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Review

Overview on Digital Twin for Autonomous Electrical Vehicles Propulsion Drive System

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Abstract: The significant progress in the electric automotive industry brought a higher need for new technological innovations. Digital Twin (DT) is one of the hottest trends of the fourth industrial revolution. It allows representing physical assets under various operating conditions in a low-cost and zero-risk environment. DTs are used in many different fields from aerospace to healthcare. However, one of the perspective applications of such technology is the automotive industry. This paper presents an overview of the implementation of DT technology in electric vehicles (EV) propulsion drive systems. A general review of DT technology is supplemented with main applications analysis and comparison between different simulation technologies. Primary attention is given to the adaptation of DT technology for EV propulsion drive systems.

Keywords: electric vehicle propulsion drive system; digital twin; hardware in the loop; real-time simulation

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1. Introduction

Considerable values have been brought to the entire industry over the last decades due to digital manufacturing. Through virtually represented factories, resources, workforces, and skills, etc., digital manufacturing builds models and simulates product and process development. The remarkable progress in communication and information technologies has advanced the development of manufacturing widely [1]. Computer-aided technologies, including Computer-Aided Design (CAD), Computer-Aided Engineering (CAE), Computer-Aided Manufacturing (CAM), Finite Element Analysis (FEA), Product Data Management (PDM), etc., are quickly developing and playing a vitally critical role in the modern industry [2,3]. Advanced data analytics and the Internet of Things (IoT) connectivity have increased the volume of data usable from manufacturing, healthcare, and smart city environments [4]. IoT environment, coupled with data analytics, provides an essential resource for predictive maintenance, fault detection, the future health of manufacturing processes, and smart city developments [5]. Digital Twin (DT) can overcome integration between IoT and data analytics through its ability to create connected physical and virtual models. A DT environment enables high-speed and real-time simulation analysis accurately [6].

This review highlights DT as a trending technology in different applications and sectors as it is ongoingly discussed in the following sections. A deductive comparison between different simulation technologies over time is discussed in Section 1.1. Different existing and prospective applications of DT are presented in Section 1.2. In Section 1.3, varieties of DT software and platforms and their specific applications are discussed. DT for AEV propulsion drive system as the main review topic is extensively discussed in Section 2. A comparative analysis between Hardware in loop HIL and DT simulations for AEV propulsion drive systems is discussed in Sections 2.2 and 2.3, respectively. Figure 1 provides an illustrative diagram of the Introduction section's content.

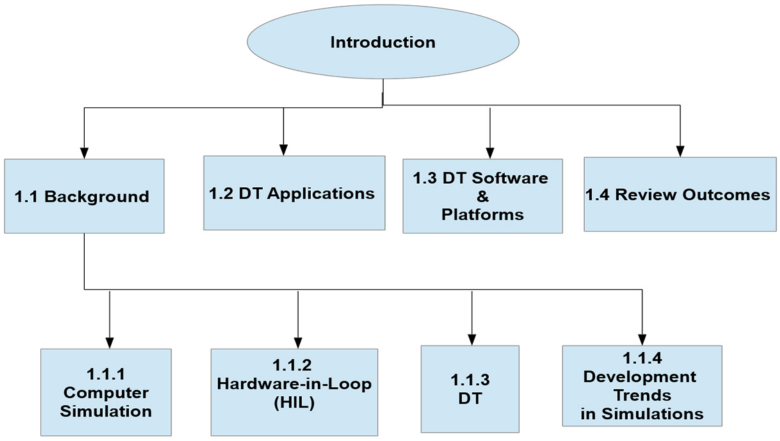

Figure 1. Introduction content diagram.

1.1. Background

Simulation history dates back to World War II when two mathematicians Jon Von Neumann and Stanislaw Ulam were puzzled by the behavior of neutrons. The problem was complicated; the hit and trial methods were too costly for them. They suggested the roulette wheel method at that time. The basic data regarding the occurrence of various events were known, into which the probabilities of separate events were merged in a step-by-step analysis to predict the outcome of entire sequence of events. Their technique had remarkable success on the neutron problem, and soon it became more popular and applicable in many business and industry applications [7]. In [8], Shannon described simulation as "the process of designing a model of a real system and conducting experiments with this model for the purpose either of understanding the behavior of the system or of evaluating various strategies (within limits imposed by a criterion or set of criteria) for the operation of the system".

1.1.1. Computer Simulation

The use of a computer is to represent the dynamic responses of a system by the behavior of another system modeled after it. A simulation uses a mathematical description, or model, of a real system in the form of a computer program. This model is composed of equations that duplicate the functional relationships within the real system. When the program is run, the resulting mathematical dynamics form an analog of the behavior of the real system, with the results presented in the form of data. For example, an electric machine can be described by a mathematical model that incorporates variables such as current, voltage, and magnetic flux. Additional mathematical equations can then be used to adjust the model to changes in certain variables, such as the winding material that is used to define heat dissipation losses.

A simulation can also take the form of a computer-graphics image that represents dynamic processes in an animated sequence, but some drawbacks pervade this technology, such as the following [9]:

- Mistakes may be made in the programming or rules of the simulation or model.
- Time may be needed to make sense of the results.
- No data exchange occurs between the real and the simulation models, which might limit the effectiveness of the results.
- People's reactions to the model or simulation might not be realistic or reliable.

