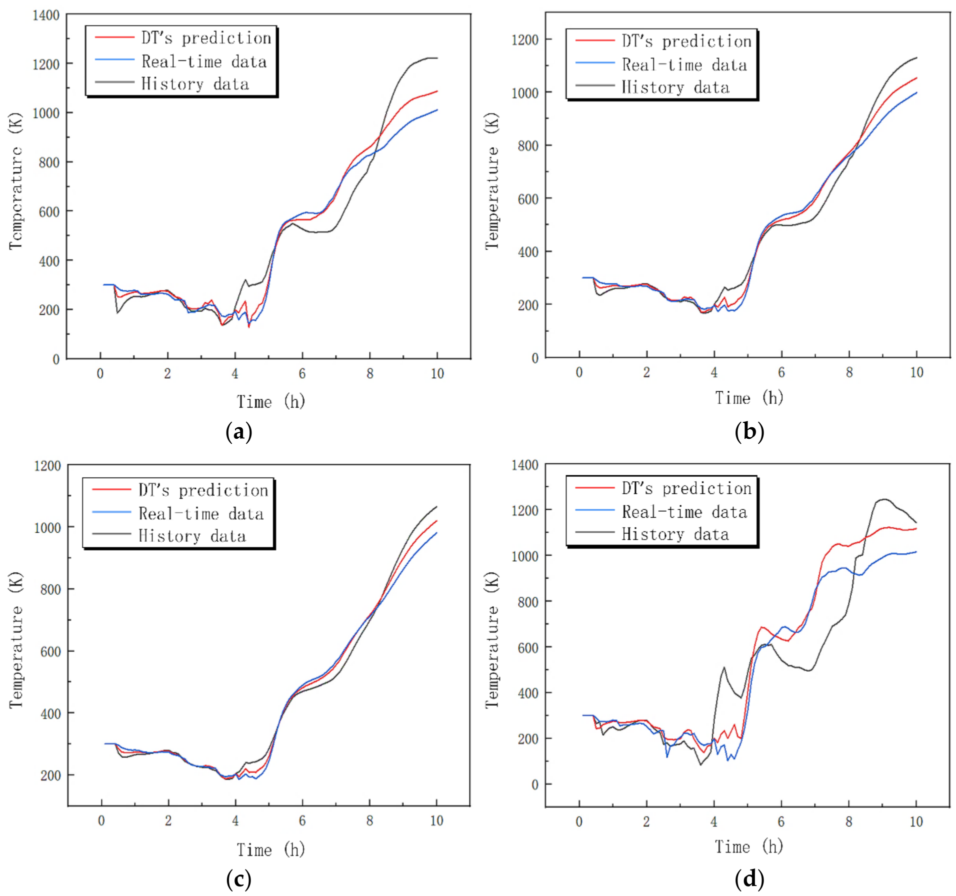


Figure 5. Comparison between DT's prediction, real-time data and historical data. (**a**) Condition 1. (**b**) Condition 2. (**c**) Condition 3. (**d**) Condition 4.

The MPD and R^2 of the DT-driven predictions and testing real-time data and historical for the turbocharger operating temperature of different sampling points are shown in Table 2. It can be concluded from the comparative results that the fitting degrees between the DT predictions and real-time data are obviously better that the results with historical data. In condition 1, which is located at the turbine inlet, the MPD between DT predictions and real-time data is 4.49%, and goodness of fit R^2 of the DT-driven model is 0.925. Relatively, the deviation between the DT predictions and historical data is higher, with a MPD of 6.28%, and theR^2 worsens with the value of 0.872. Condition 2 and condition 3 highlight the good performances of the DT predicted results; the MDPs are 3.61% and 3.18% when compared with real-time data, respectively. More importantly, the effect of the DT model and historical results are relatively perfect with a high goodness of fit R^2 and with the values of 0.933 and 0.947, respectively. The temperature distribution of exhaust gas at the turbine outlet is uneven, which aggravates the fluctuations in operating temperature collected by the sensors. Therefore, in condition 4, a slightly higher deviation occurs between the DT predictions and tests, with a MDP of 4.91%.

Table 2. Comparison of DT-driven predictions and actual data of ship engine system.

