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Digital Twin Technologies for Vehicular Prototyping: A Survey

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ABSTRACT Digital Twin (DT) technology is widely regarded as one of the most promising tools for industry development, demonstrating substantial application across numerous cyber-physical systems. Gradually, this technology has been introduced into modern vehicular systems focusing on its application in intelligent driving, connected vehicles, automotive engineering, aircraft health, and many more. By creating dynamic, virtual replicas of physical vehicles and their associated components, DT enables unprecedented levels of analysis, simulation, and real-time monitoring, thereby enhancing performance, safety, and sustainability. This paper offers a comprehensive review, extending beyond digital twins to include various prototyping approaches for target-specific applications focusing on the smart vehicular systems across automotive, aviation, and maritime domains driving the evolution of next-generation vehicular infrastructure.

INDEX TERMS Digital twin, automotive, aviation, maritime, simulation, models.

I. INTRODUCTION

VEHICLES are increasingly becoming more central in our lives due to advancements in both the economy and technology. Yet, making vehicles smarter and more environmentally friendly introduces challenges, such as increased complexity and costs for design and maintenance. The modern vehicular system spans a wide array of domains, including automotive, aviation, and maritime industries, all of which are critical to the global economy and transportation infrastructure. After smartphones and computers, cars have become the third-largest networked device thanks to the growth and popularization of sensor technologies and the Internet of Things (IoT). This technological expansion is not only revolutionizing how vehicles are designed but also how they interact with users and their surroundings. The incorporation of digital twin technology alongside IoT advances intelligent manufacturing, enabling greater automation and precision in vehicle production. Digital twins, virtual representations of physical assets, are becoming instrumental across various sectors, including automotive, aviation, and maritime industries. In vehicles, these digital counterparts provide real-time monitoring of performance and maintenance needs, thereby optimizing the entire lifecycle of design, manufacturing, and operational use. Compared to cars, aircraft are even more sophisticated, integrating a greater volume of software and hardware components. These systems require advanced avionics for navigation, communication, and flight control–far more complex than automotive electronics. The use of digital twins in aviation allows for continuous simulation of aircraft subsystems, including propulsion, aerodynamics, and safety mechanisms, ensuring optimal performance and compliance with stringent regulatory standards. Likewise, in maritime industries, digital twins of ships and their subsystems enable real-time tracking of vessel operations, structural health, and engine performance. This allows for simulations of various navigational and operational scenarios, improving decision-making and operational efficiency.

The increasing complexity of technologically equipped vehicles has made digital twins essential for modern vehicular systems, as they address significant challenges in traditional development paradigms, maintenance procedures, and innovation strategies. As vehicles evolve

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into data-rich platforms, the entire lifecycle — from design and manufacturing to maintenance and operation — becomes a data-intensive process [1]. The integration of digital twins offers an effective way to manage this data, providing deep insights into vehicle performance and maintenance by simulating real-time operations and enabling continuous monitoring, which reduces downtime and improves safety [2]. Furthermore, leveraging technologies such as machine learning, artificial intelligence, and big data enhances automotive manufacturing, leading to more efficient production, personalized transportation solutions, and increased vehicle longevity. Adopting these innovative methodologies to tackle the complexities of modern vehicles necessitates a paradigm shift in automotive development, testing, and maintenance. Digital twins and various prototypes are at the forefront of this shift, bridging the gap between physical and digital systems. In the automotive sector, each vehicle can be paired with its own digital twin, creating a dynamic, real-time replica of its state and behavior. Similarly, in aviation and maritime industries, digital twins enable real-time simulations and monitoring of various components, ensuring optimal performance and efficiency. By continuously analyzing and adapting to data from physical vehicles, these digital models facilitate improved design, enhanced safety measures, and more precise maintenance schedules, driving innovation and sustainability across all transportation sectors.

While advanced prototyping approaches and requirements are important, a more practical understanding can be gained by reviewing established research, particularly in the context of the future of vehicles. Although several surveys address various aspects of transportation, often focusing exclusively on automotive, aviation, or specific perspectives, there is no comprehensive survey that covers all prototyping approaches across the three major smart vehicular systems — automotive, aviation, and maritime — in a unified and thorough manner. To better understand the scope of prototyping in the vehicular industry, we provide an overview of significant ongoing research in the automotive, aviation, and maritime domains. Fig. 1 shows a taxonomy of prototyping technologies that we discuss in this paper.

This study is not limited to digital twins but also considers various other prototyping technologies, some of which may seem more abstract but are closely aligned with the concept of digital twins. Furthermore, we explore the enabling technologies behind these approaches and provide insights into future research directions that could shape the development of intelligent vehicles. In light of the literature gap and the need for a unified perspective on prototyping in automotive, aviation, and maritime domains, our review addresses the following questions:

- *RQ1:* Which prototyping approaches, including but not limited to digital twins, are currently being utilized across these three sectors, and how do they complement or diverge from one another?

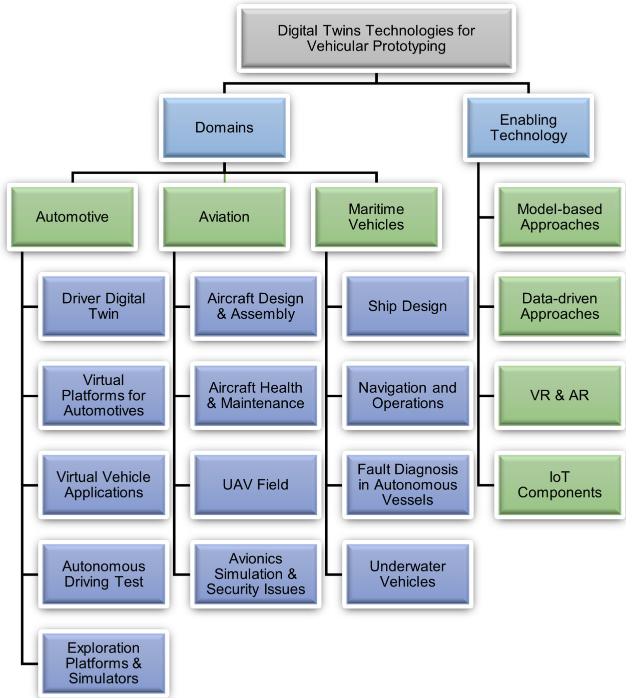

FIGURE 1. A taxonomy of prototyping technologies of vehicular systems.

- *RQ2:* What enabling technologies are most critical to implementing these approaches effectively, and how do they shape the advancement of intelligent vehicles?
- *RQ3:* How can insights gained from these approaches inform future research directions, promoting more effective and sustainable development of next-generation vehicular infrastructure?

These research questions are critical because they address the growing need for a comprehensive understanding of prototyping approaches across the automotive, aviation, and maritime sectors, which are increasingly converging under the broader umbrella of intelligent transportation. By identifying the attributes of existing prototyping techniques (RQ1), we can uncover gaps and opportunities for cross-sector innovations that enhance efficiency, safety, and reliability. Investigating the enabling technologies (RQ2) is essential for understanding the foundational tools and methodologies that drive advancements in smart vehicular systems, ensuring their scalability and real-world applicability. Lastly, by exploring future research directions (RQ3), we can provide valuable insights that guide policymakers, researchers, and industry leaders in developing more integrated, sustainable, and forward-looking transportation solutions. Addressing these questions will not only advance scientific knowledge but also contribute to the technological evolution of next-generation vehicular systems.

The remainder of the paper is organized as follows. Section II discusses the various aspects of prototyping in vehicular systems, including definitions, concepts, markets, and challenges. Sections III–V discuss various applications of digital twin and related technologies in automotive, aviation, and maritime vehicle domains respectively. Section VI presents an overview of enabling technology for the vehicular sector. Section VII addresses the future research directions. We conclude in Section VIII.

II. PROTOTYPING IN VEHICULAR SYSTEMS

A. PROTOTYPING TECHNOLOGIES DEFINITION

The term 'digital twin' has emerged as the frontrunner among prototyping technologies, being the most widely adopted and utilized across various industries. While the definition of a digital twin differs across various sources [3], [4], [5], the fundamental idea remains consistent — A digital twin represents a digital counterpart of a physical entity, whether animate or inanimate. This technology enables the real-time tracking and alignment of physical operations with their virtual equivalents. DTs have several perspectives: as a virtual mirror of a physical object, a simulation with one-way data flow from physical to virtual [6], and an integrated system where the physical and virtual counterparts continuously interact. This technology has been widely applied in aerospace, manufacturing, design, production process optimization, and smart cities, driven by the advent of industrial IoT [7].

