Digital Twin Technology

A Review and Its Application Model for Prognostics and Health Management of Microelectronics

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Review

Digital Twin Technology—A Review and Its Application Model for Prognostics and Health Management of Microelectronics

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Abstract: Digital Twins (DT) play a key role in Industry 4.0 applications, and the technology is in the process of being mature. Since its conceptualisation, it has been heavily contextualised and often misinterpreted as being merely a virtual model. Thus, it is crucial to define it clearly and have a deeper understanding of its architecture, workflow, and implementation scales. This paper reviews the notion of a Digital Twin represented in the literature and analyses different kinds of descriptions, including several definitions and architectural models. A new fit-for-all definition is proposed which describes the underlying technology without being context-specific and also overcomes the pitfalls of the existing generalised definitions. In addition, the existing three-dimensional and five-dimensional models of the DT architecture and their characteristic features are analysed. A new simplified two-branched model of DT is introduced, which retains a clear separation between the real and virtual spaces and outlines the latter based on the two key modelling approaches. This model is then extended for condition monitoring of electronic components and systems, and a hybrid approach to Prognostics and Health Management (PHM) is further elaborated on. The proposed framework, enabled by the two-branched Digital Twin model, combines the physics-of-degradation and data-driven approaches and empowers the next generation of reliability assessment methods. Finally, the benefits, challenges, and outlook of the proposed approach are also discussed.

Keywords: Digital Twin; Industry 4.0; microelectronics reliability; physics of degradation; material modelling; multi-physics simulation; data-driven model; condition monitoring; hybrid PHM

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1. Introduction

The Digital Twin is one of the key technologies in Industry 4.0, i.e., the fourth industrial revolution. It plays a crucial role in transforming industry, and many major companies already use Digital Twins for solving problems and improving efficiency [1,2]. The idea of a Digital Twin (DT) is relatively new. It was conceptualised during the very beginning of the 21st century and has gained traction mainly during the last decade [3]. The primary reason behind it is the digitalisation of the industry, which has been accelerated by newly emerging Information Technology (IT) and its infrastructure. It was also marked at the peak of Gartner's hype-cycle curve in 2018 with a total expected duration of 5–10 years to reach the productivity plateau [4]. Thus, the concept of the Digital Twin is still not fully mature and keeps evolving and becoming more elaborate.

The concept originally emerged in the aerospace industry and developed in the manufacturing domain. It was further adopted by several other sectors such as healthcare, telecommunication, construction, agriculture, energy, environment, etc. During its evolution, it has seen large fragmentation regarding its definitions and models. A Digital Twin can be generally described as a continuously updated virtual representation of an object, system, or process which replicates all phases in the lifecycle of its physical counterpart. Although this underlying idea remains the same, many applications and publications define it as too context-specific. Several definitions have been thoroughly analysed in this paper to identify the pitfalls as well as the common thread among them. In addition, the good aspects and relevant keywords from these definitions have been highlighted, and a new generalised and concise definition of a Digital Twin is formulated.

As a key technology in the ongoing Industry 4.0 (and the upcoming Industry 5.0), there is a clear need for more clarity on the concept of a Digital Twin and to provide additional descriptions in the form of an architectural model and its working principle. A Digital Twin is also often misinterpreted as being the same as any model in the virtual space. However, DT is actually much more than this, and a representation in the virtual space is just one facet of it [5]. Thus, it is also critical to define clear boundaries and criteria to classify a digital model of a system as its Digital Twin. This paper also addresses this by analysing the three- and five-dimensional models for the generalised Digital Twin architecture and commenting on their characteristic features. Moreover, a new simplified two-branched model of DT is introduced that keeps the real and virtual spaces distinct and is designed based on the two key modelling approaches: physics-based and data-driven modelling.

Alongside the DT technology, the evolution of electronics has also played an important role in Industry 4.0. During the second decade of the 21st century, the number of electronic devices used in various applications has seen tremendous growth. The 'electronification' of several industries over the last few decades has been accelerated by newly emerging information technology, the incorporation of more and more electronic components (e.g., sensors) into conventional products and systems, and the integration of computer-aided and software-based technologies into traditional industries. As an example, about 200 billion *ARM*-based chips in total were shipped by the year 2021 [6]. Another important example is the automotive domain. According to a 2019 report by Deloitte [7], electronic systems in a modern car constitute about 35% of its total cost, and it is expected to have close to a 50% share by the year 2030. The embedded electronics are also responsible for assisting in primary functions and mission-critical tasks of a system, such as a modern car or a machine in the manufacturing/assembly line. Thus, the reliability of electronic components has become ever so important.