	Compared to Real-Time Data		**Compared to Historical Data**	
	MPD	R^2	**MPD**	R^2
Condition 1	4.49%	0.925	6.28%	0.872
Condition 2	3.61%	0.964	4.52%	0.933
Condition 3	3.18%	0.969	3.55%	0.947
Condition 4	4.91%	0.903	7.71%	0.811

Figure 5 indicates that the DT-driven predictions have a high degree of coincidence with the real-time data, and the maximum value of MPD between them is 4.91%, within an acceptable range in practice of the ship industry. It shows that the DT model can effectively predict the parameters of the diesel engine system. Figure 5 shows that the historical data of the turbocharger is higher than the predictions and real-time data, which indicates that continuous improvement for the BNN model is necessary. Overall, the results show that DT-driven process management can provide support for monitoring the abnormal operation of turbochargers. Relying on the DT-driven system, the safety engineer with more professional knowledge can check the interaction between the virtual models and physical entities in front of the virtual models. Then, it can be selected as the most scientific emergency measures, and such decision-making adds a deeper safety guarantee to ship engine room operations.

3.3. DT-Driven Process Management for Ship Operation in Port

The ship operation process covers the new risks, liabilities and developments in the maritime sector associated with updated technologies. In the ship operation and transportation stage, the real-time monitoring and simulation function of the ship running state can be realized by combining design and construction with real-time operation data acquired by sensors, so as to provide real-time feedback, real-time evaluation and optimal decisions. As a company dedicated to making smart shipping a reality, Eniram collects historical and real-time data of ships in Finland and its surrounding environment. Eniram establishes DT-based models of ship navigation based on statistical data, uses real-time data and prediction models to realize context awareness and energy efficiency management, and reduces fuel consumption and pollution emissions of the ships [27,28]. In addition, Wartsila uses advanced 3D modeling, sensing and simulation technology to build DT-based models to optimize and manage health risks of ship engines from design and construction to operation, significantly improving the level of equipment maintenance and management. More providers and their DT applications can be observed in Table 3.

Table 3. Main providers and DT applications in the ship industry.

Provider	Country	Proposed Application	Refs.
Eniram/Wartsila	Finland	DT models to realize energy efficiency management, reduce fuel consumption and pollution emissions of ships.	[27,28]
Shandong Shipping Corporation (SDSC)	China	DT models to shaft torsional vibration, hull fatigue deformation, ship navigation state, structural health and equipment fault warning anytime and anywhere.	[29]
Ericsson	Sweden	DT applications to handle ship cargo types, such as containers, roll-on cargo, general cargo and more.	[30]
AVEVA	UK	DT platform to promote ship operational awareness and improve crisis response, integration and collaboration across functional departments, sharing of information and coordination of daily ship activities and processes.	[31]
Siemens	Germany	DT models of marine depot to monitor the status during the ship maintenance cycles of their assets.	[32]
China Classification Society (CCS)	China	DT applications to verify health assessment and condition, evaluation of functions related to ships and offshore installations.	[33]
Navantia	Spain	DT models to support the identification of deficiencies when comparing the ship physical system with its DT model, predictive maintenance based on state and conditions, decision-making.	[34]

In another aspect, a DT model is used to monitor and forecast large container ships in the port operation process. DT acts as a bridge between the digital scene and physical ship/port scene. It is an ideal approach to fuse the two scenes and provide virtual representation of physical objects and processes. In this study, in order to build a DT model for the ship operation scene, the first step is to obtain and process data, collect ship profile data, ship length and width, structural dimensions and related materials of various components on ship. Then, these parameters are used to create a virtual model in Maya for building the geometric model of the container ship and port. In order to reduce the time for the computer to load the geometric model and reduce the occupation of CPU and GPU, it is also necessary to optimize the model. A fpx file is generated from the built white model, and imported into Unity 3D for subsequent processing of material addition. The model is read directly in Unity 3D, as shown in Figure 6. Shaders are made by adding texture pictures and maps of the real equipment, and corresponding materials are added to the read in model after completion, which can improve the virtual simulation effect of the model. After the 3D numerical model is built, it is necessary to receive real-time information and data to simulate the behavior and dynamics of the ship and form a real-time interactive model based on the DT. Different types of sensors (temperature sensor, humidity sensor, wind speed sensor, gas concentration sensor, etc.) can be arranged around the hull and container for data acquisition and processing. The data testing process is undertaken in the experiment site of the port area. Compared with the real scene, the layout of the experiment site has a high degree of scene reduction, which belongs to the experiment site of equal proportion scene reduction. In addition to ships and container yards, large cranes, forklifts and other equipment used in ports are built. It aims to research the accident risk of containers carrying hazardous goods in the process management of large container ships. Therefore, when constructing the DT model, the container model is refined accordingly. In the experimental site, a real container is selected and loaded with marine diesel oil (MDO) and n-heptane. They are placed in the container, in order to simulate the dangerous goods in the actual container. Herein, the volatile gas concentration sensor (see Figure 6) is installed inside the container, which is used to collect concentration data of the dangerous goods inside the container. The data is associated with the DT-based model and displayed on the visual interface of the DT platform in real-time. It can intuitively understand the state change in the hazardous goods in the container. On the other hand, it can also predict the change trend through the DT model. As a result, it can judge whether the hazardous goods in the container have the possibility of accident risk.