1.1.2. Hardware-in-the-Loop (HIL)

At some point, thorough and reliable tests are necessary to verify and validate the design. However, as modern systems grow in complexity, particularly in software, this critical step is more easily said than performed [10]. The need for real-time simulation tools was necessary to overcome the problems concerning conventional computer simulations.

Hardware-in-the-Loop (HIL) simulation is a technique where physical signals from a controller are connected to a test system that physically simulates the situation, tricking the controller into thinking it is in the assembled product. Test and design iteration takes place as though the real-world system is being used, and one can easily run through thousands of possible scenarios to properly exercise your controller without the cost and time associated with actual physical tests. HIL helps to test the behavior of your control algorithms without physical prototypes. It is especially useful when testing your control algorithm on a real physical system is costly or dangerous. HIL simulation is widely used in the automotive, aerospace and defense, and industrial automation and machinery industries to test embedded designs. HIL is also being adopted in medical devices, communications, semiconductors, and other industries. For HIL to be of value, the quality of the simulation software is of utmost importance. Simulation software must be paired with hardware that not only accounts for system specifications such as connector type and I/O but also allows for fault insertion and the ability to test real-world scenarios [11]. A simple example of a HIL simulation system is an EV motor control unit MCU. The motor control unit MCU is responsible for converting sensor measurements into action such as adjusting the inverter frequency when the accelerator is depressed. A HIL test replaces the motor with a simulation comprising hardware and software that interacts with real I/O as though the physical motor was present. Due to the fact that updates can be made in software, you can quickly incorporate MCU, test a wide breadth of relevant scenarios, and expand test coverage as needed to fearlessly and comprehensively test without risk to a physical system.

In addition to the slightly high cost of real-time simulators, the main drawbacks of HIL systems are the complexity of development and verification. Figure 2 shows the basic components of a HIL system.

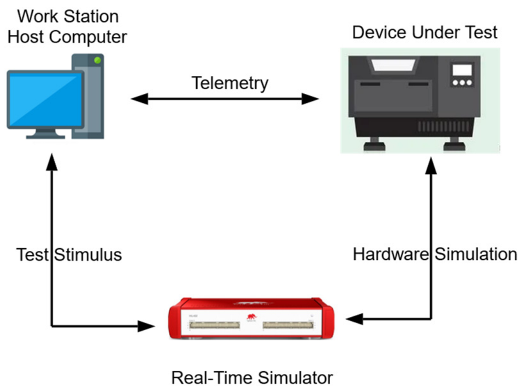

Figure 2. Hardware-in-the-Loop (HIL) System.

1.1.3. Digital Twins

Formal ideas around Digital Twins DT have been around since the early 2000s [2]. The concept of the first DT model was publicly introduced in 2002 by Grieves [12]. In early 2012, the first paper setting a key for DT definition was released by National Aeronautical Space Administration (NASA) [13]. They defined it as an integrated multiphysics, multiscale, and probabilistic simulation of a system that uses the best physical models, sensors, fleet history, etc., to simulate the life of its corresponding physical twin.

Chen [14] defined DT as a computerized model of a physical system that mirrors its functional features. Zheng et al. [15] said that DT is a virtual information set that describes actual physical assets. Mandi [16] defined DT as a virtual instance of a physical system (twin) continually updated with the latter's performance, maintenance, and health status data throughout the physical system's life cycle.

DTs also known as computational mega models mirror systems or avatars and can be defined as a digital representation of a physical object, process, or service. A digital twin can be a digital replica of an object in the physical world, such as a jet engine or wind farm, or even larger items such as buildings or even entire cities. In addition to physical assets, digital twin technology can be used to replicate processes in order to collect data to predict how they will perform.

A digital twin is, in essence, a computer program that uses real-world data to create simulations that can predict how a product or process will perform. These programs can integrate the IoT, artificial intelligence, and software analytics to enhance the output.

With the advancement of machine learning and factors such as Big Data, these virtual models have become a staple in modern engineering to drive innovation and improve performance [17].

A simple example explaining the DT of an object is a wind turbine outfitted with various sensors related to vital areas of functionality. These sensors produce data about different aspects of wind turbine performance, such as energy output, temperature, weather conditions, and more. These data are then relayed to a processing system and applied to the digital copy. Once informed with such data, the virtual model can be used to run simulations, study performance issues, and generate possible improvements, all to generate valuable insights—which can then be applied back to the original physical object. Figure 3 shows the main concept of the DT system.

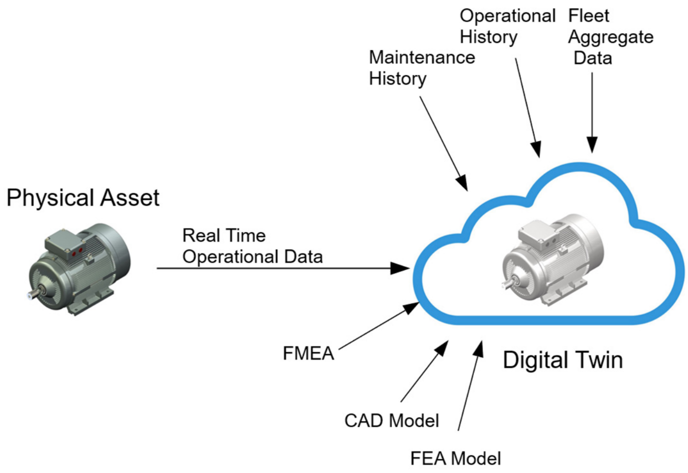

Figure 3. Digital Twin (DT) system.