The industries are expected to move from an 'application-based' to a 'degradation-based' wave in reliability in the near future [8], which means the focus would transition from a *physics-of-failure* to a *physics-of-degradation* approach to estimate a product's service lifetime. Thus, it is important for the reliability assessment to move from the current qualification test-based methodology to a newer condition monitoring-based approach that would enable product-level diagnostics and prognostics capabilities and individual health management at scale. This can be achieved using a Digital Twin-based framework. Thus, a comprehensive knowledge of the fundamentals of the Digital Twin technology becomes crucial for the microelectronics domain. This paper, therefore, extends the newly proposed two-branched DT model for the condition monitoring of electronic components and systems. This model also facilitates a hybrid approach to the Prognostics and Health Management (PHM) of microelectronics.

This article has been structured to achieve the following goals—to review the notion of Digital Twins in the context of Industry 4.0, to comment on the existing definitions and architecture models of DT, and to propose improved versions of those with a focus on microelectronics as a product for the latter. It is, thus, organised in three parts. Sections 2 and 3 describe and analyse the development and adoption of DT by different industries, including the evolution of the underlying IT technologies. A review of different kinds of DT definitions has also been presented. Through identifying the highlights and shortcomings of the existing ones, a new updated definition has been proposed.

Sections 4 and 5 describe the basic architecture of a Digital Twin-based system and review a few existing and well-known workflow models. The limitations of those are identified, and a new simplified model based on two key modelling approaches is proposed. Finally, Sections 6 and 7 outline an implementation of Digital Twins for the PHM of microelectronics by expanding the proposed two-branched model for this context. In addition, a holistic approach for the hybrid PHM of electronic components and electronics-enabled systems is also highlighted with the help of the new DT model. Lastly, the key advantages, challenges, and future roadmap are discussed.

2. Related Work—Development and Definition

The idea of a Digital Twin was first introduced by Dr Michael Grieves in 2003 in a university course on product lifecycle management, while the term was used much later in his 2011 book [9] and more elaborated on in his 2014 white paper [10]. The first mentions of a Digital Twin can be found in the technology roadmap of the National Aeronautics and Space Administration (NASA) in 2012 (draft in 2010) [11,12]. The 2012 publication by Glaessgen and Stargel [13] lists the Digital Twin as a key technology and, thus, is also cited by a plethora of recent publications as the origin of the Digital Twin concept. It was later adopted by different industries, and thus, several contextualised adaptations of a Digital Twin can be found in the literature.

Thus, the first two decades of the 21st century were the two key periods, respectively, for the formulation and early adoption of the Digital Twin technology. Its roots, however, go far further in the past. Digital Twins are enabled by the underlying foundational technologies developed during the 3rd industrial revolution, also known as the Computer Revolution, during the last 30 years of the 20th century. Therefore, in order to understand the concept more comprehensively, it is important to have an overview of the technological development and milestones, in the context of digitalisation, over the past 50 years.

2.1. Digitalisation Stages and Highlights

The evolution of digitalisation has gone through four progressive stages: digital enablement, digitalisation assistance, digital control and link, and cyber-physical integration [3]. Table 1 summarises the highlights of these four stages. The first stage refers to the process of converting paper documents into digital forms. In this phase, around the year 1950, only the most essential information was digitalised for storage, processing, and transfer. In the late 1970s, computers became small and inexpensive enough to be purchased by individuals, when a large-scale integration made it possible to construct a sufficiently powerful microprocessor on a single semiconductor chip [14].

Computers further evolved in the 1980s to have a graphical user interface (GUI). With the extensive applications of computer-aided, i.e., CAX technologies (e.g., CAD, CAE, and CAM), the paradigm of digitalisation shifted toward assisting engineers to work with computers effectively. The digitalisation of entire businesses was possible in the 1990s with the development of the internet and advanced control technologies [15]. With the increasing spread of workstations and personal computers, the number of simulation users grew rapidly and the simulation technology further evolved. Today, simulation is the basis for design decisions, validation and testing, not only for components, but also for complete systems in nearly all application fields [16].

Electronic components became more and more compact during the first decade of the 21st century, which resulted in the evolution of consumer electronics such as compact, lightweight laptops, smartphones, and later smart devices along with the services associated with them, e.g., cloud storage. As a result, a new generation of information technologies such as the Internet of Things (IoT), cloud computing, big data analytics, and Artificial Intelligence (AI) emerged. They enabled the convergence of physical and virtual worlds, which is also referred to as the cyber-physical integration [17], and, therefore, digitalisation is now becoming one of the main drivers of innovation in all sectors [18].

The progress in the latter half of the digitalisation era dramatically improved the capabilities of computers. As a result, simulation technology also evolved along with it. The Digital Twin is the next wave in simulation technology [16,19]. In fact, it is rooted in some existing technologies, such as 3D modelling, system simulation, digital prototyping (including geometric, functional, and behavioural prototyping), etc. Thus, the Digital Twin technology stands on the concrete foundations of the technologies developed during the Computer Revolution or the Information Age.