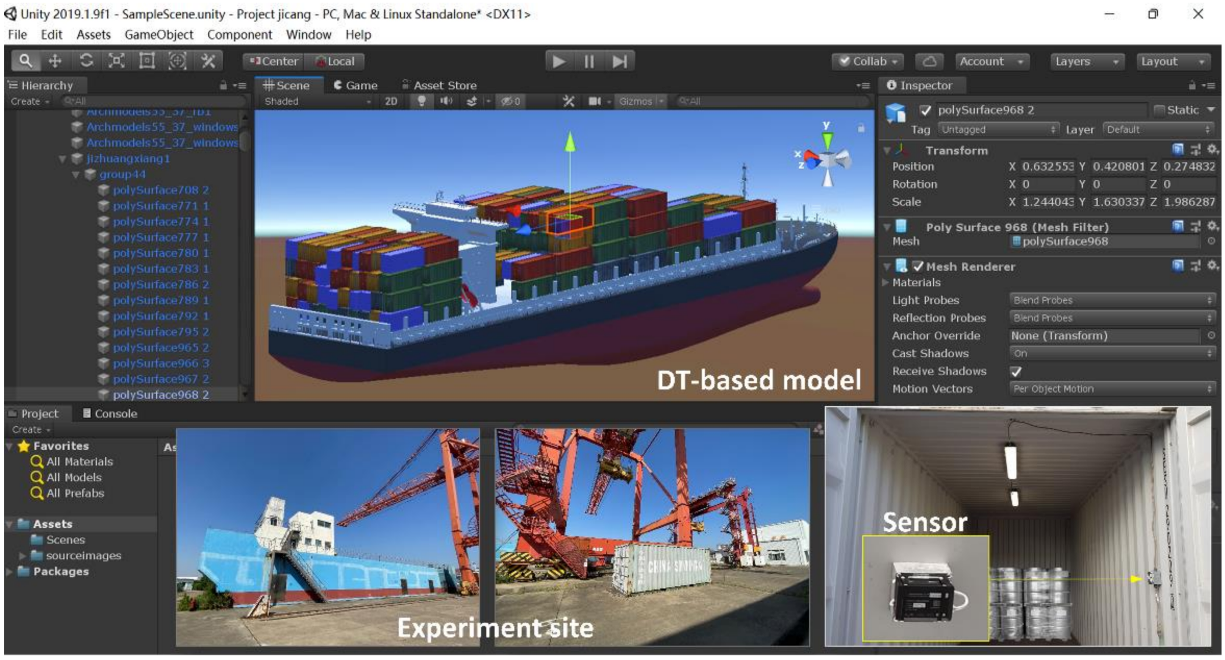


Figure 6. Integrated ship and cargo container with DT modeling combing multilayers.

