Simulation Method in Automotive, Aviation and Maritime Industries for Digital Twin: A Brief Survey

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***Abstract*—In this work, a brief survey of simulation methods used to create digital twins (DTs) or assist DTs in the automotive, aviation, and marine industries is presented. The simulation methods are classified as model-driven, data-driven, and hybrid methods. In addition, simulation methods in these three industries are studied from the phases of design, manufacturing, and operation. The similarities, differences and characteristics of the simulation methods applied to the automotive, aviation and maritime industries are discussed and summarized from several aspects. Model-driven approaches are used more frequently than the other two methods in design and manufacturing phases, while hybrid methods have great potential to support different operations of DT-related studies in the reviewed three industries. In addition, issues of prognostics and health management (PHM) such as fault diagnosis, remaining useful life (RUL) has recently been more inclined to be studied using data-driven approaches. According to our analysis we believe that as DT technology evolves, the hybrid approach will become the mainstream strategy for DT-based modeling.**

***Index Terms*—simulation method, digital twin, automotive, aviation, maritime**

I. Introduction

Industry 4.0 poses new challenges to traditional manufacturing, which requires proper digital infrastructure, good knowledge of digitalization, trusted cybersecurity and skilled workers. Digital twin (DT) is considered as one of the key technologies to achieve these goals and has attracted a lot of attention in the last years. DT is mainly a virtual replica of any conceivable physical entity and is a highly transformative technology with profound implications [1].

In order to achieve a complete, efficient and high-fidelity DT model, it is important to choose a suitable simulation method in virtual entity modeling, DT visualization, prognostics and health management (PHM), etc. Currently, simulation methods can be broadly classified into three categories, i.e., model-driven, data-driven, and hybrid methods.

The model-driven approach has been around for quite some time and includes single or multiple physical models. It is powerful because it relies on a deep understanding of systems and processes, which brings productivity, quality and simplicity. Model-driven approaches allow different levels of fidelity and provide sophisticated advanced numerical methods that can be reduced to low-fidelity analytical models to speed up real-time simulations as required by the DT process [2]. However, models cannot accommodate infinite complexity and generally must be simplified considering computational cost and feasibility, which limits the complexity of modeling systems. At the same time, model-driven approaches are expensive and take time in terms of experts and suitable methods to seek.

In contrast, data-driven approaches based purely on observed empirical data have gained tremendous momentum in recent years. It can model highly complex nonlinear relationships without prior knowledge of physical systems and processes, and physical correlations between inputs and outputs, like a black box. Artificial intelligence (AI) tools can discover features and train classifiers by extracting patterns from training datasets. There are several data-driven models applied to DT research, such as supervised methods like linear regression, random forests, artificial neural networks (ANN), support vector machines (SVM), semi-supervised or unsupervised methods like hidden Markov models (HMM) and k-means clustering, reinforcement learning like Q learning algorithm. However, for many data-driven methods, it requires a large amount of data to obtain meaningful results, which is sometimes difficult considering practical application scenarios.

A hybrid approach is a combination of model-driven and data-driven methods that combines the advantages of both approaches. The approach involves the use of physical laws derived from the model-driven approach and statistical data from the data-driven approach, with the aim of reducing errors in the predicted attributes while keeping the computation time reasonably low. The accuracy of the hybrid model depends on the ratio between the physical information required for the model-driven part and the statistical information required for the data-driven part. In cases where the amount of physical information is higher than the statistical data, it becomes important to correctly define a consistent amount of physical data to obtain good results [2].

Currently, DT has been studied in a range of fields in recent years. Among them, the automotive [3], aviation [4] and maritime [5] industries share many common features in many aspects, including design, manufacturing, assembly, operation, test and maintenance, and can benefit from each other if the differences and similarities between these three industries are systematically studied. For example, the use of similation methods in the study of the three industries.

In this work, a brief survey of simulation methods for creating or assisting DT in the automotive, aviation and maritime industries was conducted. In addition, simulation methods in these three industries were studied from the stages of design, manufacturing and operation. The objective is to discuss and summarize the similarities and differences in several aspects of the simulation methods applied in the automotive, aviation, and maritime industries.

Section II presents the simulation methods used by the DT model in the automotive, aviation, and marine industries. Section III presents and analyzes the simulation methodology from the stages of design, manufacturing and operation based on the three industries studied and concludes the features from those analysis. Section IV concludes the paper.