Table 1. The stages and highlights of the digitalisation era leading to the Digital Twin technology.

Stage	Description	Year	Highlights
1.	Digital Enablement	1950s	→ Paper documents to digital
		1970s	→ Sufficiently powerful microprocessor on a single semiconductor chip → Computers became small and inexpensive, thus, purchased by individuals
2.	Digitalisation Assistance	1980s	→ GUI, applications of CAX technologies (CAD, CAE, CAM)
3.	Digital Control and Link	1990s	→ Digitalisation of entire businesses → Development of the Internet and advanced control technologies → Simulation technology further evolved and users grew rapidly
4.	Cyber-Physical Integration	2000s	→ Electronic components became more and more compact → Consumer electronics: lightweight laptops, smartphones
		2010s	→ New generation of IT emerged: IoT, cloud computing, big data analytics, AI → Enabled convergence of physical and virtual worlds
		2020s	→ Digital Twin is the next wave in simulation technology → Rooted in existing technologies (3D modelling, digital prototyping)

2.2. The Definition

The Digital Twin has been defined in the literature in a variety of ways. They range from a very high-level abstract and simplistic definition to a highly contextualised and rooted formulation. The 2012 publication by Glaessgen and Stargel [13] is cited by a plethora of publications as the origin of the Digital Twin definition [3,16,20–22]. It describes a Digital Twin as follows:

> "*an integrated multi-physics, multiscale, probabilistic simulation of an as-built vehicle or system that uses the best available physical models, sensor updates, fleet history, etc., to mirror the life of its corresponding flying twin*".

Since it originated in the aerospace application, it includes the term 'flying twin' in the definition. It is also the most commonly used 'base' definition, which is then adopted and heavily contextualised for other applications. Other examples of contextual adaptations of this definition can be found in the literature [23–25].

The Digital Twin was later adopted by many different industries, predominantly by the manufacturing industry. As more and more research was dedicated towards this technology [3], the number of relevant publications began to grow exponentially [22]. As a result, various different definitions of Digital Twin appeared in the literature. The multi-scale simulation capability facilitated by the structure of Digital Twin, which is discussed later in detail in Sections 4 and 5, allows the visualisation of a product or process at different levels of granularity. Hence, the definitions vary based on the context and the application.

For example, the Digital Twin is defined in the context of production machines and related procedures (installation, commissioning, training, and optimisation) in [26], while it is defined for a manufacturing process in [27], as well as with reference to a service or business in [28].

Various definitions of the Digital Twin published during 2012–2016, the period after Industry 4.0 was defined, were analysed by Negri et al. [25] to retract it from the initial conceptualisation in the aerospace field to the most recent interpretations in the smart manufacturing domain. It is quite common to find definitions and models of DT in the context of manufacturing, as it was the next predominant industry to adopt DT. One such example of that is as follows: "*a coupled model of the real machine that operates in the cloud platform and simulates the health condition with an integrated knowledge from both data-driven analytical algorithms as well as other available physical knowledge*" [29]; and another one in the Structural Engineering field is: "*a high-fidelity structural model that incorporates fatigue damage and presents a fairly complete digital counterpart of the actual structural system of interest*" [30]. The former mentions a 'machine', while the latter mentions a 'structural system' and its 'fatigue damage'. Both are good examples of a DT definition being too context-specific. In order to understand the concept of the Digital Twin in a more comprehensive manner, it is crucial to form a detailed yet precise definition of a Digital Twin. Table 2 lists some of the more generalised definitions found in the literature. Important keywords that underline the unique qualities of a Digital Twin are also highlighted.

Table 2. A list of more generalised definitions of a Digital Twin found in the literature.

Source	Definition
[13]	*an integrated multiphysics, multiscale, probabilistic simulation of a complex product, which functions to mirror the lifecycle of its corresponding physical twin.*
[16]	*a comprehensive physical and functional description of a component, product or system, which includes more or less all information which could be useful in all the (current and subsequent) lifecycle phases.*
[18]	*a collection of model-based simulations and data analytics, necessitated by requirements of the modern competitive industrial environment at all stages of design and production, to predict the outcome, optimize, correct and evaluate.*
[20]	*an integrated multiphysics, multiscale, probabilistic, and ultra-realistic simulation of systems or products which can mirror the life of its corresponding twin using available physical models, history data, and real-time data.*
[23]	*a multiphysics and multiscale simulation model that mirrors the corresponding physical twin, allowing the extension of the simulation to all life cycle phases of the system.*
[24]	*an organic whole of a physical asset or entity as well as its digitized representation, which mutually communicate, promote, and co-evolve through bidirectional interactions.*
[26]	*an operational replica that can be used for testing, commissioning, and training.*
[27]	*a replication of real physical production system, that enables bidirectional control with the physical process and is used for system optimization, monitoring, diagnostics and prognostics using the integration of artificial intelligence, machine learning and software analytics with a large volume of data from physical systems.*
[28]	*a virtual equivalent of an actual physical product or service.*
[31]	*a comprehensive digital representation of an individual product that includes the properties, condition, and behaviour of the real-life object through a set of realistic models and data, which can simulate its actual behaviour in the deployed environment.*
[32]	*a technology enabling the replication of the development and manufacturing of a product or production system over the course of its entire lifecycle, and to thereby predict behaviour, optimize operational utilization and apply knowledge gained in the context of earlier design and production efforts.*
[33]	*a virtual representation of real-world entities and processes, synchronized at a specified frequency and fidelity.*
[34]	*an instantiated model (numerical, analytical, hybrid) of a specific asset or device, which is deployed (in the cloud or on an edge device) and connected to the physical device, where the connection may be established through sensors installed at the device or other sources collecting specific information, delivering a continuous data stream fed into the model or as boundary condition or as reference value.*