At first glance, we can find common ground between DT and HIL simulations as they both fall under real-time simulations, but the essential difference between DTand HIL simulation is that for the latter one you build a software model of the core but have it interface with and direct real hardware (circuitry and mechanical) to assess the performance of your controller. For DT, you create a software-only model of the system being controlled and then provide it with inputs and outputs from the controller being tested and see how well your controller acts and whether it performs what it is supposed to be performing.

Although simulations and DTs both utilize digital models to replicate a system's various processes, a digital twin is actuallyl a virtual environment, which makes it considerably richer for study. The difference between digital twin and simulation is largely a matter of scale: While a simulation typically studies one particular process, a digital twin can itself run any number of useful simulations to study multiple processes. The differences do not end there. For example, simulations usually do not benefit from having real-time data. However, digital twins are designed around a two-way flow of information that first occurs when object sensors provide relevant data to the system processor and then happens again when insights created by the processor are shared back with the source object.

By having better and constantly updated data related to a wide range of areas, combined with the added computing power that accompanies a virtual environment, digital twins can study more issues from far more vantage points than standard simulations can—with greater ultimate potential to improve products and processes. In a word, Table 1 shows a brief comparison between discussed simulation technologies.

Table 1. Comparison between computer simulation, HIL, and DT.

	Computer Simulation	HIL	DT
Data element and interaction	Static	Active	Active
Simulation Basis	Potential parameters	Real time feedback	Real time feed back
Scope	Narrow-Primary design	Narrow-Advanced	Wide-Advanced

1.1.4. Types of Digital Twins

There are various types of digital twins depending on the level of product magnification. The biggest difference between these twins is the area of application [18].

Component twins/Parts twins: They are the basic unit of the DT and the smallest example of a functioning component. Parts twins are roughly the same thing but pertain to components of slightly less importance.

Asset twins: When two or more components work together, they form what is known as an asset. Asset twins allow you to study the interaction of those components, creating a wealth of performance data that can be processed and then turned into actionable insights.

System or Unit twins: The next level of magnification involves a system or unit twins, which enable you to observe how different assets come together to form an entire functioning system. System twins provide visibility regarding the interaction of assets and may suggest performance enhancements.

Process twins: The macro-level of magnification reveal how systems work together to create an entire production facility. They can help determine precise timing schemes that ultimately influence overall effectiveness.

1.1.5. Development Trends in Simulations

For decades, computer simulation tools were effective enough to answer specific design and modeling equations; however, by that time, they became limited due to the complexity of systems and the high amount of data being processed [19]. Proceeding to real-time, for a while, in-the-loop simulations could be a time, money, and effort saver by helping to identify errors before they occur in the target environment or at the customer. These simulations can be performed in various forms depending on the stage of the product development. Model-in-the-Loop (MIL), Software-in-the-Loop (SIL), Processor-in-the-Loop (PIL) simulation, and (HIL) are different forms of In-the-Loop simulations. There are proponents of DT who say HIL simulation is "so yesterday" and is no longer needed and proponents of HITL who claim that DTs are overhyped, oversold, and overly dependent on the fidelity of the model to reality [18]. Others opinions say that the best solution might be a hybrid of both DT and HIL. Figure 4 shows the timeline of the evolution of simulation technologies starting from the first individual simulation application and ending with DT technology.

1.2. Applications of Digital Twins

DTs' first appearance was in industries of product and manufacturing design, then emerged in industries such as aerospace, automation, shipbuilding, healthcare, and smart cities [20].

Manufacturing: relies on high-cost equipment that generates a high volume of data, which facilitates creating DTs, because manufacturers are always looking for a method to track and monitor products to save time and money. This is why DTs seek to make the most significant impact within this setting. The current growth is in line with the industry 4.0 concept, coined the fourth industrial revolution; this harnesses the connectivity of devices to make the concept of DT a reality for manufacturing processes [21–23]. DT has the potential to provide real-time status on machines' performance as well as production line feedback.

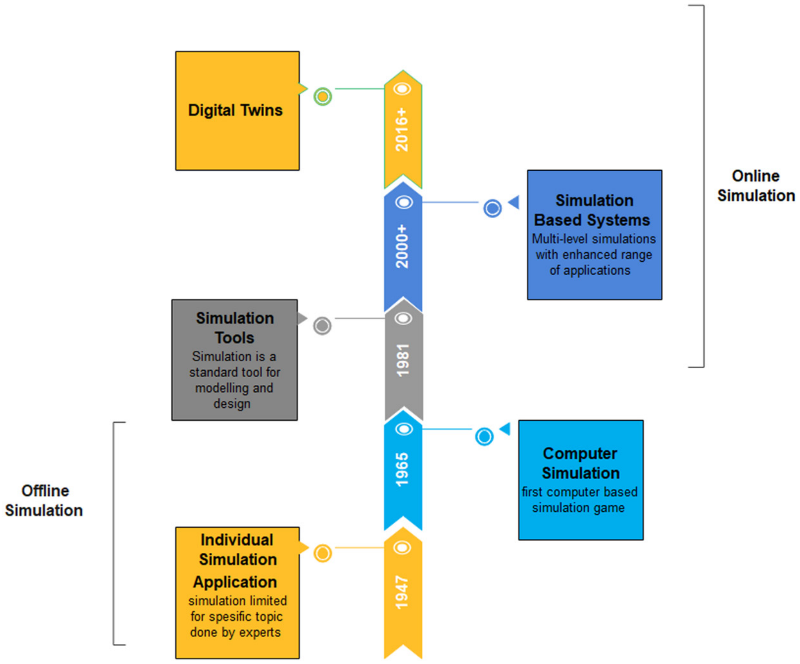

Figure 4. Evolution timeline of simulation technology.