Currently, there is significant interest in the exploration and development of IoT systems. Researchers began examining physical systems at an abstract level due to the proliferation of new technologies connected by the Internet [14]. Structured prototyping of systems, subsystems, and components as virtual counterparts is a recent development, although digital twins and various forms of "modeling and simulation" have been around for several decades with the rapid growth of computers. In addition to digital twins, there are numerous terms frequently used in the transportation industry, such as — virtual prototype, virtualization, virtual platform, virtual vehicle, aero-DT, virtual replica, and digitalization [15]. While these terms share similarities and are often used interchangeably, they represent distinct concepts and are applied in different contexts depending on the specific requirements of the industry or application. We summarize some common terms with their definitions in Table 1.

TABLE 1. Prototyping terms definitions.

Terms	Definition
Driver Digital Twin (DDT)	A virtual model that mirrors a real driver, incorporating their unique driving data and behavioral patterns [8]. Utilizing real-world data, the DDT system offers both real-time and analytical services in a virtual environment, including driving style analysis and interactive prediction.
Virtual vehicle	A digital representation or simulation of a physical vehicle. This concept is widely used in the automotive industry for various purposes, including design, testing, optimization, and performance evaluation. The term "virtual vehicle" was first coined by Sakaguchi et al. [9] for merging control of vehicles on highways. "Virtual platoons" [10] have also been employed for cooperative autonomous vehicles.
Virtual Platform	In the *cyber* world, virtual prototyping has gained popularity, primarily focusing on digital hardware, embedded software, and System-on-Chips (SoCs). This software-based modeling system, often referred to as a "virtual platform" can accurately replicate the operation of specific SoCs or digital hardware. The main objective is to create an abstract model of the hardware as early in the design phase as possible, even before RTL models are available or silicon fabrication begins.
Airframe Digital Twin (ADT)	The US Air Force is exploring a new DT framework to drive innovation in aviation. This physics-based framework provides comprehensive digital data on aircraft performance, safety, and reliability throughout their lifespan, aiding decision-making in acquisition, operation, and maintenance [11], [12]. First introduced at the 2013 ICAF conference, the ADT concept has since been adopted in various aviation prototyping domains, particularly in airframe design [13].

B. DIGITAL TWIN MARKET IN VEHICULAR SYSTEMS

In 2021, the digital twin industry was valued at \$6.5 billion. By 2030, it is projected to reach \$125.7 billion, growing at a compound annual growth rate (CAGR) of 39.48% [16]. This rapid growth is driven by increasing adoption across various sectors, reflecting the trend towards digital transformation and the use of IoT technologies for improved decision-making and efficiency. The automotive and transportation industries held the largest share of the digital twin market with aerospace having the second largest share as shown in Fig. 2 [17]. The increasing demand for efficient product design and development has positioned the automotive industry as a leader in prototyping technology among all vehicular sectors. The global digital twins market in the automotive industry is segmented by type, application, technology, and region. In terms of technology, the market is divided into IoT, simulation tools, Artificial Intelligence (AI), Machine Learning (ML), and others, with Fig. 3 [18] highlighting the growing importance of simulation tools, *i.e.*, digital twins and other related prototyping technologies. This trend underscores the critical role these technologies play in advancing automotive design and development.

C. CHALLENGES IN VEHICULAR PROTOTYPING

The evolution of prototyping in vehicular systems has been significantly influenced by the advent of digital twins, virtual platforms, and various prototyping technologies. These innovations have addressed the complex challenges

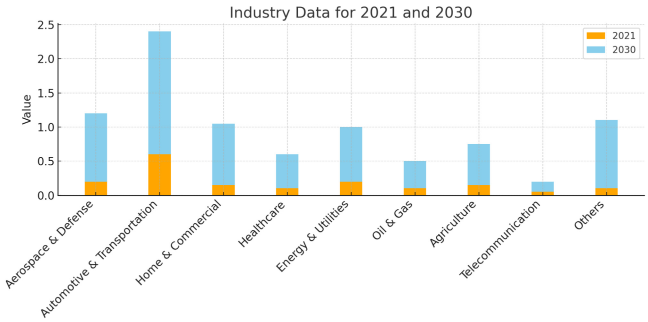

FIGURE 2. Digital twin market by industry.

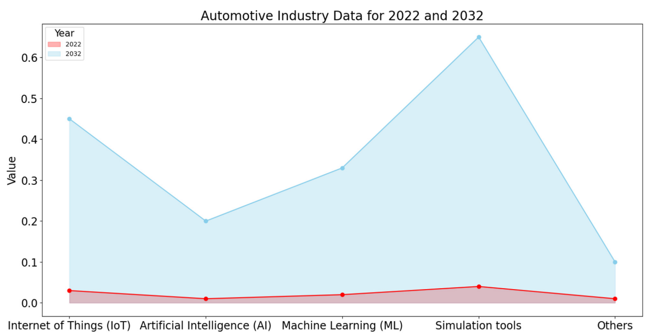

FIGURE 3. Digital twin automotive market by technology.

by enabling more accurate simulation and testing environments. Together, these technologies have revolutionized prototyping for vehicular cyber-physical systems (CPS), detecting errors, enhancing efficiency, reducing costs, and accelerating development cycles. Traditional methods struggle to identify these errors before hardware and software assembly. Virtual prototyping offers a solution by allowing early design error detection, facilitating the exploration of CPS configurations, and enhancing understanding of both hardware and software aspects. This approach supports embedded control system engineers in improving overall system functionality. Current vehicular system-level development (*e.g.*, [19], [20]) primarily targets the physical components or explores domain-specific applications without adequately connecting these aspects to real-time application services. Virtual prototypes address this gap by enabling real-time system monitoring and diagnostics, thereby ensuring the physical systems and application layers work seamlessly together, informed by real-time data analysis and control adjustments [21].

Modern vehicles equipped with advanced technologies like sensors, connectivity, and autonomous driving capabilities, are often cited as prime examples of complex cyber-physical systems. They integrate computational (cyber) processes with physical components, enabling them to interact with their environment and other systems in complex ways. Digital twins and other prototyping technologies are crucial in the vehicular industry, including automotive, aviation, and maritime sectors, for several reasons:

- *Virtual Prototyping:* The creation of virtual prototypes enables engineers to test and refine designs before physical models are built. This accelerates the design process and reduces costs associated with physical prototyping.
- *Simulation and Analysis:* Engineers can simulate various scenarios and analyze the performance of vehicle components under different conditions, leading to more robust and optimized designs.
- *Predictive Maintenance:* Real-time data on vehicle performance supported by advanced prototyping techniques, allows for predictive maintenance. This helps in identifying potential issues before they become critical, reducing downtime and maintenance costs [22].
- *Operational Efficiency:* By monitoring and analyzing data for prototypes, operators can optimize routes, fuel consumption, and overall vehicle efficiency.
- *Risk Assessment:* Comprehensive risk assessments are enabled by simulating potential failure modes and their impacts. This helps design safer vehicles and improve regulatory compliance.
- *Regulatory Testing:* Virtual testing can complement physical testing to ensure vehicles meet safety and regulatory standards.
- *Product Lifecycle Management:* Supporting the complete vehicle lifespan, including design, production, operation, and decommissioning, provides a continuous feedback loop for improvements and updates [23].
- *Sustainability:* By optimizing design, operation, and maintenance, these technologies contribute to more sustainable practices, reducing waste and resource consumption.
- *Rapid Innovation:* Prototyping technologies enable rapid iteration and innovation, allowing companies to stay competitive in a fast-evolving market.
- *Customization:* The ability to customize vehicles to meet specific customer requirements improves customer satisfaction and market reach.
- *IoT and Connectivity:* Leveraging IoT technologies to collect and analyze real-time data from connected vehicles enables advanced prototyping, such as simulating vehicle behavior through digital twins, thereby enhancing connectivity and smart functionalities.
- *Autonomous Systems:* In the development of autonomous vehicles, these tools play a crucial role in simulating and testing autonomous systems, ensuring their reliability and safety before deployment.