After carefully reviewing these definitions (and their sources), a common thread can be drawn to understand the underlying concept on a deeper level. Thus, an even more generalised description can be formulated. This is addressed by the following definition:

> *Digital Twin is a continuously updated multi-physics, multiscale, probabilistic simulation model of a physical entity (an object, a system, or a process) utilising big data, bilateral connectivity, and advanced software analytics to provide product monitoring, diagnostics, prognostics, and optimisation services.*

The above definition also summarises the function of a Digital Twin and highlights its nuances and the involved technology. Therefore, it is an example of a concise definition that is also fit for all types of applications of the Digital Twin technology.

3. Related Work—Adoption in Industry

The Digital Twin has become a commonly used phrase in the context of products, processes, businesses, and more. Originating in the aerospace industry, the concept evolved in the manufacturing sector and was later embraced by many other industries such as healthcare [35,36], telecommunication [37–39], fashion [40–42], consumer electronics [43,44], construction [45], environment [46,47], agriculture [48], energy [49,50], privacy and cyber-security services [51,52], internet-based services and advertisement [53,54], and several other applications [55].

3.1. Industry 4.0 and Smart Manufacturing

The adoption of the Digital Twin by the manufacturing industry is linked with Industry 4.0, which represents the digital transformation of manufacturing/production and related industries and value creation processes [56]. This ongoing transformation of the traditional manufacturing industry was first defined as Industry 4.0 at Hannover Messe, Germany, in 2011 [57]. The introduction of next-generation information technologies, such as the Internet of Things, has facilitated the evolution of traditional systems into cyber-physical systems. IoT enables embedding electronics, software, sensors, and network connectivity into devices, in order to allow the collection and exchange of data through the internet [58]. Thus, cyber-physical systems get networked and can communicate with each other, enabling new ways of production, value creation, and real-time optimisation, and therefore, create the capabilities needed for smart factories [56]. Software and network connectivity extend the functionality of mechatronic systems, allowing the traditional mechatronic disciplines—mechanics, electric, and electronics—to be realised in a more integrated way [16].

The evolution of IoT and cyber-physical systems, along with the development of simulation technology, has enabled the implementation of the Digital Twin in the manufacturing industry. A Digital Twin contains a physical entity as well as its digitised representation of the manufacturing entities (machines, equipment, environment, and even products). Both components mutually communicate, promote, and co-evolve with each other through bidirectional interactions [24], which are facilitated by Industry 4.0. The Digital Twin was first applied to Industry 4.0 by Siemens in 2016 [3]. Additionally, the introduction of commercial software tools for the creation of a Digital Twin, such as Predix (GE digital), Simcenter 3D (Siemens), Twin Builder (ANSYS), Digital Twin Application Builder (COMSOL Multiphysics) demonstrates its importance for the industry as a whole. In addition, integration of two or more software tools, such as Creo 3D (PTC) with ANSYS Live Discovery and Maximo Manage (IBM) with Digital Twin Exchange (IBM), further facilitates building DTs.

The review by Negri et al. [25] suggests that the scientific literature that describes the contextualisation of the Digital Twin concept in the manufacturing domain is still in its infancy. There is a need for future research on relevant industrial applications to investigate and demonstrate the wide range of applications and benefits to realise the full potential of Digital Twin. An article by Aheleroff et al. [59] describes a holistic reference architecture model of DT for several other Industry 4.0 applications beyond the manufacturing domain.