Product development: is a long and intricate process. For instance, it takes up to 6 years to design and launch a new car model [24]. It needs to be a seamless transition from the preceding model to the new model. A slight mistake during the process can undermine the brand's value and profitability [21]. A DT helps to integrate data between previous-generation models with the new concept in their digital formats. Twinning also enables seamless communication between product designers, end customers, and other stakeholders. When it comes to product testing, having a DT negates the need to wait for performance data gathered during vehicle trials to determine its performance and quality [25].

Predictive maintenance: DT provides the manufacturer the ability to predict issues sooner, and their use increases connectivity and feedback between devices, in turn improving reliability and performance. AI algorithms coupled with DTs have the potential for greater accuracy as the machine can hold large amounts of data needed for performance and prediction analysis. DT is creating an environment to test products as well as a system that acts on real-time data; within a manufacturing setting, this has the potential to be a largely valuable asset [26,27].

Aerospace: Before DTs were found, physical twins were used in aerospace engineering. An example of this is the Apollo 13 program in the 1970s where NASA scientists on Earth were able to simulate the conditions of the ship and find answers when critical issues arose. Later in 2002, the DT concept is introduced by John Vickers from NASA [28]. Today, experts acknowledge the importance of DT in the aerospace sector where 75% of air force executives have cast the vote of confidence in favor of the digital twin, according to Business Wire's survey report [29]. With DTs, engineers can use predictive analytics to foresee any future problem involving airframes, engines, or other components to ensure the safety of the people on board.

Automotive: The development of an automotive is a long and complex process. Typically, new car model manufacturing might take five to six years—from the design stage to launch in the market [22]. The key to the success and long-term sustainability of an automotive organization is the effective design [30]. Even a small drawback in the product design can erode the company's brand value for a long time. With digital twin technology, it become easier to cover all phases of the automotive industry starting from design, development, monitoring, and maintenance of the vehicle. After the revolutionary development in batteries technology and the emergence of electric automobiles that place them on the list of global demand, digitization of automotive manufacturing and development process has become an urgent necessity [31].

Smart cities: have always relied on IoT technology for a while but with the increased number of smart cities, more connected communities are found; as a result, the need for new technologies such as DTs has increased. It can be used in planning new smart cities and help with ongoing developments of current smart cities [32]. There are also benefits within energy-saving as the collected data from IoT provides an excellent insight into how utilities are being distributed and used. In a digital twin city, the data of the operating status of infrastructure, the deployment of municipal resources, and the flow of people, logistics, and vehicles will be collected by sensors, cameras, and various digital subsystems. Modern communication technologies such as 5G are responsible for delivering data to the cloud and the city government to be monitored and processed; this makes the city more efficient [33].

Healthcare: The DT's provides researchers, doctors, hospitals, and healthcare providers the ability to simulate environments specific to their needs, whether it be real-time or looking to future developments and uses [34]. In addition to this, DTs can be used simultaneously with AI algorithms to make smarter predictions and decisions. Many applications within healthcare do not directly include the patient but are beneficial for ongoing care and treatment, hence the key role such systems have on patient care. DT for healthcare is in its infancy, but its potential is vast, from using it for bed management to large-scale wards and hospital management. Posessing the ability to simulate and act in real-time is even more paramount within healthcare as it can be the difference between life and death. DT could also assist with predictive maintenance and ongoing repair of medical equipment. The DT within the medical environment has the potential, along with Artificial Intelligence (AI), to make life-saving decisions based on real-time and historical data [35].

Ocean: Sustained ocean observations are an essential part of worldwide efforts to understand and protect marine ecological systems. Observation processes could be samples collected on ships; measurements from instruments on fixed platforms; autonomous and drifting systems; submersible platforms; and remote observing systems such as satellites and aircraft. Previously, ocean observation was a complex process and collecting data from it takes a long time and excessive cost because of different standards, nomenclature, and baselines. Digital Twin for oceans was a turning point that integrated a wide range of data sources, modeling and simulation, AI algorithms, and specialized tools including relevant best practices. DT forms a new globally shared capacity to access, manipulate, analyze, and visualize marine information. It enables users and partners to create ocean-related development scenarios, addressing issues such as green energy developments (renewable and non-renewable), mining impacts, fisheries and mariculture, marine protected area sitting, nature-based solutions, and ocean-based tourism. European Union (EU) was the first to take the initiative of investing in DT technology for the ocean by launching many projects in several member countries. Blue-Cloud is one of the ocean DT projects released by the EU aiming to the integrate all European assets related to seas and oceans with top-tier digital technologies into a digital component representing a consistent high-resolution, multi-dimensional, and (nearly) real-time description of the ocean [36].