A DT-driven system mainly includes driving equipment, extension equipment, host computer and other related system equipment. Among them, the driving equipment drives and charges the expansion equipment after receiving the information collection instruction of the host computer, and performs the collection task of the relevant parameters. Meanwhile, the acquired data are transmitted to the host computer for the support and simulation of the DT-based models. The core component of the driving equipment is the controller, which also includes different circuit interfaces. In this study, the controller is connected with the expansion equipment through the RS-485 interface circuit, and the USB interface and network interface of the expansion equipment are connected with the host computer through the circuit. As a standard interface of the PEL's communication, RS-485 can be the main signal transmission and output interface of the digital twinning data acquisition [35,36]. Through RS-485 communication, the DSL transmits the temperature, humidity, wind speed, gas concentration and other parameters in the ship operation stages collected by the sensors in the PEL to DT-driven models and screen in the VML. This data sensor is connected to the adjacent test station, and the serial server summarizes the data, which is then connected to the Ethernet switch. After the data are transmitted to the local server by wired and wireless networks, the OPC server can be used to save the data from the sensors to the database. Then, C# is chosen as the programming language for driving the VML (towards the DT-based virtual models) based on the data of the actual physical models. The further step is to verify, analyze and optimize. Using the existing collected data and accumulated historical data to analyze the running ship, one can establish a mathematical prediction model based on machine learning and predict the next state, which is helpful to prevent wrong decision-making, carry out preventive maintenance and reduce adverse accidents. Figure 7 is the process of building a ship safety management platform to realize the functions of monitoring and early warning. A DT-based management platform is related to the functional details, including real-time and secure network communication, data governance, twin model simulation, human-computer interaction dynamic display, intelligent algorithm expansion interface and other functions. As for the overall technical architecture of the DT-driven platform, the languages involved in the platform development are mainly C++, Python, and Java Script, supplemented by other scripting languages to support the distributed deployment and corresponding high concurrency and high availability requirements. In order to ensure the safety and reliability of operation, the platform adopts the Linux operating system. In terms of platform governance, the docker is selected as the application container engine, Prometheus is mobilized to build the service monitoring system and time series database, and the Grafana data visualization tool is used to count, monitor and alarm the platform performance indicators, so as to guarantee the safe operation of the system [37,38]. Combined with the DT framework diagram of the ship industry in Figure 2, it can be observed that the platform realizes the optimization of the ship operation path and health management by integrating all the data of the PEL and VML.