3.2. Health, Telecommunication, and Other Industries

Health 4.0, analogous to Industry 4.0, is a commonly used terminology in the healthcare industry. It refers to progressive virtualisation for enabling personalised and next-to-real-time health and care solutions for patients, professionals, and formal and informal carers [60]. Digital Twin technology holds the promise to deliver Health 4.0 [61]. In personalised healthcare, the Digital Twin can be defined as a life-long, rich data record of a person combined with AI-powered models [62], which can provide proactive and preventive care in real-time without being in close proximity [61]. For example, HeartModel—a clinical application launched by Philips in 2015—can assess several cardiac functions and provide insight into a possible heart failure [63]. A Digital Twin can provide assistance in determining the right therapy option for a specific patient, and can also be used to predict the outcome of specific procedures. On a larger scale, if behavioural data and contextual social factors are also integrated, Digital Twins can also help to better manage chronic diseases and population health [62].

In telecommunication, the fifth generation standard for broadband cellular networks, i.e., 5G, has been rolling out worldwide since 2019. A simulation-based approach is being extensively used to evaluate network coverage in cities by visualising wave propagation from several transmitter–receiver pairs located at different locations. An example presented in [64] illustrates a Digital Twin of an entire city, which by its definition is continuously updated over time to monitor changes in the city topology and, therefore, can provide suggestions for modification and maintenance of networking equipment. In the construction industry, Digital Twins can enable design and energy-performance optimisation, real-time structural health monitoring, predictive and proactive maintenance, and efficient supply chain management. This is enabled by a combination of 3D modelling (such as a building information model) and data collection and analysis using an IoT sensor network [65,66].

DTs are great tools in environmental sciences to enable more data-driven investigations to address challenges such as climate change, a loss of biodiversity, flooding, and water and subsurface management, and can facilitate risk-based decision-making [67,68]. The agriculture industry (Agriculture 4.0) benefits from the adoption of DT technology, which can be applied to several of its subdomains, viz., farming, processing, consumption, and the supply and value chain. It enables crop monitoring, resource optimisation and cultivation, livestock management, soil quality management, and the identification of bottlenecks and waste [69,70]. In the energy sector, DTs are applied to a variety of aspects such as energy management, conservation systems, transmission (grids), storage, and consumption for both traditional and renewable energy.

The fashion and retail industry has been adopting Digital Twin technology in two ways. The first way is for creating personalised products such as smart textiles, shoes, and wearables. The Digital Twin of a customer can be used for analysing personal style, fit, and other parameters such as the financial capability to design as well as recommend products. Similar to the healthcare industry, this approach can also be implemented for a larger demography. The second approach is by using Digital Twin for products, such as footwear and shoes, for monitoring their degradation over time and detecting different ways of failure, and later to use this information for improving the design as well as the fabrication process [71]. Internet-based advertisement businesses run by companies such as Google, YouTube, and Meta (formerly Facebook), as well as online retail services such as Amazon have been using a Digital Twin approach, which is also referred to as surveillance capitalism, to create and maintain updated models of their users' interests to provide relevant advertisements and buying recommendations [72].

3.3. Reliability of Electronic Systems

The adoption of Digital Twin technology was enabled by the incorporation of more and more electronics, such as sensors, into conventional products and systems, as well as the integration of computer-aided and software-based technologies into traditional industries. IoT-enabled smart-home products such as AI-powered smart speakers, smart coffee machines, smart thermostats, etc., are classic examples of this. Similarly, consumer electronics such as computers, laptops, and smartphones consist mostly of electronic components. Another good example is the automotive industry. According to a survey, about 35% of the cost of a modern car constitutes the cost of electronics used in it. Moreover, it is expected to have a 50% share by the year 2030 [7].

Therefore, the reliability of these products as a whole, as well as of their electronic subsystems, has become highly critical. A Digital Twin enables the ability of system optimisation, monitoring, diagnostics, and prognostics using the integration of AI, machine learning, and big data analytics. It can be used for predicting failures and estimating the lifetime of electronic components, which then allows for scheduling preventive maintenance. As an example, Apple Inc. announced a replacement program for display control modules of certain iPhones manufactured between November 2019 and May 2020 foreseeing the display issue, where the displays are expected to stop responding to touch due to the faulty display module [73,74]. Launching a preventive maintenance program like this allows the company to save time and costs and avoid customer dissatisfaction as well as unwanted lawsuits. This is facilitated by implementing Digital Twin technology, which allows the continuous monitoring of the degradation of electronic components over their entire lifespan. Thus, prognostics and health management are facilitated by a Digital Twin-based implementation.

4. Methodology—Digital Twin Architecture

The industry-wide adoption of the Digital Twin technology makes it ever so crucial to study its architecture, in order to understand its workflow and functions. Similar to the definition of a Digital Twin, its architecture has also seen some transformations and contextual adaptations, which are built on the same conceptual base.

4.1. Basic Structure

The basic structure of a Digital Twin system consists of a physical entity, its virtual representation, and an active connection between the real and virtual space for information flow. Figure 1 shows the baseline architecture of a Digital Twin system. The physical entity can be any object, system, or process. It can also be implemented on different scales of an ecosystem. For instance, a manufacturing facility can have DTs of the product, machines and tools, processes, a control volume, or even the entire business. In the context of microelectronic systems, a product-specific implementation is the most relevant one when reliability and lifetime prediction are in focus.