III. APPLICATIONS IN SMART AUTOMOTIVE DOMAIN

The smart automotive system domain has been one of the most extensively explored areas among all vehicular systems for various types of prototyping. Several review papers [24], [25], [26], [27] have addressed the application of digital twin technology in the automotive sector from various perspectives. In addressing a major part of **RQ1**, our work examines these applications alongside related prototyping

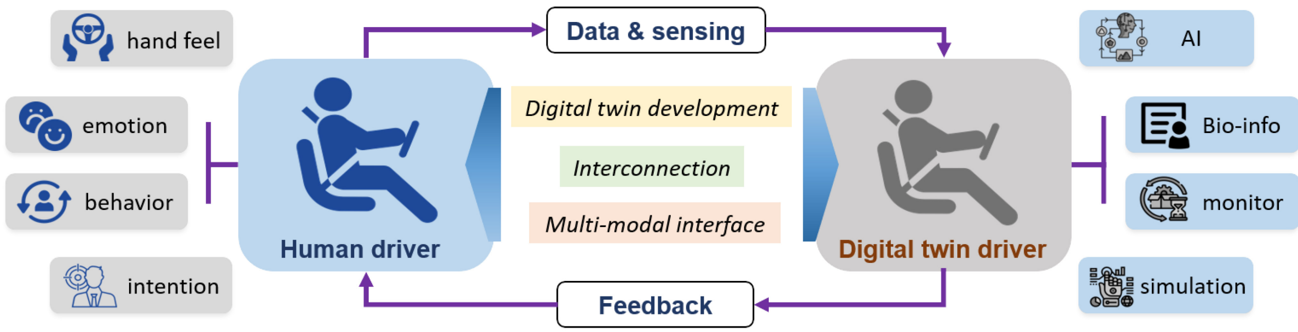

FIGURE 4. Driver digital twin overview.

approaches, providing a broader understanding to support emerging research in this field.

A. DRIVER DIGITAL TWINS

DDT system plays an essential role in intelligently and securely enhancing driver assistance. Its range of applications acts as a vital link between the digital and physical environments, enabling the DDT system to function in a closed-loop mode. Existing applications such as Advanced Driver Assistance Systems (ADAS), shared control, and driver safety monitoring have been under study for decades [27]. The introduction of the DDT system is poised to not only refine the functionality of these existing applications but also to introduce new possibilities that could significantly improve user experiences. Fig. 4 shows an overview of the DDT concept.

Lio et al. [8] developed DDT to predict personalized lane-change behavior in mixed-traffic environments, enhancing the interaction between automated and human-driven vehicles. The system, evaluated through co-simulation and field tests, demonstrated significant prediction accuracy improvements, detecting lane-change intentions on average 6 seconds in advance with a high level of precision. Ma et al. [28] introduced a novel DDT framework that leverages a transformer-based module and a temporal localization approach to enhance the detection of distracted driving behaviors, integrating driver emotion recognition as a novel element. Their method, tested on three major benchmarks, outperforms existing approaches, confirming its superior accuracy in recognizing driver actions and temporal changes in distracted behaviors.

Apart from the above-mentioned DDT studies, there are various DDT-enabled key applications that do not use the term "driver digital twin" but discuss similar work to enhance the intelligence, personality, and adaptability of driving automation systems at several levels. Several works developed driver models based on behavior and characteristics. Wang et al. [29] proposed a learning-based approach to model driver behavior and reduce speed-tracking errors by classifying drivers into different types using the k-nearest neighbors algorithm and predicting errors with a nonlinear autoregressive neural network. Through simulations and field tests, this approach leads to a 53% reduction in speed error variance and a 3% decrease in energy consumption by compensating for these errors in real-time. Wei et al. [30] calibrated and verified the human-like Wiedemann car-following model using driving simulator data, developing a nonlinear model predictive control (MPC) controller to mimic human car-following behavior. Through testing in three different scenarios, the proposed controller enables autonomous vehicles to exhibit human-like and smooth trajectories, enhancing naturalness in vehicle behavior across various phases and transition zones. Furthermore, a couple of studies [31], [32] explore enhancing Adaptive Cruise Control (ACC) by incorporating personalized driver behaviors and preferences into the system's operation. These approaches utilize machine learning algorithms, demographic data, and behavioral models to tailor ACC features like Stop and Go (S&G), optimizing comfort and efficiency based on individual driving styles and reducing the need for manual interactions with the automated system.

In the area of personalized driving model, Lefèvre et al. [33] proposed a learning-based driver modeling approach that identifies maneuvers and predicts future driver inputs on highways, applying this to provide personalized driving assistance. Utilizing a combination of real data and simulation, the model predicts unintentional lane departures and estimates preferred accelerations, using model predictive controllers to maintain lane integrity and offer personalized adaptive cruise control. Another driver model [34] integrates the Gaussian mixture model and hidden Markov model to predict unintended lane-departure and correction behaviors accurately. This model supports a model-based prediction algorithm and a driver-friendly warning strategy, which, through naturalistic driving data validation, demonstrated a significant reduction in false warnings, decreasing to an average of 3.13% at a 1-second prediction interval. Schnelle et al. proposed a couple of works [35], [36] on driver steering model, integrating a compensatory transfer function with an anticipatory component based on road geometry to predict and replicate individual driving behaviors for safety and efficiency in ADAS. These models, validated using human subject test data and steering wheel angle signals, demonstrate the ability to differentiate between drivers and accurately predict behaviors for various driving maneuvers, including rare collision avoidance scenarios based solely on daily driving data. Li et al. [37] introduced a novel driver model for autonomous vehicles that aligns the cars' movements with the behavioral characteristics of driver owners, based on attributes such as personality, emotion, driving experience, age, and gender. The effectiveness of this model is confirmed through statistical analysis showing a power-law distribution in behavior patterns, and both hardware-in-loop simulations and real driving experiments further validate it. Furthermore, studies [38], [39] have explored driver behavior and driving pattern simulations, validating their findings through case studies using driving simulation experiments.

B. VIRTUAL VEHICLE APPLICATIONS

Virtual vehicles often form part of DT technology, where a digital replica of a physical vehicle is created and used to monitor and optimize its real-world counterpart. This can include real-time data collection and analysis to predict maintenance needs and enhance performance. Virtual vehicles play an important role in the development of autonomous vehicles. They are used to simulate various driving scenarios and test the vehicle's autonomous systems, ensuring that they can handle a wide range of situations safely and effectively.

Debada et al. [40] proposed an innovative distributed coordinating system for connected autonomous vehicles (CAVs) based on virtual vehicles, enabling them to position virtual vehicles to share intended maneuvers and request cooperation. Simulation results demonstrate that this framework significantly enhances performance, especially in a three-legged single-lane roundabout, although mixing CAVs with unconnected vehicles leads to performance degradation and highlights the need for effective coordination strategies. Leitao et al. [41] developed a framework for the control and simulation of numerous autonomous agents in real-time interactive systems, specifically focusing on autonomous vehicles and pedestrians within the DriS simulator. Their approach, which employs a scripting language based on Grafcet, allows for the imposition of both short-term orders and long-term goals, enabling the model to handle both environmental traffic and controlled vehicles effectively. Egerstedt et al. [42] proposed two model-independent solutions for controlling wheel-based mobile platforms using a virtual vehicle approach, where the reference point's motion on the desired trajectory is determined by a differential equation with error feedback. These solutions, being robust to errors and disturbances, employ stable control algorithms that function as proportional regulators with arbitrary positive gains, as evidenced by experimental results.

Another similar study [43] explored the coordination control of leader-follower systems by implementing a virtual vehicle strategy, which minimizes the amount of information needed from the leader. This method stabilizes the virtual vehicle to the leader, providing a reference velocity for the follower's synchronization control, demonstrating uniformly semi-globally practically asymptotically stable closed-loop errors with only position/heading measurements. An existing autonomous vehicle (AV) data set was used in a tutorial article [44] to analyze a suggested framework for building, parameterizing, and verifying a virtual vehicle environment. It reviews several open-source and commercial simulation tools, discusses the selection of AV data sets for validation, demonstrates recreating real-world scenes in simulation, and suggests metrics for analyzing AV-perception algorithms using data from both virtual and real-world environments.

Popular navigation systems for the Internet of Vehicles (IoV) assist drivers in planning routes and navigating real-time road congestion. However, these systems may inadvertently cause congestion on alternate routes, so Lei et al. [45] introduced a virtual vehicle concept in IoV to study non-atomic routing and uses strategic concession games to minimize both individual and total travel times, showing that cooperation significantly reduces efficiency loss compared to non-cooperative approaches. Liu and Ma [46] developed a method for collecting and archiving artery data in real-time at the University of Minnesota, which gathers high-resolution event-based traffic data from multiple intersections to estimate time-dependent travel times using a virtual probe vehicle algorithm. Field studies demonstrated that under different traffic scenarios, the suggested approach can produce precise time-dependent travel times by self-correcting errors through the synchronization of virtual and real probe vehicle trajectories. Tsanakas et al. [47] proposed a novel approach for generating Virtual Vehicle Trajectories (VVT) to improve emission modeling accuracy, addressing the limitations of traditional VVT methods that simplify vehicle kinematics. Empirical evaluations show that their method enhances emission estimations when compared to traditional approaches, especially under specific experimental conditions. Moreover, the application of virtual vehicles has been instrumental in several studies including the role of virtual vehicle cab [48], cooperative maneuver planning [49], predictive approach for automated vehicle control [50], and connecting transport [51].