II. Simulation Methods Used in Digital Twin-Related Research in The Automotive, Aviation and Marine Industries

In this section, the simulation methods used in DT-related studies are investigated based on our review of papers from the automotive, aviation, and maritime industries. Fig. 1 shows the proportion of the types of simulation methods used in DT-related research in the automotive, aviation, and maritime industries based on the reviewed papers. As can be seen from Fig. 1, the proportions of model-driven, data-driven, and hybrid methods show a similar distribution across the three industries studied, with model-driven methods accounting for approximately 50%, data-driven methods for approximately 30%, and hybrid methods for approximately 20%. This may be due to the fact that all three industries reviewed have many common features in the design, manufacturing, and operation phases.

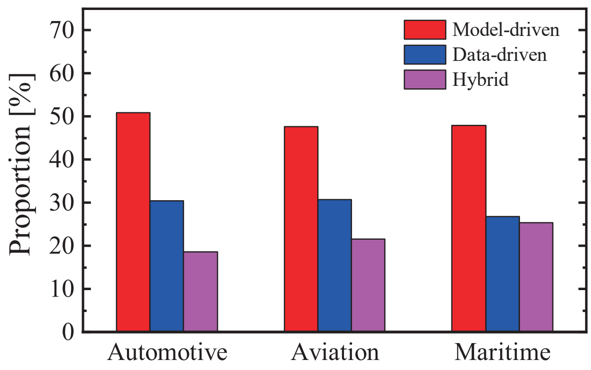

Fig. 1. The proportion of the types of simulation methods used in DT-related research in the automotive, aviation, and maritime industries based on the reviewed papers.

A. Automotive Industry

Research on the automotive industry using DT technology focuses on autonomous vehicles (AVs), electric vehicles (EVs), automotive production lines or assembly lines, traffic environments and drivers.

Model-driven approaches are often used in topics such as smart assembly, intelligent manufacturing, autonomous driving, and performance evaluation. For example, battery system management and its electrochemical performance evaluation in electric vehicles have received much attention, and one of the most commonly used physics-based models is Newman's pseudo-2D (P2D) model [6]. The P2D model can accurately describe the time-evolving response of lithium-ion batteries (LIBs) over a wide range of operations, making it a good starting point for next-generation battery management systems. According to the papers we reviewed, IPG Carmaker, CARLA, Carsim and Unity 3D are generally the most commonly chosen software for 3D modelling in the automotive industry using model-driven approaches.

On the other hand, data-driven approaches are commonly used for topics such as fault diagnosis, vehicle-cloud communication, lane change prediction. A variety of methods have been applied in the automotive industry, including neural networks [7], random forests [8], you only look once (YOLO) [9], deep transfer learning [10], support vector machines (SVM) [11], long short-term memory (LSTM) [12], graph attention networks [12], recurrent neural networks [13], swarm algorithms [14], etc. Compared to the aviation and maritime industries, it has the most types of data-driven methods in the automotive industry from the papers we reviewed.

B. Aviation Industry

The aviation industry is considered technology-intensive and requires highly reliable and advanced systems. Aircraft have complex system structures, including aero engines, airframes, control systems, hydraulic systems, cockpits and other systems. The aviation industry is facing challenges such as digital transformation, high production and operation costs, low maintenance efficiency, and technology intensity, and DT is considered one of the key technologies to solve these problems [4].

From the papers we reviewed, in the aviation industry, most of the research related to DT is focused on one system or one module of the aircraft, while in the automotive industry, DT can be applied to multiple systems, sometimes even the whole automotive system. This is because the systems and system integration in the aviation industry are more complex, so the models and sub-models are not flexible and adaptable enough to connect the whole system considering the development of current DT technology.

Model-driven approaches are also frequently used in the aviation field. For abstract models, the model-based approach is used in the aerospace industry with the help of MATLAB/Slimulik software. 3D models are simulated with the support of software such as CATIA, ANSYS, Siemens NX, Unity, etc. in order to study system modeling, performance evaluation, aviation education, intelligent assembly and manufacturing in the aviation industry. In addition, virtual reality (VR) and augment reality (AR) technologies are often utilized in the aviation industry as a visualization layer in DT to create more immersive simulations.

In recent years, data-driven methods have flourished in the aviation industry with the remarkable development of data transmission, data storage, and data fusion. Several algorithms are also in progress, including supervised methods for random forests [15], convolutional neural networks (CNNs) [16], semi-supervised or supervised methods for LSTMs [17], and HMMs [18].