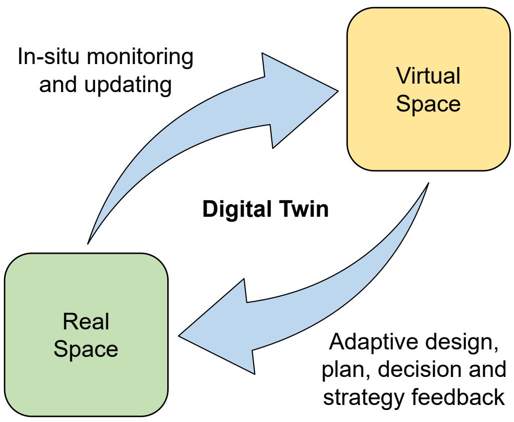

Figure 1. The basic architecture of a Digital Twin system, consisting of a physical entity, its virtual representation, and an active connection between the real and virtual space for information flow.

The connectivity between the physical entity and its virtual representation is what sets a Digital Twin system apart from just a nominal model. The connections facilitate data exchange, which enables a continuous update of the model rather than it remaining static. Similarly, the results generated from the updated model can be used as feedback for improving the physical product. Thus, bilateral connectivity is the key to building an effective Digital Twin system.

4.2. Types of Connections

The continuous update of the digital model in a DT system is achieved by the information exchange through its connection to the physical entity. These connections can have different levels of complexity. They can be roughly categorised into three types: (i) weak, (ii) cloud-based, and (iii) embedded connections. Each of these approaches is suitable for different kinds of applications and use cases. Figure 2 illustrates the key differences in the aforementioned three kinds of connections to a Digital Twin. A weak connection utilises a unidirectional flow of information, i.e., from the product to its model. There is no closed loop, and thus, the continuously updated model serves as a supporting tool and has limited functionality. This configuration is sometimes referred to as a 'Digital Shadow' [75]. It can mainly be used for virtual prototyping and product/process design.

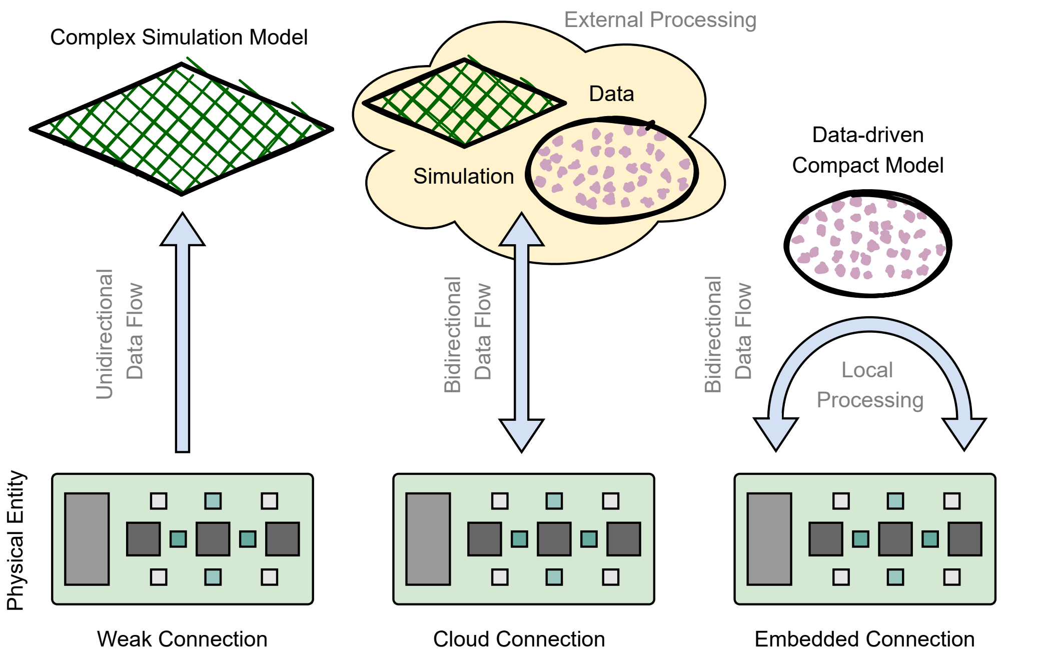

Figure 2. Three types of connections in a Digital Twin system, viz., weak, cloud-based, and embedded, each of which differs in the direction of the information flow and the complexity of the models.