C. VIRTUAL PLATFORMS FOR AUTOMOTIVES

This virtual platform serves as a customizable environment for design optimization and software development. This approach has proven advantageous for early software and hardware development, verification, validation, and hardware-software co-design [52], [53]. Moreover, virtual platforms have been supported by various commercial frameworks [54]. The objective of this approach is to create a simplified model of the hardware device that provides a configurable platform at an early stage in the design process. This is advantageous even before silicon prototypes or detailed register-transfer level (RTL) models are developed. Such platforms are invaluable for software development and design optimization. Additionally, it has proven effective in the early stages of software and hardware

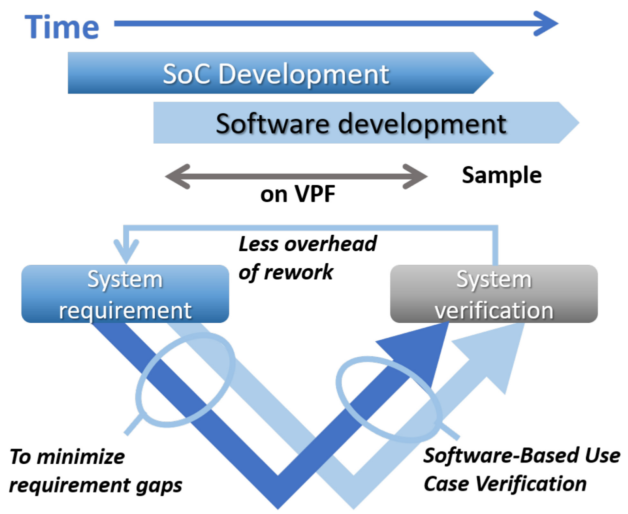

FIGURE 5. R-Car Virtual Platform [58] overview.

development, verification, and validation, and in facilitating hardware-software co-design [52], [53]. Pro-SiVIC is a virtual platform simulation software by ESI Group designed to simulate vehicle sensor systems. It is particularly useful for testing autonomous vehicles and ADAS [55], [56], [57], allowing for the creation of realistic 3D simulations of various scenarios including road users and environmental interactions. The platform helps in sensor development by simulating how sensors perceive different environments, which assists in integration and testing processes, ultimately enhancing the development of safety systems in vehicles. It runs on Windows 10 and features tools for trajectory design, Python API integration, and 3D model imports. The R-Car Virtual Platform (VPF) [58] is a noteworthy simulation environment that enables software design and system verification without a physical device, emulating the R-Car device's functions at the register interface level. It supports a seamless transition from pre-silicon to post-silicon development, providing binary compatibility with the actual device and facilitating early system verification, regression testing, and cooperative operation of device and control software. Fig. 5 shows their platform overview as it provides a generic outlook of the virtual platform concept for automotives.

Strobl et al. [59] discussed the growing adoption of virtualization in embedded devices like avionics systems and mobile phones, highlighting its first significant use in video game consoles. Despite its potential to consolidate numerous Electronic Control Units (ECUs) into a few Domain Controller Units (DCUs), virtualization has yet to be employed in automotive electronics, a gap this paper aims to address by presenting the benefits of automotive virtualization, particularly for DCUs. Safari et al. [60] proposed an integrated framework for Virtual Verification and Validation (VVV) that simulates and emulates a complete automotive system at three levels: System on Chip (SoC), ECU, and system level. This framework enhances the automotive V-cycle by supporting simultaneous software and hardware development, provides detailed methods for debugging AUTOSAR applications, and offers tools for system tracing, profiling, and debugging, ultimately reducing the development cycle as system complexity increases. A Virtualized Automotive Display System, as proposed by Lee et al. [61], introduces a system called VADI to virtualize a GPU and its attached display device for modern vehicles. This system manages two execution domains for automotive control and in-vehicle infotainment (IVI) software, ensuring isolated GPU operation and compliance with ISO safety standards by maintaining a minimum of 30 fps in failure scenarios and achieving 60 fps under synthetic workloads.

D. AUTONOMOUS DRIVING TEST

Autonomous driving is a key part of the world's goal to create smarter, safer transportation systems. There have been increased efforts in the recent past contributing to autonomous driving [62], [63], [64]. However, Autonomous Vehicles (AVs) will be subject to inherent risks that cannot be completely mitigated, raising important questions about risk management, including which risks can be accepted [65]. DTs play a crucial role in the development, testing, and deployment of AVs by providing a virtual representation of physical assets, processes, and systems, enabling comprehensive simulation and analysis. The need for DTs in autonomous driving technologies stems from two major concerns: safety and cost. Tests conducted in a simulation environment and transferring the learned driving knowledge to the real world form a critical aspect of autonomous driving DTs. In the context of AVs, DTs can represent the vehicle, its environment, or the broader transportation ecosystem, continuously updating with real-time data for accurate simulation and optimization [66]. The vehicle model digitally replicates mechanical, electrical, and software systems, while the environment model includes other vehicles, pedestrians, and objects detected by GPS, LIDAR, RADAR, and other sensors. Key challenges include real-time data integration, maintaining high-fidelity models, ensuring cybersecurity, and scaling DT infrastructure to accommodate evolving AV systems and environments.

In the autonomous vehicle space, DTs enable testing and refinement before physical prototypes are built. This reduces the cost and accelerates development. A survey by Hu et al. [67] explored how simulation technologies like sim2real, DTs, and parallel intelligence (PI) contribute to autonomous driving. It reviews the latest algorithms, models, and simulators, detailing the progression from sim2real to DTs and PI. Additionally, the article discusses the challenges and future prospects for these technologies in enhancing autonomous driving. Reference [26] proposes a framework using a DT to test connected autonomous driving in controlled environments, utilizing DT maneuvers to simulate real driving tests in virtual complex road scenarios. It examines DTs from various perspectives, including their foundations, development, industrial applications, cyber-physical integration, and core components, highlighting both their applications and the challenges they face. Reference [68] reviews the integration of DTs into the design and deployment of Internet of Vehicles (IoV) systems, identifying it as an understudied area. It explains the benefits DTs can offer to IoV system designers and implementers and outlines various challenges and opportunities for future research in this field. This study [69] provides a comprehensive review of DT technology in smart electric vehicles, bridging individual research efforts and offering a technically informed and neutral overview. It systematically explores the inception and evolution of DT technology, highlighting contributions to smart vehicle systems and addressing challenges. The review covers domains such as advanced driver assistance, battery management, power electronics, power drive systems, autonomous navigation, and vehicle health monitoring. It also examines the techno-socio-economic impact and potential obstacles to further development, presenting an extensive and holistic perspective on DT applications in smart electric vehicles.

Almeaibed et al. [70] addressed the challenges and solutions for ensuring safety and security in autonomous vehicle systems using DT. It aims to establish a standard framework for vehicular DTs to enhance data collection, processing, and analytics. To illustrate the effectiveness of this approach, the article includes a case study of a vehicle follower model where radar sensor data is manipulated to simulate a collision scenario. Using the Unity game engine, Wang et al. [66] proposed a simulation architecture for automated and connected vehicles. The simulation comprises a physical and a digital environment, with the latter split into three layers: external tools such as Python, MATLAB, SUMO, and AWS to improve functionality, Unity scripting for software, and Unity game objects to simulate hardware. A case study on personalized adaptive cruise control (P-ACC) demonstrates the effectiveness of this approach, showing how the ACC system can be tailored to individual driver preferences using cloud computing. Thonhofer et al. [71] developed a DT-based information model to provide high-quality, machine-usable data for automated driving functions, addressing the challenge of formalizing complex and incomplete information. By proposing and validating a system architecture through three implementations, they demonstrate its effectiveness in supporting decision-making at a highway tunnel construction site in Austria and across the Test Bed Lower Saxony in Germany.

E. EXPLORATION PLATFORMS AND SIMULATORS

Automotive security has experienced considerable growth and still possesses ample potential for further enhancements. This progress became particularly noticeable when various exploration platforms and simulators significantly impacted and contributed to the field. Exploration platforms and software-based simulators enable operators to replicate or simulate phenomena anticipated to occur in actual performance under test conditions, allowing seamless exploration of the intended target components and systems These platforms vary widely in their approach and technology. Some align more closely with the concepts of DTs or virtual reality frameworks. Others rely on a model-based approach, which enables operators to replicate or simulate phenomena anticipated to occur in actual performance under test conditions, allowing seamless exploration of the intended target components and systems [83]. They utilized simulations to predict and analyze the behavior of automotive security systems under different conditions and threats. Furthermore, exploration platforms help to seamlessly explore vehicular electronics, automotive system-level scenarios, traffic

TABLE 2. List of exploration platforms.