Construction: As technology becomes more pervasive and smart buildings and precincts develop, real estate companies have tended to use their smarts to anticipate both customer and technological needs. A good method for performing this and to cut time and cost is digitalization. This technologically enabled process can deliver greater strategic value for the real estate industry as a whole. DTs can optimize operations and improve customer experience, and a twin can also deliver benefits across the full lifecycle of a building by simulating complex scenarios [37]. Buildings as a complex, high-value asset present an ideal opportunity for realizing the benefits of a DT. The full construction process can be planned, visualized, and optimized before the ground is even broken. Construction sites can be managed more effectively, with the ability to predict exactly how delays and decisions will impact overall construction. Moreover, the ability to monitor safety and compliance in real-time can save lives by predicting emergencies before they occur [38].

Figure 5 summarizes the applications discussed in this subchapter. In short, although DTs invaded many sectors, they are still new and not sufficiently covered for other applications, as is the case of EV propulsion drive systems, which will be addressed in the next section. The future of DT is nearly limitless due to the fact that increasing amounts of cognitive power are constantly being devoted to their use. Thus, DTs are constantly gaining new skills and capabilities, which means they can continue to generate insights needed to make products better and processes more efficient.

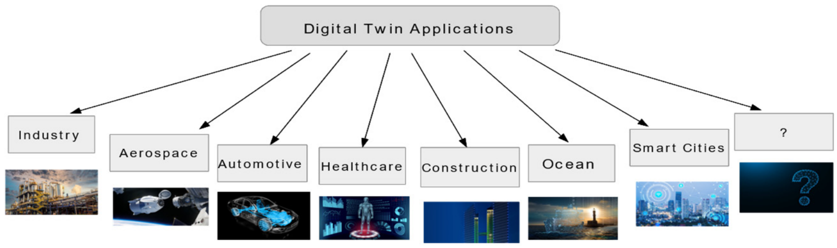

Figure 5. Digital Twin applications map.

1.3. Digital Twins Software and Platforms

DT requires advanced software able to generate a digital simulation of a physical entity. DT software is designed to monitor asset performance as well as to run simulations to predict potential outcomes or maintenance that might face the asset. There are many software and platforms from different companies that support DT simulation that are more suitable for engineering applications, such as the following:

Azure Digital Twin: Microsoft's platform enables the creation of twin graphs based on digital models of entire environments, which could be buildings, factories, farms, energy networks, railways, stadiums, and even entire cities. These digital models can be used to gain insights that drive better products, optimized operations, reduced costs, and breakthrough customer experiences.

AWS IoT: Amazon's platform. It's mainly used for remotely monitoring as it enables exchanging data and information between a remote emulation or simulation and the physical twin. AWS brings AI and IoT together to make devices more intelligent. You can create models in the cloud and deploy them to devices where they run two-times faster compared to other offerings.

Giraffe: A DT tool is used for construction applications. It accelerates the ability to scale by conducting site analysis in real-time with building design. Giraffe enables overlaying data, querying, and automatically calculating the proof of concept.

Perdix Platform: General Electric's platform. It is a complete solution for industrial monitoring and event management. This platform delivers shared capabilities that industrial applications require: asset connectivity, edge technologies, analytics, machine learning, Big Data processing, and asset-centric digital twins.

ETAP ADMS: Advanced Distribution Management System (ADMS) is a flexible solution for addressing the core requirement of the new digital grid to provide resiliency and reliability to the network. It provides an intelligent and robust decision support platform based on a unified Digital Twin of the electrical network with a collection of Geospatial-based distribution network applications integrated with mission-critical operational solutions to reliably and securely manage, control, visualize, and optimize small to vast distribution networks and smart grids.

Ansys Twin Builder: It is a platform that allows engineers to create simulation-based digital twins-digital representations of assets with real-world sensor inputs. It is mainly used for industrial applications for design, test, predictive maintenance, and optimization. Ansys Twin Bulder has different sub-platforms for each usage and different industrial applications.

Digital-Twin-Distiller: A python-based platform for DT simulation suitable for manufacturing applications. It allows researchers to develop and deploy simulation models. It aims to link research and engineering work environments to preserve simulation validation [39].

1.4. Review Outcomes

From the previous context, the trended technology of DT was addressed from different sides. The comparison between computer simulations, HIL, and DT highlighted the advantages of the last one. DTs receive real-time updates from the physical asset, process, or system. Therefore, the tests, assessments, and analysis work conducted by engineers are based on real-world conditions. As the state of the digital twin dynamically changes as it receives new data from the physical world, it matures, producing outputs that are more accurate and valuable. DTs can provide engineers with virtual tools that allow them to look at, explore, and assess physical assets, processes, and systems. With this ability, it is possible to obtain an accurate view of what is happening now, as well as what will happen in the future. Many applications have been well covered by DT technology but some still in the early stages, which will be discussed in the next section. Many companies have developed software and platforms to keep pace with DT technology in line with their products.

2. Overview of Recent Trends in EV Drive Systems

2.1. Background

As it can be observed from the literature review in the previous section, the automotive industry is one of the top existing applications of DT; however, research studies concerning Electric Vehicles EV propulsion drive systems are so limited and in need of being studied deeply.