C. Maritime industry

The maritime industry is more like the aviation industry because their aircraft or vessels are high value, between \$100-200 million, have a life span of about 25-30 years, and experience cyclical markets. Therefore, it makes sense that the aviation and maritime industries have a higher percentage of papers than the automotive industry in the stage of maintenance.

From the papers we reviewed, model-driven approaches in the maritime industry address issues such as hydrodynamic performance testing, ship and sea state monitoring, marine engine measurement and control, and fatigue prediction, etc. For example, hydrodynamic seakeeping model, full-ship finite element analysis (FEA) model, spectral fatigue analysis model, and Monte Carlo fatigue prognosis model are used to study fatigue damage monitoring and prediction for specific ships [19]. On the other hand, data-driven approaches such as Q-learning [20], Bayesian neural networks (BNN) [21], ANN [22], and LTSM [5] are applied for fault detection of marine engine, speed loss estimation, etc.

Hybrid methods have recently been frequently applied to the maritime industry in combination with DT. Han et al. [23] proposed a hybrid approach combining the wave buoy analogy method (WBA) and the Gaussian process regression method (data-driven). The data-driven approach is compensated by the WBA method based on the uncertainty of the estimation results, thus avoiding the failure of the sea state estimation. Wang et al. [24] proposed a hybrid modeling approach that incorporates a priori knowledge describing the dynamic effects of the ship into a data-driven calibrator to produce a representative model with high predictive power, completing the ship DT with a high-fidelity model. On the research vessel Gunnerus, simulations and full-scale experiments were conducted to exemplify this concept.

III. Simulation Method In The Product Life-Cycle

DT-related studies are usually outlined from a product life-cycle perspective. For the three industries studied, automotive, aviation and marine, their product life cycles are not identical,

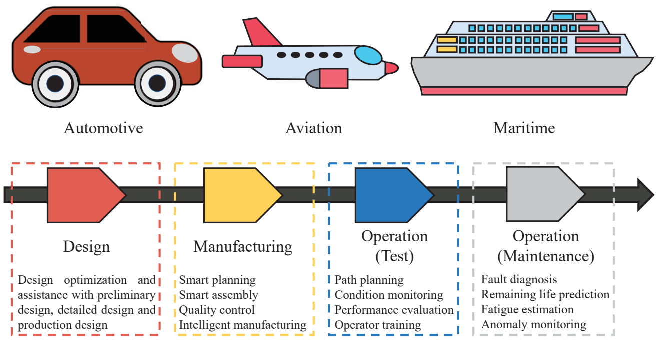

Fig. 2. Main phase studied in this work in the automotive, aviation and maritime industries.

and each has its own characteristics. In this work, we focus on the phases of design, manufacturing, operation (also includes test and maintenance parts) that all three industries value. Fig. 2 shows the main phase studied in this work in the automotive, aviation and maritime industries.

A. Design and Manufacturing Phases

DT can be used to design new products in a more responsive, efficient, and cost-effective manner. In the three industries studied, three modeling approaches were used in preliminary design, detailed design, and production design. Shen et al. [25] proposed a novel holistic DT-based approach including virtual world design (VR experiments and numerical simulations) and real-world validation (tunnel simulation experiments and field experiments) to improve the design of luminaires and decorations in the interior areas of tunnels. Winkler et al. [26] proposed a generalized mobility scheme for various framework, as well as the design of a holistic aerial mobility management concept based on a physical model for electric vertical mobility. Mombiela and Zadeh [27] proposed an integrated design and control algorithm for the design of ship power systems during the preliminary design phase.

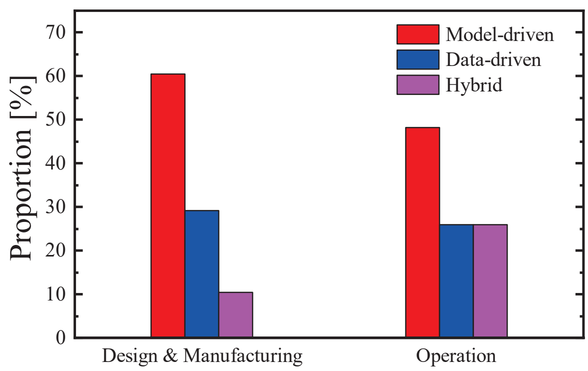

Fig. 3. Simulation method type proportion used in DT-related studies in the product life-cycle based on the reviewed papers

A significant percentage of the research in the automotive and aviation industries focused on the manufacturing and assembly stages, while only a small percentage of the papers in the maritime industry used DT technology in manufacturing and assembly stages. The reason for this is probably because DT technology was originally widely used in manufacturing industry, and the automotive and aviation industries overlap more with manufacturing than the maritime industry.