Title	Application
Ahura [72]	An open racing car simulator controller based on heuristics, featuring five modules: the dynamic adjuster, opponent manager, steering controller, speed controller, and stuck handler
AutoDRIVE [73]	A simulator for scaled autonomous vehicle research and education
Carla [74]	A comprehensive framework for the development, training, and validation of autonomous driving systems
IVE [75]	An immersive virtual environment to study safety vulnerabilities in automotive systems in response to cyberattack concerns
Metropolis [76]	Exploring the design space of automotive platforms with a focus on software distribution, architecture, and network setup
Sumo [77]	A portable, open-source, microscopic, and continuous multi-modal traffic modeling program that can manage large networks
TORCS [78]	A modern, modular, highly portable multi-player, multi-agent racing car simulator
VANETsim [79]	An open-source simulator for analyzing security and privacy concepts in Vehicular Ad Hoc Networks
ViSE [80]	A digital twin exploration platform focusing on automotive functional safety and various security vulnerabilities by exploring use cases
ViVE [81]	Modeling and simulation of vehicular electronics through various system-level use cases
VISSIM [82]	Modeling, simulating, and analyzing traffic and transportation systems

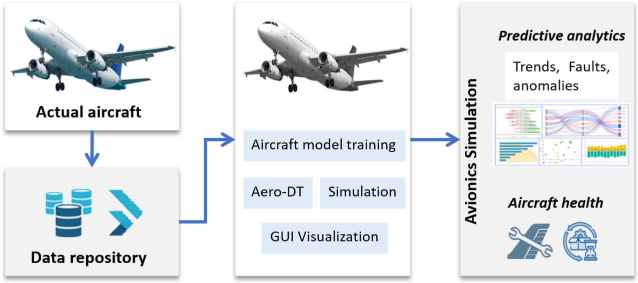

FIGURE 6. ADT model simplified overview.

simulations, etc. Table 2 gives an overview of several exploration platforms and automotive simulators focusing on various aspects of the automotive and transportation domain. The platforms discussed here are those that have either made a significant impact in the research domain or are part of emerging research. Commercial offerings, *i.e.*, established modeling software packages, are not included in this analysis.

IV. APPLICATIONS IN SMART AVIATION DOMAIN

In the world of IoT-based smart aviation, the concept of a digital twin represents a groundbreaking shift. DTs create a digital replica of physical aircraft, incorporating real-time data to model, predict, and enhance the performance and maintenance of the aircraft throughout its lifecycle. By interfacing with IoT, DTs facilitate enhanced decision-making, improve operational efficiency, and contribute to the safety and sustainability of aviation operations. Several studies [84], [85] have conducted surveys on the application of DTs throughout the lifecycle of aviation systems. A simplified overview of ADT is shown in Fig. 6. We explore the principal applications of prototyping, focusing primarily on aircraft design, health monitoring, and the UAF field.

A. AIRCRAFT DESIGN AND ASSEMBLY

The design and assembly of aircraft encompass intricate processes marked by significant complexity and evolving methodologies. Initially grounded in static strength principles, aircraft structural design has progressively incorporated concepts such as safe life, damage tolerance, and stand-alone tracking [86], [87]. Despite these advancements, challenges persist, including the high degree of variable coupling, insufficient data, and difficulties in obtaining performance indicators. Given that aircraft are highly complex products, their assembly processes are characterized by high complexity, dynamic nature, uncertainty, and frequent maintenance requirements.

Managing the lifecycle of complex, safety-critical systems from design to operation remains challenging due to the need to track dependencies, changes, and updates. Therefore, Bachelor et al. [88] discussed how model-based DT and thread concepts can improve the model-based design process by addressing issues related to IT infrastructure integration and tool interoperability. A case study on the design of an ice protection system for a regional aircraft is used to illustrate these concepts. AeroVR [89], an immersive aerospace design environment, facilitates the aerodynamic design process through interactive visualization of geometry and performance. The paper breaks down the design into functional structures, defines primary and secondary tasks, explains the system implementation, and uses an engine compressor blade design study as a prototype to validate the interface's expressiveness and usability.

In the line of the aircraft assembly process, Demartini et al. [90] illustrated the critical role of systems that combine manufacturing operation management (MOM) and product lifecycle management (PLM) in achieving Digital Manufacturing by enabling seamless information exchange through DTs and Digital Threads. Developed within the Siemens Industry Software framework under the AirGreen 2 project, this approach optimizes production operations, scheduling, and performance analysis, thereby enhancing cost efficiency, time management, and quality in manufacturing processes. A couple of studies by Cai et al. [91], [92] emphasized that an aircraft's final assembly is crucial for determining an aircraft's reliability and service life. They highlight the challenges in quality management, such as handling multi-source heterogeneous data and non-uniform data exchange formats, and propose using the aircraft DT to enhance quality management by creating a unified data source and employing data mining tools to accurately identify quality issues. A different approach was taken by Guo et al. [93] to improve assembly coordination technology by developing a working mode based on the Digital Coordination Model (DCM) instead of hard master tooling. They demonstrated that this DCM-based mode significantly enhances assembly accuracy, coordination accuracy, and efficiency, increasing assembly efficiency by about 40%.

B. AIRCRAFT HEALTH AND MAINTENANCE

Aircraft health is critical not only for ensuring safety in aviation but also for optimizing operational efficiency and minimizing maintenance costs. As aviation technology evolves, maintaining the robustness and reliability of aircraft systems has become more complex and demanding. In this context, the advent of the DTs marks a significant leap forward. Through continuous updates and simulation capabilities, DTs provide a powerful tool for managing the lifecycle of aircraft, making aviation safer, more efficient, and economically viable. Integrated Vehicle Health Management (IVHM) facilitates Condition-Based Maintenance (CBM) by monitoring, diagnosing, and predicting the health and performance of aerospace systems [94]. In aerospace, DTs enhance IVHM by predicting issues before they occur, optimizing maintenance schedules, and reducing operational costs. The functioning of an IVHM system is guided by the OSA-CBM framework, which outlines steps for data collection, processing, and analysis to monitor, diagnose, and predict the health of aircraft components as shown in Fig. 7

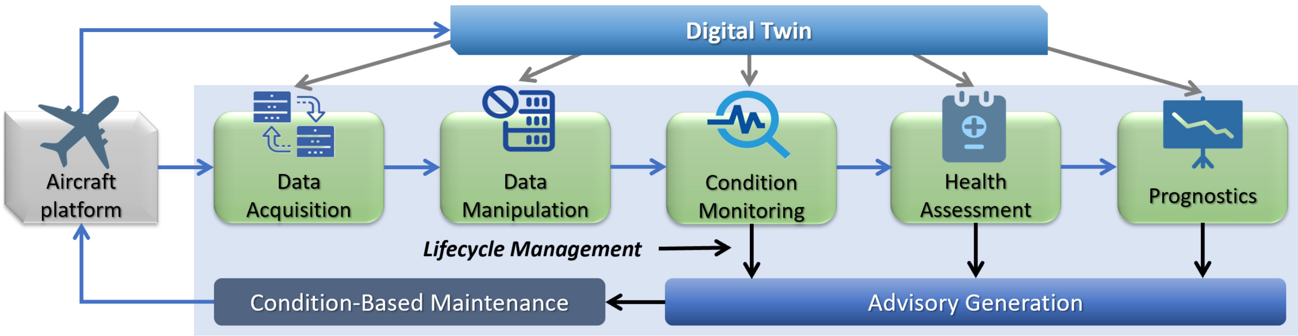

FIGURE 7. IVHM framework with digital twin.

(adapted from [94], [95]). The DT enhances this process by providing a virtual representation of the aircraft, ensuring the reliability of condition monitoring, diagnosis, and prognosis results. These insights are then used to schedule maintenance programs efficiently.

There are various approaches and components of health monitoring that utilize DTs to comprehensively evaluate aircraft health. Li et al. [96] proposed using a dynamic Bayesian network to create a versatile probabilistic model for diagnosis and prognosis, advancing the DT vision in aircraft health monitoring. By integrating physics models and handling various uncertainties, this approach effectively predicts and tracks crack growth, reducing time costs through a modified network structure and particle filter implementation. Zakrajsek and Mall [97] developed a DT model to predict aircraft tire wear at touchdown, incorporating a physics-based tire wear equation and using Monte Carlo and Cotter sensitivity analyses to assess uncertainty. The DT model calculates the Probability of Failure (POF) under various conditions, showing potential benefits for cost savings and tire health monitoring, with future enhancements recommended for more accurate life predictions. A noteworthy work [98] on IVHM processes described a data-driven approach to synthesizing and analyzing DTs of avionics functions using machine learning classification algorithms to address issues such as function loss and behavioral indications, ultimately enhancing the design and development stages of the avionics lifecycle.