Electric vehicles (EV) include fully (battery) and hybrid EVs in continuous growth by the time, and in 2020 it increased by 43% more than in 2019 [40]. Information Handling Services (IHS) Markit predicts that EVs could capture 45% of the new car market already in 2040 and nearly 80% by 2050 due to great technological advances, decreased manufacturing costs, and international policies that facilitate EV expansion. Figure 6 shows a comparison between EVs, including battery (BEV) and plug-in hybrid (PHEV), fuel cell (FCV), and traditional internal combustion engine (ICE) vehicles [41].

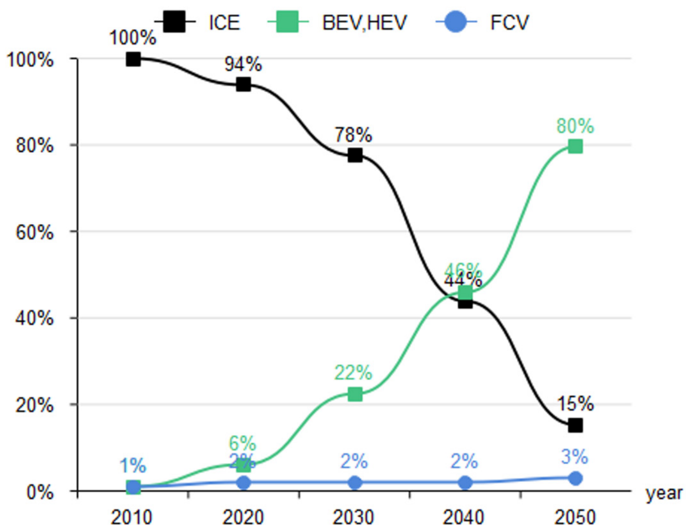

Figure 6. Comparison between global EV, ICE, and FCV markets.

EV propulsion drive system is considered the core element of the vehicle. It needs to be efficient, reliable, and economically sufficient to yield satisfactory EV operation performance [42]. EV propulsion drive system comprises both mechanical and electrical parts, as shown in Figure 7. In this review, the electrical parts are the main topics of focus.

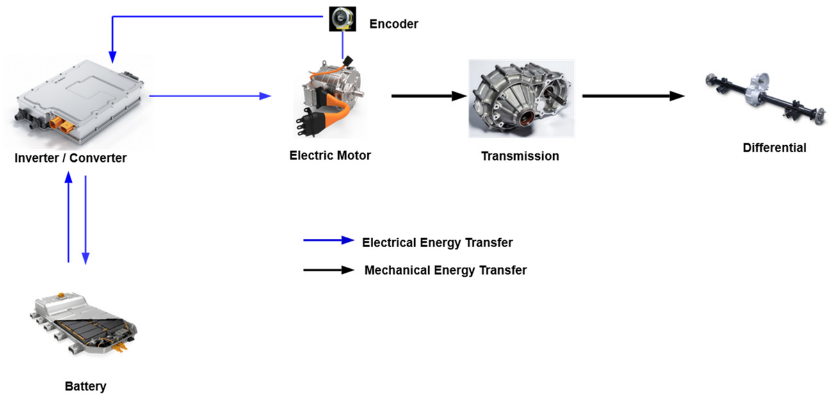

Figure 7. Electrical Vehicle (EV) drive system components.

Battery: Many research studies considered the battery as a component of the EV drive system, including its attached heating and management systems [43]. The maximum driving distance of an EV is often determined by the battery's capacity—the higher the capacity, the higher the driving distance. Lithium-ion batteries (LIBs), Lithium Nickel Manganese-Cobalt (NMC) oxide, and Lithium Nickel-Cobalt-Aluminium (NCA) oxide are dominating the EV battery industry with nearly 96% of market share in 2019 [44,45]. The EV battery has a direct impact on inverter design and operation. DT technology can be investigated in EV battery health monitoring, faults detection, and lifetime prediction.

Inverter/Converter: The power electronics component of the drive system. It comprises three sub-components: DC-DC converter, inverter, and motor control unit MCU. The main DC-DC Converter converts the battery high voltage DC into low voltage DC to power headlights, interior lights, wiper and window motors, fans, pumps, and many other systems.

The inverter includes a motor control unit (MCU) that is usually an integrated unit. An inverter converts the battery's high DC voltage into AC variable frequency voltage, which is then used to regulate the motor speed. MCU implements the control algorithm of the EV motor. It configures motor speed and torque after receiving comments from the vehicle control unit (VCU) via CAN-bus communication and then translates them into power signals by the inverter to be fed to the motor. The inverter is responsible for executing acceleration and deceleration, which is crucial in maximizing the EV's drivability. During vehicle braking, it can regenerate DC power back to the battery for charging. It is a very sensitive part of the EV as it is the focal point between the stationary energy and the kinetic energy part of the EV [46,47]. Silicon (Si) insulated gate bipolar transistor (IGBT) was widely used in EV drive inverters since 1980. It has the combined advantages of the simple gate-drive of a field-effect transistor and the high current, low conduction loss of bipolar transistor. IGBTs can block high voltages with low on-state conduction losses and well-controlled switching times. However, they are limited by how fast they can switch while delivering low on-state conduction losses. This results in a need for costly and large-size thermal-management methods and a limitation on power-conversion system efficiency. With the revolutionary progress in power electronics development such as SiC (silicon carbide) and GaN (gallium nitride), metal-oxide-semiconductor field-effect transistor (MOSFET)-based inverters are alternatives, while still possessing higher prices; they provide a better thermal profile, lower switching losses, higher efficiency, and longer lifetime [48]. Building a DT model of the EV inverter would be an ideal solution for EV manufacturers as well as researchers for development, health monitoring, fault detection, and also components' lifetime prediction.