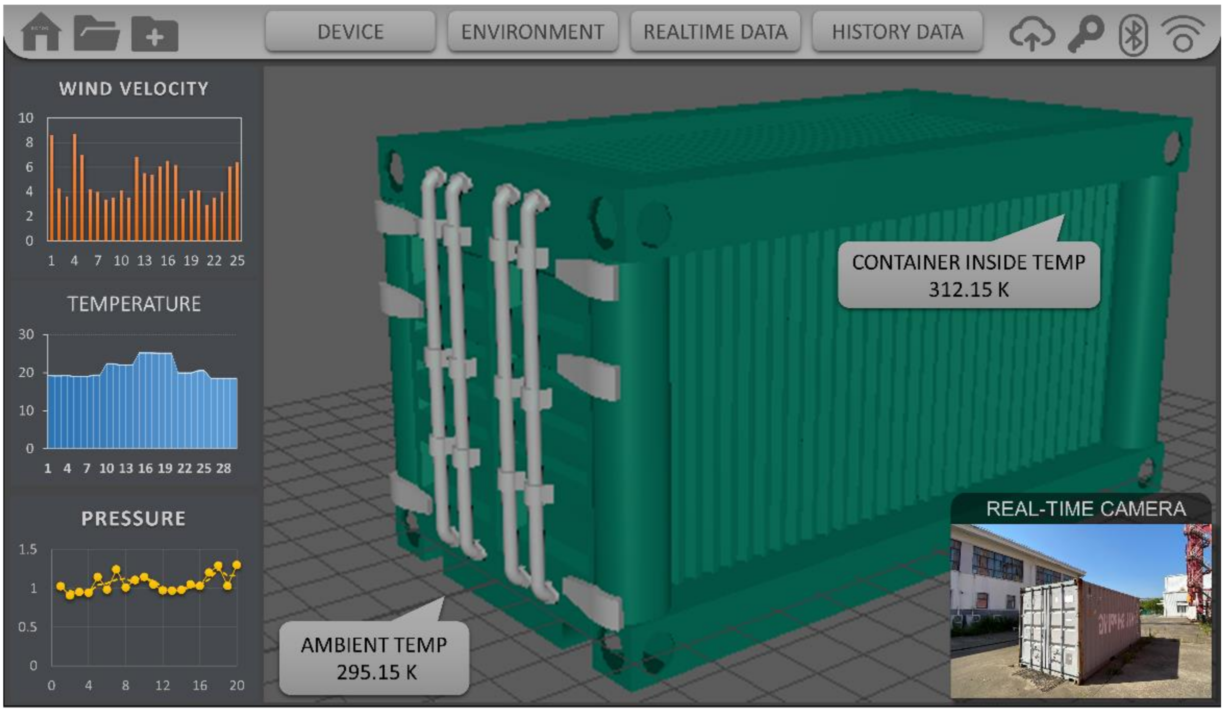


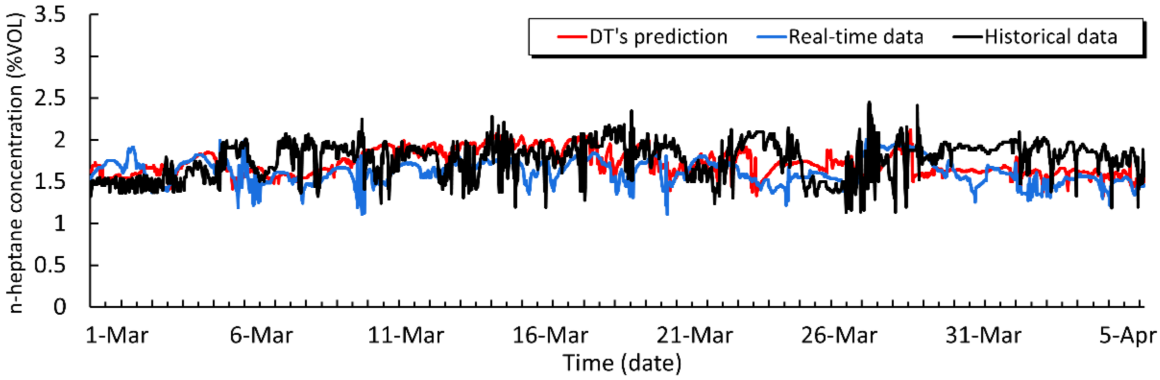
Figure 7. DT-driven platform for shipping cargo container in the operation process.

In this study, the hazardous goods container carried by ships is selected as the characteristic object of ship operation. Different from the data acquisition for the DT model, the data acquisition type for the ship operation process in port is more complex. This is because the container is affected by a variety of complex factors when operating in a port, and these factors will have a great impact on dangerous goods in the container. The port environment is the most important factor. For example, the rise of the ambient temperature will directly lead to the spontaneous combustion of hazardous goods inside a confined container. Based on this, this study improves the original BNN from the input side considering the complexity of ship operating environment. Depth auto encoders are used to represent more complex features, that is, key feature quantities are extracted according to environment factors. The purpose is to reduce the dimension of the feature factor, so as to reduce the input of invalid data, and then achieve the goal of highlighting the key features. Since the concentration of hazardous goods is the data type of time series, one-dimensional convolutional NN can be used to mine the data features, so as to extract the associated information of time series data and deeply learn the change trend of concentration of dangerous goods. In this context, the preprocessing process of the characteristic data of the whole ship operation process is constituted. With the probability layer of BNN, the structure is improved based on the original BNN. It can realize more effective input of hazardous cargo container characteristic data in the complex process of ship operation. The DT-based model is applied as the optimal prediction model for management optimization of the shipping cargo container. The concentrations of MDO and n-heptane of the 19,000 TEU hazardous cargo container ship in a certain state are predicted, and the comparative results are presented in Table 4. The DT model is used to predict the concentration for each of the two hazardous cargo materials in the shipping containers at the experiment site. The comparison between DT-driven and real-time data indicate that the MPD of n-heptane concentration is slightly higher than the value of MDO. In the n-heptane case, it can be found that the goodness of fit R^2 between DT-driven prediction and real-time data is 0832. Relatively, the goodness of fit R^2 obtained in MDO case is better, with a MDP of 0.881.