In the field of Structural Health Management (SHM), the precise identification and assessment of aircraft damage under diverse flight conditions are enabled by advancements in interdisciplinary integrated tools. SHM systems provide real-time estimates of the amount of damage and safe load-bearing capability by utilizing multiphysics models, sensor data, and inputs from in-service vehicles. A study [99] employed guided wave responses and a genetic algorithm optimization procedure to estimate damage size, position, and orientation by comparing signal responses between damaged and undamaged structures. Similarly, Lai et al. [100] presented a DT-based structural health monitoring framework combining measurement and computational data. The framework involves four steps: using AI-driven load identification, applying multi-fidelity surrogate models, developing an online rain flow counting algorithm, and fusing data into a 3D scene. The MCC-DT framework is demonstrated using an aircraft model to verify its applicability and effectiveness. Instead of focusing on individual aircraft, some studies [101], [102], [103] proposed frameworks for fleet-wide monitoring, diagnostics, and health management, using a multi-level approach that begins with threshold exceedance monitoring and progresses to fault detection for isolated problematic engines. Various techniques for the identification, isolation, and quantification of faults are compared and tested on fleet data, and the limitations of both physics-based and machine-learning techniques are discussed to highlight the need for effective fleet diagnostics.

For intelligent predictive maintenance, numerous researchers have achieved significant advancements through the use of DT prototyping, making valuable contributions to the field. Liu et al. [104] reviewed the framework for developing a DT integrated with industrial IoT to enhance the autonomy of aerospace platforms, highlighting the importance of data fusion techniques. They also discussed the Information flow from unprocessed data to advanced decision-making, emphasizing the roles of fusion between sensors, models, and models with sensors in aircraft predictive maintenance. Xiong et al. [105] studied an aero-engine predictive maintenance framework driven by DT, focusing on mining the implicit digital twin (IDT) model and verifying its validity through consistency evaluation of virtual and real data assets. They demonstrate the effectiveness of combining a data-driven approach with an LSTM deep learning model, achieving high prediction accuracy with an RMSE of 13.12 when 80% of the dataset is used for training, surpassing other experimental schemes. Furthermore, various technologies can enhance remote collaboration and increase the efficiency of aircraft maintenance, such as augmented reality (AR) [106], DT by Rolls Royce [107], and component-level simulations [108].

C. UAV FIELD

With the growing size, participation, and volume of traffic, the uncrewed aerial vehicle (UAV) market has emerged as one of the aviation industry's most dynamic sectors. At the moment, some emerging research is being conducted on UAV DTs, which are primarily used as auxiliary tools in other DT domains [85]. A noteworthy aspect of these research works is that they have been conducted by the same group of researchers across multiple papers. Lv et al.. have a couple of works where 1) they explored the application effects and limitations of UAVs in 5G/B5G communication, demonstrating that their proposed algorithm significantly enhances estimation accuracy and robustness compared to traditional methods [109], and 2) demonstrated that DTs in UAVs can significantly improve the speed, accuracy, and efficiency of delivering medical resources during COVID-19 prevention and control, with their model achieving 95.58% accuracy [110]. By employing the use of deep reinforcement learning (DRL), a group of researchers published three works, all of which used deep reinforcement learning (DRL). The first one [111] proposed a novel DT-based intelligent cooperation framework for UAV swarms, integrating a high-fidelity DT model and a machine-learning algorithm to optimize and control UAV behavior. The second one [112] proposed a DT-enabled DRL training framework, specifically an actor-critic DRL algorithm, to improve the practicality and performance of flocking motion in multi-UAV systems. The third one [113] proposed a new multi-agent DRL, *i.e.*, a MADRL method called DNQMIX, along with a DT-driven training framework, to enhance the efficiency and performance of multi-UAV cooperative target search in dynamic environments. Moreover, Li et al. [114] and Tang et al. [115] also utilized the DRL approach to improve task assignment and path planning efficiency in multi-UAV systems.

Another group of researchers had a couple of works where 1) they have introduced a novel DT simulation platform for multi-rotor UAVs that integrates Unity, ROS, MATLAB, and SimulIDE to verify and track the UAV's lifecycle, providing multi-dimensional and multi-scale simulations to improve development efficiency and functionality [116] and 2) presented the first integration of DT, 5G, cloud platform, and VR technologies for UAV autonomy development, proposing "DTUAV" — a comprehensive DT framework and demonstrating its effectiveness through multiple experiments in real-time monitoring, VR interaction, and remote supervision [117]. For the Internet of Vehicle networks, Hazarika et al. [118] proposed a DT-assisted intelligent delay-sensitive task offloading scheme utilizing UAVs as relays to improve resource allocation for delay-intolerant tasks. They introduced a multi-network DRL-based resource allocation algorithm (RADiT), which significantly enhances energy efficiency and reduces network delay compared to the soft actor-critic (SAC) algorithm and a non-DRL greedy approach. Moreover, there are significant other UAV-focused works, *e.g.*, vertical take-off and landing (VTOL) [119], path planning [120], AI-based framework [121], and warehouse management system [122].

D. AVIONICS SIMULATION AND SECURITY ISSUES

Simulation of various avionics functions and the analysis of cyber-attacks on avionics networks have been crucial areas for digital twin exploration. Kandaz et al. [123] developed a simulation-based DT of a high-speed turbomachine, specifically a fan with a nominal speed of 16,500 rpm, for the aerospace industry, utilizing multi-physics engineering simulations and validated via experimental data. This DT, capable of performing various operational scenarios and stress tests, demonstrates significant potential in enhancing operation and maintenance practices through dynamic reduced-order models and what-if analyses, benefiting O&M teams, asset owners, and OEMs. Fraser et al. [124] investigated the vulnerability of UAVs to contemporary cyber threats and proposed remedies utilizing data-driven techniques and DT structures to detect anomalies and intrusions in real-time. These concepts were validated by applying novelty detection to GPS spoofing attacks on UAV flight data. Various machine learning models — both deep learning and classical — were employed to determine which models were best suited for the proposed design, yielding promising results. Another work by Kuleshov et al. [125] presented a novel academia-industry collaboration between Purdue University and Boeing, aimed at addressing vulnerabilities and cyberattacks on airplane avionics networks through a DT model. This collaboration, part of the Data Mine Corporate Partners program, allowed students to simulate and analyze potential cyber threats on general-purpose computers, providing valuable insights and fostering the development of new cybersecurity approaches in aviation.

V. APPLICATIONS IN MARITIME VEHICLE DOMAIN

Maritime transport is the most economical means of transporting people and cargo, serving as the backbone of international trade. Much of what we possess has traveled by sea, even though maritime transportation often does not receive adequate recognition. Numerous innovations in this field have had a profound impact on human life. From being wind-powered to now utilizing batteries, maritime transport has undergone significant advancements. The use of DTs is one such innovation. Although most DTs in the maritime industry have been primarily studied for ships [126], we will highlight notable works here that explore applications across various types of maritime vehicles.

A. SHIP DESIGN

Testing full-scale ships is prohibitively expensive, so the principle of similitude is employed, using scaled models to test designs. While cost-effective and easier, this method lacked accuracy. With the advent of Computer Aided Engineering (CAE), engineers began using Finite Element Analysis (FEA) software to simulate and validate structural and fluid dynamics. DTs enable virtual testing and validation of new designs and modifications, reducing the need for physical prototypes and accelerating innovation

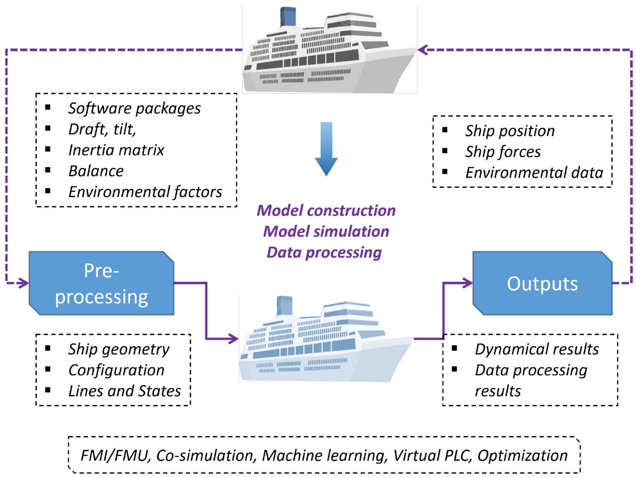

FIGURE 8. DT driven approach for prototyping in ships.

and deployment. DTs also allow engineers to simulate various environmental conditions and operational scenarios to optimize performance and make necessary adjustments. Fig. 8 shows DT activity in maritime vehicles, showing the ship as an illustrative example.