In the automotive and aviation industries, the main part of the physical entity in a DT model is usually a production line or an assembly line, or a shop floor when the focus is on the manufacturing and assembly phases. For the automotive industry, Mendi et al. [28] applied DT techniques to an automotive production line in the manufacturing phase. The production line is visualized by the game engine Unity and the data is analyzed by some data-driven methods of AI algorithms. Their results showed that DT technology could achieve a 6.01% efficiency improvement and 87.56% downtime improvement compared to companies that did not use DT technology. For the aviation industry, Bombinski et al. [29] presented a concept of a production monitoring system for the aircraft production line based on edge computing techniques and a data-driven approach using artificial intelligence algorithms (e.g., SVM or HMM) to estimate progressive tool wear and detect accelerated tool wear and catastrophic tool failures with the aim of avoiding production shortages and increasing productivity. In the maritime industry, Kunkera et al. [30] emphasizes the concept of 'advanced outing' to achieve savings in shipbuilding and high standards of environmental protection and workplace safety. Based on statistical and empirical data from observing shipyards, they use DT technology to improve shipbuilding with a model-based approach supported by software of AVEVA Marine, Rhino and NAPA, etc.

Fig. 3 shows the simulation method type proportion used in DT-related studies in the stages of design and manufacturing, and operation based on the reviewed papers. As can be seen from the figure, model-driven methods dominate over other methods in the design and manufacturing phases, accounting for about 60%, probably due to the fact that researchers and engineers still tend to use model-driven methods in the early stages of the product life-cycle, building 2D or 3D models through commercial software and having more faith in engineering science knowledge that numerical models reflect the relationships between physical phenomena.

B. Operation Phase

The operations phase of this work also included test and maintenance phases. The study found that a number of different topics were studied for the automotive, aviation and maritime industries, including route planning, performance evaluation, condition monitoring and operator training, which are common parts of all three industries.

In the automotive industry, research topics in the operation phase include lane change detection and prediction, electrochemical performance of power system in EV or hybrid electric vehicles, driver education, and situational awareness studies of drivers. Liu et al. [31] developed a novel vision-cloud data fusion method that combines camera images with DT information from the cloud to help intelligent vehicles make better decisions. The effectiveness of the proposed data fusion method is verified by a case study of lane change prediction with a data-driven approach using a three-layer multilayer perceptron (MLP) classifier in the model. Based on the simulation results, the proposed model is shown to significantly improve highway driving performance.

With the development of EV and hybrid electric vehicles, their power systems have received a great deal of attention. As the core of the power source of these vehicles, LIB and fuel cell systems are intensively studied for performance evaluation during the test part of the operation phase and for remaining useful life (RUL) prediction and fault diagnosis during the maintenance part of the operation phase. Heinrich et al. [32] proposed a new selection method to create a balanced dataset by compressing the huge vehicle time series data obtained from LIBs in EVs and using it for data-driven electric simulations with battery DT. The results show that compared to network training without pre-processed datasets, the prediction of the response battery voltage done by the LSTM battery model performance can be improved by 16%. Bartolucci et al. [33] proposed a DT for a fuel cell hybrid electric vehicle by introducing a thermal model considering heat transfer and heat loss and some control strategies to accurately model the auxiliary system to describe the vehicle behavior.

In the aviation industry, research includes aviation education, flight testing, and aero-engine performance evaluation in operation phase. Siyaev and Jo [16] proposed a speech interaction module using a data-driven approach with CNN to improve mixed reality (MR) education and training of aviation trainee engineers for Boeing 737 aircraft maintenance. The proposed module helps trainees to control operations effectively and enhances interaction with the aircraft DT model. McClellan et al. [34] proposed a two-level data-driven DT concept for autonomous aircraft landing to predict the real-time state and in-flight aerodynamic forces and moments of the aircraft. Their DT is based on the linearization of a high-fidelity, viscous, nonlinear computational model of flight dynamics around a pre-designed glide path.