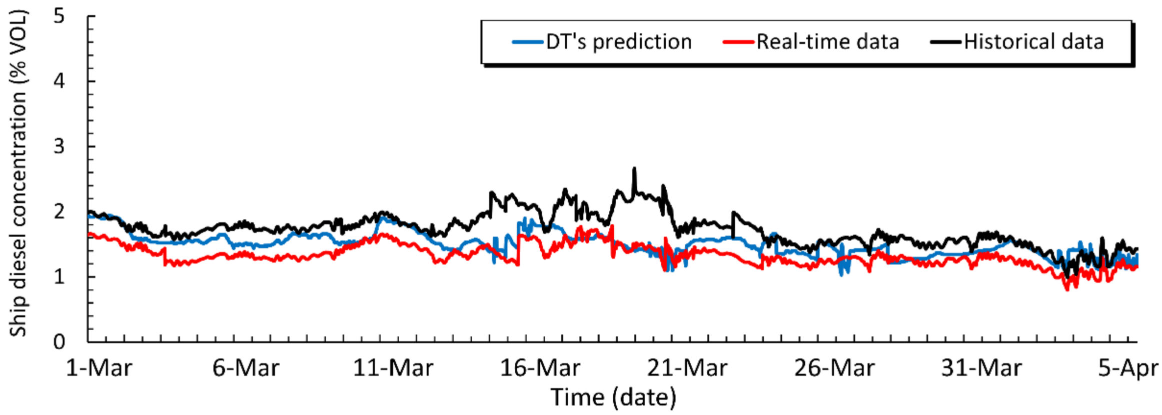
Table 4. Comparison of DT-driven predictions and actual data of shipping cargo container.

	Compared to Real-Time Data		**Compared to Historical Data**	
	MPD	R^2	**MPD**	R^2
n-Heptane (%vol)	7.61%	0.832	9.37%	0.708
Ship diesel (%vol)	5.22%	0.881	8.91%	0.754

Figure 8a shows the comparative results of the n-heptane concentration obtained by actual data collection, which highlights the differences in the performance of the DT-driven model. The black curve represents historical data, the red curve represents predictions by DT model, and the blue curve represents real-time data. The predictions of the DT model are obtained based on real-time data and historical data, so the trend of the three curves is basically consistent on the whole. Among them, the historical data of the n-heptane concentration change on board is obtained from our previous experiment. The historical data is slightly higher than the data collected in real-time and the predictions of DT model. It may be caused by the difference in environmental factors in the previous experiment. It results in a MPD of 9.37% between the historical data and DT-driven predicted data. Relatively, the MPD between the real-time data and DT-driven predictions is 7.61%. Figure 8b presents the temporal characteristic curve of the concentration of MDO loaded in a shipping container. It shows that the three curves representing historical data, real-time data and the DT-driven predicted data are approximately in good agreement. The MPD between the DT-driven data and historical data is 8.91%, while that between DT-driven data and real-time data is 5.22%. The results show that the DT-based model proposed in this study has good performance in predicting the trend of characteristic parameters. Moreover, it can be used as the basis to distinguish whether the dangerous cargo forms an initial ignition state inside the container during the ship operation process. In terms of prediction accuracy, further improvement and optimization of the DT-based model are still needed. Generally, based on DT-driven visualization, the platform of operational monitoring is constructed, which can effectually realize the process management of ship operation, data sharing, prediction optimization and port sustainable environment. With the change in the real-time data of DT, the marine personnel can improve the ability of troubleshooting, risk prediction, guidance and regulation of problems that may occur in the port operation stage of the ship industry.



(**a**)



(**b**)

Figure 8. Comparison of concentrations with DT's prediction, real-time data and historical data. (**a**) Time-varying characteristic of n-heptane concentration. (**b**) Time-varying characteristic of ship diesel concentration.

3.4. Challenges of DT Applications in Ship Industry Process

DT technologies have been embedded in the process management in the ship industry at the initial period of application, yet mature DT-drive models and platforms need to be further practiced. To improve DT applications in the process management of the ship industry, the following challenges are likely to be encountered.

- DT-based models of process management in the ship industry are built on certain computer-aided software, while 3D modeling focuses on restoring structural strength, geometric dimension and other information. The difficulties of multi-source information (e.g., ship design, process, quality inspec-tion) integration and sharing trigger a big challenge to the enhanced restoration degree of computer-aided software to real entities in the whole process management of the ship industry.
- Once a DT-based model is applied to process management, a large amount of data will be generated. It is a thorny issue to properly and safely deal with these data. Although traditional data storage methods can store and retrieve the data generated in the ship industry, it cannot meet the demand of real-time query and rapid response to the data.