A cloud-based connection setup explicitly utilises a powerful computing infrastructure external to (and in most cases, distant from) the physical entity. This connection allows for the real-time monitoring of a product, data filtering, and transmission. A cloud-based platform facilitates processing and producing large amounts of collected data. These data can then be utilised for product or process improvement with closed-loop connectivity. Another advantage of this is the capability to run bigger and more complex simulation models on an external computational node. A caveat of this implementation is the higher latency and energy consumption due to the involved data transmission. This, however, depends on several parameters (such as the available connectivity speed, the service provider of the computing infrastructure, and the overall scale), and thus, can be controlled and mitigated.

An embedded connection moves the computation to the edge, which allows models to run locally. It also incorporates real-time monitoring and data collection but processes the data on an edge-computing infrastructure. This saves the cost and energy of transmitting the data to an external server and, thus, is more efficient. In this way, integrated closed-loop control and decision-making can be achieved. The shortcoming of this approach is the limited computational power available at the edge, e.g., a microcontroller unit. Therefore, only simpler and computationally lighter (compact) models, such as response surfaces or meta-models, can be utilised in this approach.

4.3. Implementation Scales

Digital Twins can be utilised at the different phases of a product's lifecycle, from an early design and prototyping phase to the later manufacturing, qualification, and in-use phases. However, the implementation varies as the product progresses through these phases. Grieves [76] suggests three different kinds of implementations: a Digital Twin Prototype (DTP) in early design stages, a Digital Twin Instance (DTI) of a designed product that is being manufactured, and a Digital Twin Aggregate (DTA) for products manufactured and deployed. Note that the classifications DTP, DTI, and DTA would apply to the cases where the physical entity is a product and is not restricted only to the manufacturing domain. Figure 3 indicates the gradual transformation of these DT implementations through different stages of the product lifecycle.

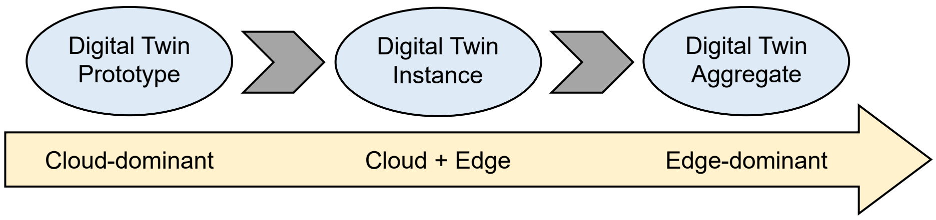

Figure 3. Different types of Digital Twins (viz., DTP, DTI, DTA) for a product, through its lifecycle stages (arrow), and the corresponding suitable computational infrastructure for these implementations.

The DTP primarily utilises a physics-based approach and complex simulation models. It can rely on a weak connection setup in the initial phases and move to a closed-loop cloud infrastructure as the product moves from the concept to the manufacturing stage. The DTI is utilised when the products are manufactured and undergo qualification tests. It uses both physics-based and data-driven approaches yet heavily relies on the former. The DTA is when the product is in the in-use phase. A data-driven approach and an embedded connection with edge-computation are most suitable for this phase. Thus, the three types of DT implementations also gradually progress from being primarily physics-based to a predominantly data-driven approach. Both cloud-based (computationally expensive) and edge-based (local processing) implementations can be combined to varying capacities depending on the need of a specific application.

5. Evaluation—Digital Twin Models

The contextual interpretations of a Digital Twin in various fields reveal several interaction models of its architecture. All of them essentially emerge from the basic architecture shown in Figure 1. Notably, two main 'generalised' models (viz., a three- and a five-dimensional model) are utilised as the baseline for various applications, and different adoptions of both can be seen widely in the literature.

5.1. Three- and Five-Dimensional Models

Initially, a three-dimensional 'information mirroring' model of a Digital Twin was published by Grieves in 2014 [10], which consists of a physical object, its model in the virtual space, and the connection enabling data exchange. Later in 2018, Tao et al. [77] introduced an updated five-dimensional version of that model. This version denotes four aspects of a DT by 'nodes'. It creates a separate node for 'data' and includes a new node called 'services'. The 'connections' stay as an independent dimension connecting each node with every other. Figure 4a,b show the three- and five-dimensional models, respectively. The three-dimensional model is a bit too similar to the basic architecture (Figure 1). Numerous adaptations of this model in the literature often seem to add and define more components, especially the 'data', within the primary three dimensions. Thus, the model itself comes across as too generic and needs some modifications for clarity.