Fonseca and Gaspar [127] proposed creating an open standard for DT data based on lessons from existing literature and previous attempts at standardizing ship data. The proposal aims to address challenges and guide the future development of services, networks, and software for DTs, with a specific application to a research vessel. Mombiela and Zadeh [128] proposed an algorithm for designing ship power systems during the preliminary design phase. It includes an embedded control for Energy Management Systems (EMS) to optimize cost, availability, safety, and emissions. The study evaluates different power system alternatives, such as full electric propulsion and fuel-based energy producers, using various performance and improvement indicators. A case study on an Offshore Supply Vessel compares battery and GENSET power contributions, analyzing battery performance and control metrics. The authors claim that the algorithm serves as a foundation for future hybrid power plant designs. Menges et al. [129] proposed enhancing autonomous surface vessels (ASVs) with a DT framework to improve situational awareness and decision-making. They integrate real-time AIS and synthetic Lidar data for sophisticated target tracking and apply a predictive safety filter based on nonlinear model predictive control (NMPC). This DT, built using the Unity game engine, enables predictive, prescriptive, and autonomous capabilities for safer and more efficient maritime operations. Some other works include ship architecture for optimization [130], open simulation platform [131], and cruise ship DT [132].

B. NAVIGATION AND OPERATIONS

Hasan et al. [133] introduced a method to enhance the reliability and efficiency of autonomous surface vessels (ASVs) using predictive DT and state estimation techniques. A predictive algorithm is developed from measured data to create a discrete-time state-space model, forecasting the system's future response. Tests conducted on the ASV by Maritime Robotics show the DT's potential as a decision support tool for ASV maintenance. Liu et al. [134] proposed an approach for improving the safety and intelligence of the Maritime Transportation System (MTS) using DTs and the Internet of Things (IoT). This work analyzes historical data from the Maritime Silk Road and constructs a DTs model with relay nodes to enhance data transmission and security. Simulation experiments validate the model's security performance, showing that interference helps maintain information confidentiality, and increasing relays improves system performance and reduces outage probability. This study concludes that the proposed model offers excellent transmission and security, supporting future intelligent and secure maritime transportation. Kaklis et al. [135] developed a DT to improve the operational efficiency of the vessel from the context of AI and Industry 4.0. Their work focuses on estimating Fuel-Oil-Consumption (FOC) for ships using a novel method with a reduced feature set to predict the main engine's rotational speed (RPM). It integrates B-Splines with deep learning architectures and compares them with existing regression techniques. The goal is to improve efficiency and environmental compliance in ship operations by using these models within a cutting-edge information system. The paper shows the effectiveness of their estimators by comparing them with actual FOC data. Additionally, a few more emerging research [130], [136], [137] focuses on autonomous navigation systems.

C. FAULT DIAGNOSIS IN AUTONOMOUS VESSELS

Bhagavathi et al. [138] introduced a DT-driven fault diagnosis method for autonomous surface vehicles, utilizing a graphical model and an adaptive extended Kalman filter algorithm. The authors claim that, unlike traditional methods, this new algorithm directly estimates fault magnitudes from sensor data. This approach is also tested on Otter by Maritime Robotics and the DT receives real-time data, estimates actuator faults, and visualizes results via a Web application. Simulation and experimental results demonstrate accurate fault detection and estimation. Hasan et al. [139] introduced a DT-based method for diagnosing faults in autonomous ships. The system collects data from ship sensors, analyzes it, calculates fault parameters, and displays them in real time. Using a dynamical model and an adaptive extended Kalman filter (AEKF) algorithm, it estimates fault severity. Yet again, this method is tested on Otter by Maritime Robotics. The method shows potential in improving ship condition monitoring, as demonstrated through simulations and practical implementation.

D. UNDERWATER VEHICLES

Similar to UAVs in aviation, DT technology has also been applied to underwater vehicles in recent publications. With the use of big data and machine learning approaches, computational fluid dynamics, and fluid operating conditions, a DT escort system model has been proposed by Gao et al. [140] to enhance the performance of underwater unmanned vehicles (UUVs). This research provides innovative approaches to maneuver early warning, wake tracking, UUV intelligent obstacle avoidance, and flow field detection, addressing issues of disconnection and loss in complex underwater environments. Martynova et al. [141] are developing a DT of an autonomous underwater vehicle to assess its effectiveness in searching for bottom objects by analyzing factors such as area size, inspection swath width, detection principles, bottom topography, and marine environment state. Using the Monte Carlo method, the simulation reproduces the movement of detection means, view sectors, and the sequential selection of detection methods based on environmental conditions and object classification characteristics.

Furthermore, several works have been done on prototyping for autonomous gliders. Hu et al. [142] proposed a novel underwater simulation platform based on DT technology, using a blended-wing-body underwater glider (BWBUG) to explore high-fidelity digital modeling in the marine environment. This platform, incorporating sensor data with a PID control algorithm and robot operating system (ROS), achieved enhanced pitch control, reducing overshoot to 0.06% and settling time to 29.5 seconds, demonstrating the potential for safety evaluation, design enhancement, and performance prediction in the design of the next generation of marine vehicles. Wen et al. [143] proposed an improved artificial potential field method for multi-agent Autonomous Underwater Glider (AUG) systems, leveraging the Maritime IoT and edge computing to enable collaborative control by a leader AUG. This approach includes a behavior-based path optimization to overcome local optima and utilizes a DT model for real-time monitoring, enhancing coordination and communication among multi-AUG groups in challenging underwater environments. Another work by Yang et al. [144] introduced a DT-driven architecture to address the challenges of Full Lifecycle Management (FLM) and Rapid Individualized Design (RID) for underwater gliders, tackling interdisciplinary complexities and environmental uncertainties. This architecture includes virtual verification, design optimization, digital modeling, and real-world implementation, demonstrated through a case study with the Petrel UG developed in China, showcasing its feasibility for other autonomous underwater vehicles as well.

VI. ENABLING TECHNOLOGIES

A range of foundational technologies is essential for developing intelligent digital twins in vehicular systems, enabling accurate modeling and real-time decision-making. Addressing **RQ2**, this section examines the key technologies that drive advancements in prototyping, shaping the future of intelligent vehicle development.

A. MODEL-BASED APPROACHES

Model-based approaches are utilized across various advanced fields, including smart assembly, intelligent manufacturing, autonomous driving, aviation training, hydrodynamic testing, marine engine measurement, etc [145]. These methods enhance precision, efficiency, and innovation by enabling simulation, optimization, and real-time monitoring of complex systems. In the case of electric vehicles, the pseudo-2D model [146] is utilized to significantly reduce simulation time and computational effort while maintaining accuracy, enabling efficient cell design, parameter optimization, and battery pack simulation. CARLA, Unity 3D, MATLAB/Simulink, CATIA, ANSYS, etc. are the most commonly used software for 3D and system modeling in the automotive industry. Boeing pioneered the use of computer-aided 3D models (CAD/CAE/CAM) in aerospace design, leading to significant cost savings and reputation gains, with high-fidelity software like CAD, Catia, ANSYS, Siemens NX, and Autodesk driving the industry for over 20 years [84]. Several other studies (*e.g.*, [147], [148]) discussed physics-based models for aero DTs. In marine applications, spectral fatigue analysis, full-ship FEA, hydrodynamic seakeeping, and Monte Carlo models are employed for fatigue damage monitoring and prediction.

Based on the principle of model-based definition (MBD), Liu et al. [149] combined the idea of biological mimicry [150], and proposed a digital twin mimic model (DTMM), which includes multiple DT sub-models, (*e.g.*, behavior model, geometry model, and process model). The process forms an in-process model by incorporating measured data into the MBD model, merging it with the designed model, and integrating behavior and context information, resulting in a self-adaptive model. The DTMM represents the product's DT model, encompassing process-oriented changes and integrating process, physical, and geometric information into a 3D model.