For the ship product test or operation stage, it may increase large amounts of real-time data latency. With regard to the aspect of data collection and sharing, data collected from different dimensions need various transmission interfaces. In order to facilitate data transmission and sharing, it is necessary to establish a unified interface protocol and standardized data format. At present, digital data service systems in models are not perfect, and sharing between different subjects' entails great security risks and conflicts of interest. These increase the difficulty to meet the related needs for the development and sharing of DT data.

- In the DT modeling process, an understanding of how to map the real-time data to virtual model and realize "virtual to real" linkage deserve further exploration. It requires the fusion of entity data and virtual data. Data stream of DT in process management is highly complex and characterized by data instability, high coupling and strong correlation. Due to the influence of acquisition environment, technology, equipment and other factors, in most cases, the collected data have various problems, including low quality, incomplete data, noisy data and redundant data. DT models in virtual space are updated according to real-time information to realize the possibility of "virtual to real" linkage and monitoring. If real-time data is not processed effectively, it undoubtedly has a significant impact on management, optimization, diagnosis, or decision making.
- After the establishment of DT-driven platforms, shipbuilding design, construction, ship navigation, cargo loading, ship maintenance and scrapping processes are gradually opening up. In the period of accelerating integration with IoTs and 6G, they are also facing a series of network security challenges. Big data security of the DT models is mainly reflected in data loss and network attacks in data transmission of process management in the ship industry. At the same time, a virtual system itself may be subject to a variety of unknown security vulnerabilities and is particularly vulnerable to external attacks. DT data used in process management rely heavily on the types of sensors connected via IoT devices, which are typically built without much consideration for network security. A data acquisition system configured with sensors generally has user login information and product information, and it has not paid enough attention to security protection. Once these things are related to the equipment and sensor network malicious attacks, it will lead to the tampering of the navigation guidance or monitoring data of the ship engine room. As a result, DT-based models will lead to errors in simulation and mapping and then the predictions and decisions will have corresponding deviations. The above-mentioned results are for large manufactures involved in the ship industry, causing extremely serious accidents. With regard to another important aspect, DT promotes the development of connectivity in process management in the ship industry, which is based on the results of twinning data sharing. However, in order to greatly improve the management efficiency of shipbuilding plants or enterprises, it will also increase the risks for data thieves. Protecting DT-driven data is as significant as protecting actual information during the process management. If the sharing platform of DT data is maliciously hacked, it directly leads to the disclosure of commercial information relating to the design or construction processes of new-type ships (such as nuclear-powered ship, liquid hydrogen carrier ship, etc.). A potential confusion in the DT-driven management system may give wrong instructions for ship operation and lead to different types of accidental risks.
- DT-based models need to design the applicable algorithm to realize the process management function of different ship industry periods. They include signal processing, machine learning, data fusion and mining, closed-loop control and other algorithms to achieve ship industry processing quality analyses, fault diagnosis and prediction, equipment health management, resource optimization, job shop scheduling and energy consumption. Therefore, an understanding of how to better develop the relevant prediction algorithm will be a future focus of technical challenges.

4. Conclusions

In this study, a digitally-enabled approach is developed for the process management of navigation and operation in the ship industry. By elaborating the specific characteristics of the ship operation process and extended DT method, a holistic framework of the DT-driven management mode with a five-tier framework is proposed. The benefits of Maya and Unity 3D in establishing DT models with platforms are leveraged to present a visualization of synchronization scenarios for the ship engine system and shipping cargo container. By integrating the parameters for the ship operation process into DT-based models, a living database that enables the DT platform to monitor and simulate is provided. An improved BNN algorithm is applied to optimize the statistical values of the critical parameters in the ship operation process to realize the dynamic prediction of failure and risk. The results show that the optimal MPD when comparing DT-driven predictions with real-time data at different scenes is 3.18% and the maximum MPD is 7.61%, respectively. This DT system can be applied in the ship industry to promote the traceability of equipment parameters and the adjustment of process management. Considering practicality, an understanding of how to balance DT accuracy and information security of the process management in the ship industry should be considered in future works.

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