Electric motor: is the base stone of the EV. It converts electric energy from the battery into kinetic energy that moves the wheels. The advantage of using the motor instead of an engine is numerous: first, the noise and the vibration. Many passengers riding EVs for the first time are surprised by how quiet and comfortable the ride feels. Moreover, the EV powertrain is smaller than the engine, thus providing additional space for efficient vehicle design—such as expanded cabin space or storage [49]. The motor is also in part an electric generator—it converts the kinetic energy generated while in neutral gear (e.g., while the car is proceeding downhill) into electric energy saved to the battery. There are five types of motors most often used in EVs: Permanent Magnet Synchronous Motors (PMSM) are the most used type by many manufacturers such as Hyundai and GM [50]. Brushless DC Motors (BLDC) are commonly used in light electric carts and electric scooters. Three-phase Induction Motors (IM) are widely used by many EV manufacturers such as Tesla [51]. Permanent Magnet Assisted Synchronous reluctance Motors (PMSynRM) recently started to be used in some Tesla models to alternate induction motors. Switched Reluctance Motors (SRM) started to gain higher interest recently, and some manufacturers such as BMW and LandRover are developing these types of motors to use in their EVs. [52].

2.2. Problem Definition

Developing optimal designs for EV drive systems is very challenging for many researchers and also EV manufacturers. Most of the studies start from computer simulation, specially designed environments. The next step is transitioning from simulation to real hardware building and testing. Usually, test benches are built to replicate simulated models, and comparative analysis between the results of the two models is approached. After building and running the test bench, optimization of the drive system components, faulty operations, and different malfunctions are normally tested. In performing this, firstly, depending on the power rating of the system, a lot of electrical energy is consumed with a direct impact on the price of the development of the system. On the other hand, testing of one system component sometimes can result in faulting another component. Moreover, testing faulty conditions requires intentionally faulting some components of the test bench. The following subsections will discuss solutions to overcome the above-mentioned issues.

2.3. Hardware in the Loop Simulation for EV Drive Systems

EV drive system design and installation are expensive and time consuming. Mainly, it consumes much time and financial resources to perform tests and debugging of the equipment. Usually, those tests are executed by constructing test rigs with real machines, but experimental designing is expensive and, in many cases, difficult to implement [53]. Thus, real-time simulators provide an efficient solution for those problems.

Mudrov et al. [54] presented a deductive study on using Power HIL (PHIL) systems for EV drive systems. They concluded that the main advantage of the PHIL system is the ability to simulate the electromechanical part behavior to take part of electrical drive power part and to make a think converter that it works with a real electrical drive. They also provided a PHIL system for EV drives based on a power converter with Field Programmable Gate Array (FPGA). The proposed system had the capability of testing a multistage inverter control system.

Poon et al. in [55] proposed a HIL platform for EV drive applications. The proposed platform can test the drive cycle and fault injection.

Berry and Gu [56] proposed a real-time HIL model of a three-phase EV power inverter system to simulate thermal behavior and internal losses using an FPGA real-time system. The presented model can accommodate any switching method of the inverter.

Collin et al. [57] provided an HIL prototype model of SiC-based drive system of PMSM. Typhoon 402 HIL module used as a system-level controller. The provided prototype was tested under Sinusoidal Pulse Width Modulation (SPWM) and Space Vector Pulse Width Modulation (SVPWM) techniques. The testbed showed the advantage of a faster switching time of the SiC device, which resulted in a total harmonic reduction in the motor current.

Mishra et al. in [58] proposed an HIL simulation model of a PMSM drive system. They used the Xilinx system generator platform coupled with the MATLAB simulation model of the drive system. They used different combinations of simulation environments to highlight the difference in system performance.

Amitkumar et al. [59] proposed a HIL simulation system to study the impact of PMSM inverter faults used for an EV drive system aiming to reduce the chance of equipment damage during testing. Three types of driving inverter gate-drive failure faults (device open-circuit fault) of one or more switches were studied. PMSM emulation system was implemented with its vector controller on an FPGA of a real-time simulator HIL to minimize controller sampling time.

From the above, it is clear to us that HIL simulation is an ideal solution to test the components of the electric propulsion system and simulate some of the malfunctions expected in it as well as provide an appropriate environment to apply optimization techniques to improve the performance of the system and achieve higher efficiency of its components, but there are aspects of shortcomings that are flawed, which is the inability to simulate the entire EV drive as one system, as well as the limited handling of artificial intelligence tools.

2.4. Digital Twin (DT) for EV Drive System

DTs for EV drive systems are frequently used for system health monitoring, diagnostics, prognostics, optimization, scenario, and risk assessment [2]. They can be created at the system level, subsystem level, individual component level, and many other assets. In this section, different approaches to DT technology used in EV drive systems will be discussed.

Wunderlich and Santi [60] proposed an approach for a real-time DT model of a power electronic converter. Based on a dynamic Nonlinear Autoregressive eXogenous neural network (NARX-ANN), combinations of time-domain, switch-averaged, large-signal, real-time, and embeddable models are used. A boost converter model with the current source was their physical model. The proposed DT model of the converter can run on any platform, including locally on the converter's digital controller. Their model is mainly used for fault detection, prognostics and health management, and scenario and risk assessment.