Fewer DT-related studies have focused on human operators in the maritime industry than in the automotive and aviation industries. The operation phase of the maritime industry usually consists of route planning, hydrodynamic and power performance assessment, and condition monitoring, etc. Lee et al. [35] introduced a real-time DT model for ship operation in seaways. In detail, they proposed an innovative DT concept using a hybrid method to predict the ocean waves and the hydrodynamic performance of the ship such as sea-keeping and maneuvering, which allows the best path to be predicted and selected available in real time. Chu et al. [36] presented coupled simulation of a heavy load crane with interactive ship motion responses in waves mainly using model-driven methods. The simulation of crane operation was implemented on a DT ship platform and meaningful physical behavior was demonstrated by the simulation results.

Besides that, many researches are related to prognostics and health management (PHM) of the maintenance part in operation phase. For the three industries we reviewed, studies focusing on the maintenance phase addressed common topics such as fault diagnosis, remaining useful life (RUL) prediction, anomaly monitoring, and fatigue estimation.

In the automotive industry, research has focused on PHM in the automotive production line, auto body and power system, and a smaller percentage of papers in the maintenance phase. Guo et al. [8] proposed a data-driven simulation method using an improved random forest algorithm and used it in a case study for fault diagnosis of an automotive rear axle assembly line to validate the method. Simulation of a balanced dataset was performed using DT technique to train the fault diagnosis model. In the aviation industry, a large part of the literature we have reviewed focuses on the maintenance phase, with emphasis on PHM of aircraft engines, airframes and wings, etc. Xiong et al. [17] investigated a DT-driven model for predictive maintenance of aero-engines to improve predictive engine maintenance. The proposed predictive maintenance model was developed by introducing a data-driven approach with a LSTM neural network model, and the effectiveness of the approach in predicting engine RUL was verified experimentally. In maritime industry, Coraddu et al. [22] proposed a two-step data-driven approach based on a feed-forward neural network to fulfill a DT ship model in order to estimate the speed loss caused by the effect of fouling on the hull and propeller.

As can be seen in Fig. 3, the increasing use of hybrid methods in the operation phase compared to other phases indicates the great potential of hybrid methods to support the different operations in the automotive, aviation and maritime industries studied. The reason is that data-driven methods in PHM in recent years can lead to faster computation, lower computational cost and better prediction accuracy if a suitable model is selected and sufficient data sets are prepared for training. Moreover, the drawbacks of data-driven methods can be mitigated with the support of model-driven methods.

Table I concludes the features of simulation methods used in phases of design, manufacturing, and operation from the reviewed papers in the automotive, aviation and marine industries. In general, the model-driven approach is used more than the other two approaches in all phases, while the data-driven and hybrid approaches tend to be used to support performance evaluation and condition monitoring in test part, and PHM in the maintenance part of the operation phase. In the future, we believe that as DT technology evolves, the hybrid approach will become the mainstream strategy for DT-based modeling, as data is at the core of this digital technology, while physical models can still provide support in many aspects to fulfill high-fidelity DT models.

TABLE I
FEATURES OF SIMULATION METHODS USED IN PHASES OF DESIGN, MANUFACTURING, AND OPERATION FROM THE REVIEWED PAPERS IN THE AUTOMOTIVE, AVIATION AND MARINE INDUSTRIES.

Phase	Feature
Design & Manufacturing	1. More papers in the manufacturing phase for the automotive and aviation industries than the maritime industry 2. Model-driven method is used more frequently than the other two methods in these two stages
Operation	1. Fault diagnosis, remaining useful life issue has recently been more inclined to be studied using a data-driven approach 2. Hybrid methods have great potential to support different operations of DT-related studies in the reviewed three industries

IV. CONCLUSION

In this work, a brief survey of simulation methods used to create DTs or assist DTs in the automotive, aviation, and marine industries is presented. The simulation methods are classified as model-driven, data-driven, and hybrid methods. In addition, simulation methods in these three industries are studied from the phases of design, manufacturing, and operation. The similarities, differences and characteristics of the simulation methods applied to the automotive, aviation and maritime industries are discussed and summarized from several aspects. Model-driven approaches are used more frequently than the other two methods in design and manufacturing phases, while hybrid methods have great potential to support different operations of DT-related studies in the reviewed three industries. In addition, issues of PHM such as fault diagnosis, RUL has recently been more inclined to be studied using data-driven approaches. According to our analysis we believe that as DT technology evolves, the hybrid approach will become the mainstream strategy for DT-based modeling.

In our future work, we will conduct a more systematic investigation of simulation methods for the automotive, aviation, and maritime industries with a more scientific procedure of literature search, selection, classification, data analysis, and summary.

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