B. DATA-DRIVEN APPROACHES

Data-driven approaches play a pivotal role in modern vehicle design, production, and performance optimization. By analyzing large-scale sensor data, telemetry logs, and user feedback, manufacturers can refine engine efficiency, accurately predict maintenance needs, and enhance key safety features. In the automotive industry, a variety of advanced algorithmic solutions are being explored: swarm optimization [151], surrogate models [152], YOLOv4 detection [153], recurrent neural networks (RNNs) [154], and decision trees [31] — all contributing to improvements in autonomous driving, advanced driver assistance systems (ADAS), fault diagnosis, and IoT communications. Meanwhile, the aviation domain has adopted long short-term memory (LSTM) networks [105], [155], [156], random forests [157], and convolutional neural networks (CNNs) [158], [159] to streamline data transmission and storage, as well as enable real-time monitoring and predictive analytics. In marine applications, speed loss estimation and fault detection often rely on artificial neural networks (ANN) [160], Q-learning methods [161], and LSTM architectures [162] to ensure reliable operations in challenging maritime conditions. Collectively, these machine learning techniques underscore the growing importance of data-driven strategies for enhancing performance, safety, and cost-effectiveness across multiple transportation sectors.

C. VIRTUAL AND AUGMENTED REALITY

VR and AR are the primary examples of immersed simulation. While AR combines the real world with a virtual environment that offers virtual support to a real scenario, VR is a technology that realizes the interaction between the virtual and the real world by creating an immersive virtual experience. Given the need for automakers to reduce time-to-market and continuously improve quality, the automobile industry has advocated the use of VR across a range of applications, including training, design, and manufacturing [163]. In the field of automotive systems, an immersive VR automotive driving learning (imseADL) [164], constructing a motor block by using VR [165] and an automotive system assessed within the Product Emergence Process (PEP) [166], have been instrumental. We already mentioned some AR applications in aviation as well. VR and AR are still in their infancy, though. The quality of the human-machine interface is a critical challenge [167]. It requires implementing and using a few particular interactive technologies, like hand- and gaze-tracking. Its development is also being hampered by a few universal issues including cost and enabling technology [84].

D. IOT COMPONENTS

When discussing integration with various IoT components, the concept of the Internet of Vehicles (IoV) emerges as a key framework, fusing Vehicular Ad-hoc Networks (VANETs) and IoT to facilitate seamless communication between in-vehicle systems (*e.g.*, onboard units and embedded processors) and intelligent road infrastructure in both urban and highway settings [68], [168]. In this context, DTs in vehicles greatly benefit from IoT components like cloud, edge computing, and onboard data acquisition systems. By embedding sensors and controllers throughout the vehicle — covering everything from engine performance to driver health indicators — real-time operational data can be continuously gathered and transmitted via CAN bus networks or wireless connections to local edge servers or the cloud. These servers then integrate and analyze the incoming vehicle data to maintain an up-to-date virtual counterpart, while cloud and edge platforms offer scalable storage and computing power for in-depth modeling and simulation. Such a bi-directional flow of information ensures synchronized operation and rapid feedback loops, ultimately enhancing both the robustness of vehicle systems and the overall quality of the driver's experience. Fig. 9 shows the integration of IoT components for vehicular prototyping.

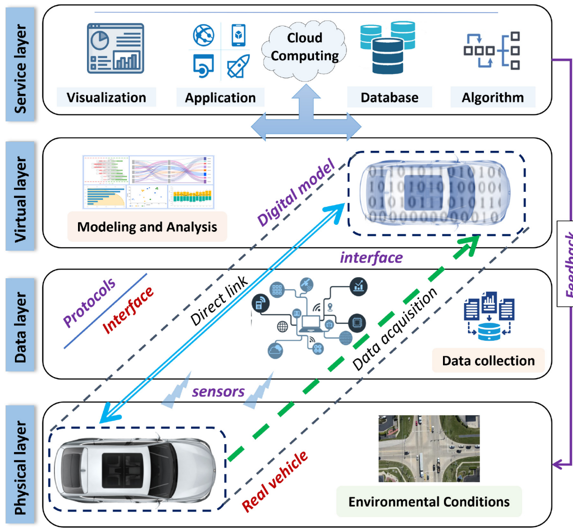

FIGURE 9. DT modeling with integration of IoT components.

VII. FUTURE RESEARCH DIRECTIONS

As prototyping technology continues to evolve, its potential applications in the vehicular sector expand significantly. To harness the full capabilities of various prototyping technologies, future research should address several key areas. In addressing **RQ3**, this section explores how insights from existing approaches can guide future research directions, fostering more effective and sustainable development of next-generation vehicular infrastructure.

A. INTEGRATION WITH EMERGING TECHNOLOGIES

Artificial Intelligence and Machine Learning: The integration of AI and ML with DT technology can enhance predictive maintenance, anomaly detection, and optimization of vehicular systems. Future research should focus on developing advanced algorithms that can process the vast amounts of data generated by DTs to provide actionable insights and automate decision-making processes.

5G and Beyond: The deployment of 5G technology offers unprecedented data transfer speeds and low latency, which are crucial for real-time DT applications. Research should explore how 5G and future communication technologies can improve the synchronization between physical and digital twins, enabling more accurate and timely updates.

Blockchain for Security and Data Integrity: Ensuring the security and integrity of data in prototyping systems is paramount. Future studies should investigate the application of blockchain technology to secure data transmission and storage, ensuring that the prototyping ecosystem is resilient against cyber threats.

B. ENHANCED MODELING AND SIMULATION CAPABILITIES

Multi-Scale and Multi-Physics Simulation: The complexity of modern vehicles necessitates the development of virtual models that can simulate multiple scales (from component-level to system-level) and multiple physical phenomena (mechanical, thermal, electrical, etc.). Research should aim to create comprehensive models that can capture the intricate interactions within vehicular systems.

Human Factors and Behavioral Modeling: Understanding and integrating human factors, such as driver behavior and interaction with the vehicle, into virtual models is essential for developing intelligent and user-centric vehicular systems. Future research should focus on creating accurate driver digital twins and personalized driver models that can predict and adapt to individual behaviors and preferences.

C. INTEROPERABILITY AND STANDARDIZATION

Cross-Domain Integration: Vehicles often operate in environments that involve multiple domains, such as automotive, aviation, and maritime. Research should explore methodologies for creating interoperable DTs that can seamlessly integrate and operate across these domains, facilitating a holistic approach to transportation and mobility.

Standardization Efforts: The widespread use of DT technology requires the establishment of industry standards for data formats, communication protocols, and modeling frameworks. Future research should contribute to the development of these standards, ensuring compatibility and ease of integration across different systems and platforms.

D. SUSTAINABILITY AND ENVIRONMENTAL IMPACT

Green Technologies and Energy Efficiency: Prototyping can play a pivotal role in enhancing the sustainability of vehicular systems. Research should focus on using virtual models to optimize energy consumption, reduce emissions, and integrate renewable energy sources into vehicle operations.

Lifecycle Analysis and Circular Economy: Future studies should investigate how DTs can be used to perform comprehensive lifecycle analyses of vehicles, from production to end-of-life. This includes exploring ways to support circular economy practices, such as recycling and remanufacturing, through DT insights.

E. USER-CENTRIC APPLICATIONS AND SOCIETAL IMPACT

Personalized Mobility Solutions: DT technology can revolutionize the way we approach transportation by offering personalized mobility solutions tailored to individual needs. Research should explore how DTs can be used to develop adaptive transportation systems that respond to real-time user demands and preferences.

Ethical and Societal Implications: As prototyping technology becomes more integrated into everyday life, it is crucial to address its ethical and societal implications. Future research should consider issues such as data privacy, the digital divide, and the potential impact of virtual models on employment and social structures [169].

By focusing on these future research directions, the potential of DT technology in transforming the vehicular industry can be fully realized, paving the way for smarter, safer, and more sustainable transportation solutions.

VIII. CONCLUSION

Digital twin technologies have had a major impact on the evolution of prototyping for modern vehicles, especially those outfitted with sophisticated sensors, connectivity, and autonomous driving features. They combine physical elements with computing (cyber) processes, allowing for intricate interactions with their surroundings and other systems. We have explored various vehicular prototyping concepts and provided detailed discussions on their applications in different contexts. We primarily focused on three distinct vehicular domains (i.e., automotive, aviation, and maritime) to provide a broader view of integrating multi-purpose prototyping solutions that fall within the scope of either digital twin or closely related technologies. As we move forward, emerging research should focus on solving more critical problems, *e.g.*, — hybrid platforms, AI-enabled solutions, and platforms with greater integration and computational capabilities that can be effective. The survey presents a collection of research works addressing challenges in the vehicular industry, which, if used wisely, could assist the industry, organizations, and researchers in improving their systems' performance and usability to higher levels of operational readiness.

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