Rjabtšikov et al. in [61] proposed a fault detection DT model for an AC 3-phase IM. Inter-turn short circuit fault detection was implemented into the motor DT. The emulator was built based on historical data and a mathematical model of the motor using Unity 3D combined with ROS service to enable online condition monitoring. The DT model in this case study was used as a virtual sensor for the physical motor model.

Toso et al. in [62] applied the DT to EV motor aiming to optimize the motor performance concerning estimating driving torque and cooling control. Thermal and electromagnetic FEA of EV induction motor was provided at first to collect the necessary data for both optimization operations. DT model of the motor was built using a micro lab box as a system-level DT.

Katukula et al. in [63] provided a DT system to monitor and analyze IM conditions. The provided DT system measures the drawn current by the motor using sensors. The collected data are fed to a simulation FEM model. The proposed DT enables a better understanding of the motor's thermomagnetic behavior and allows the ability to predict possible faults.

Rassõlkin et al. in [64] provided a methodology of collecting required data from an autonomous EV loading motor drive system based on the empirical performance model than using the collected data to develop a DT model. The data collected concerned the estimation of the drive system's performance. Unity 3D was used as a host environment for simulation and visualization of the motor DT model.

Brandtstaedter et al. in [65] presented DT model for fault detection. A 50 MW PMSM of an electric drive train was numerically simulated, and the framework of fault identification was presented. Unbalanced detection and temperature prediction in the rotor system were tested and verified using the digital model.

Jitong et al. in [66] presented a DT model of a three-phase IM. The provided model is built at first to realize the motor design then to monitor the motor equipment's normal operation to detect the entire lifecycle and shorten maintenance time. A 3D simulation model of the physical motor was built using 3D Max. Based on Unity 3D software, the digital twin was built depending on the provided simulation model. Data acquisition between real and digital models was made using an SQL server.

Venkatesan et al. [67] provided a DT system of an EV-PMSM drive system for health monitoring and prognosis purposes such as outputs casing temperature, winding temperature, time to refill the bearing lubricant, and percentage deterioration of magnetic flux to compute remaining useful life (RUL) of permanent magnet (PM). They presented two approaches for motor health monitoring: one to monitor the motor performance in-house and the other remotely. The provided DT model was built in MATLAB/Simulink, with Artificial Neural Network (ANN) and fuzzy logic to map the system inputs.

From the above analysis, it could be observed that DTs offer advanced solutions in the development of EV drive systems due to their ability to exchange a huge amount of data with the real model in no time and their ability to represent components, assets, or the entire system. DTs also have the possibility of working for different purposes such as prognosis, fault detection, health monitoring, lifetime prediction, and optimization. Table 2 provides a comparison between HIL simulation technology and DT for AEV drive systems.

Table 2. Comparison between HIL and DT technologies for EV drive systems.

Points of Comparison	Hardware-in-Loop (HIL)	Digital Twin (DT)
Simulation	Real-time (Online)	Real-time (Online)
Applications	Design; Testing; Optimization; Fault Detection	Design; Diagnosis; Optimization; Predictive Maintenance; Fault Detection; Health Monitoring; Life Time Prediction
Areas of Applications	Component; Subsystem	Component Subsystem; Whole System
Cost	High	Moderate
Reliability	High	Very High

3. Conclusions and Future Work

3.1. Conclusions

An extensive overview of DT technology has been provided. Compared to previous simulation technology, it is a powerful alternative and a major development in the topic of digital simulation and the connection between the virtual and physical worlds. DT is already applied in many different applications such as industry, aerospace, automotive, healthcare, and oceans. They offer a lot of functions such as health monitoring, fault detection, optimization, prognosis, and lifetime prediction. Although automotive is one of the current DT applications, most researchers care about vehicle design, motion, and visualization. Concerning EV propulsion drive system, it is still too new of a topic to say it is covered by DT technology. The analytical comparison between using HIL simulations and DTs for EV propulsion drive systems resulted in the following: HIL simulation is suitable for testing a drive system component or at most an asset. It is recommended to be applied in the phase of designing or testing the performance of the system. It also might be used for some common fault detection. DT is more effective after obtaining the physical drive system model. Due to their great ability to deal with a huge amounts of different datasets, DTs can be built for a component, asset, or the entire drive system. They can also be adapted for multiple uses, such as predictive maintenance, fault detection, health monitoring, and lifetime prediction, depending on the model basis and the type of data exchanged with the physical model. DTs can also be built to optimize the performance of the drive system that might be suitable for research and development purposes.

3.2. Future Works

A combination of HIL simulations and DTs is the best solution depending on the stage of the work, such as the following:

1. For EV propulsion drive system design, the first stage is to build simulation models of different system components;
2. Verifying different models using HIL simulation tests;
3. Building EV propulsion drive system physical models (test bench);

4. Building DT models of the EV drive system starting with components, then assets, and finally the entire system model. DT models will be built based on previously collected data from HIL simulation tests and the current exchanged data with the physical model.
5. Various datasets from the physical EV drive system can be obtained by the implementation of different sensors and data acquisition platforms. The DT model may include regulation for both virtual and physical entities that can be used for maintenance, diagnostic, optimization, and system development.

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