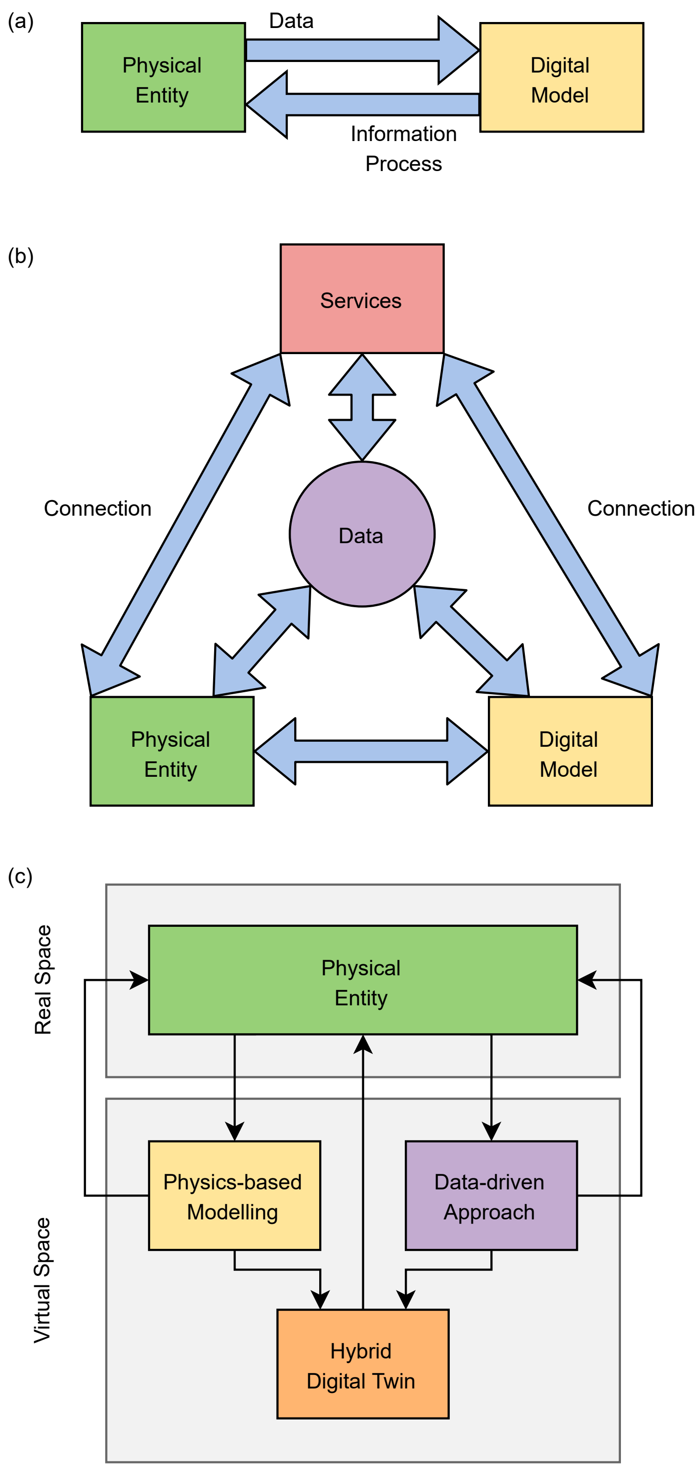

Figure 4. The comparison of three different generalised models of the Digital Twin architecture: (**a**) three-dimensional model by Grieves [10], (**b**) five-dimensional model by Tao et al. [77], (**c**) the new two-branch model. The newly proposed 'generalised two-branched model' has a simplified approach to structuring a Digital Twin system for PHM with a clear separation between the real and virtual spaces. The two main modelling approaches (viz., physics-based and data-driven) form the two branches of the digital models, which can be combined to a different capacity for hybrid PHM.

The five-dimensional model adds some value to the architecture by defining 'data' as a separate entity. In addition, the outputs that the digital models and data processing can produce are collected together in the 'services' node. Moreover, every node can receive an input and provide some feedback to every other node. This has been explained in detail in the paper [78], where the five-dimensional model is greatly expanded on. The shortcoming of this model is, however, the lack of a clear separation between the physical and virtual spaces. The representation may indicate an equal weight to all four nodes. In reality, that depends on the application. One of the nodes can be significantly bigger (i.e., more important and/or resource-intensive) than the other. Another challenge it poses is in expanding this representation for different phases in a product's lifecycle. Thus, we identified a need for a more simplified model that can address these challenges and represent a DT architecture even more clearly.

5.2. Generalised Two-Branched Model

The two-branch model, indicated in Figure 4c, builds on the basic architecture while adopting some of the elements from the aforementioned models. It has a simplified approach to structuring a Digital Twin system, especially for product-specific PHM, with a clear separation between the real and virtual spaces. The two branches of the digital models are based on the two main modelling approaches: physics-based and data-driven modelling. Either one of these two branches can be the digital model on its own, which can provide 'services', and form a closed feedback-loop with the physical product. Furthermore, the two modelling approaches can be combined to a varied capacity to obtain a hybrid Digital Twin. This becomes more relevant when the DT implementation takes the forms DTI and DTA (described in Section 4). The digital models can draw inputs from one or more phases in the product lifecycle. Figure 5 elaborates on this with an expanded version of the two-branched model. It is prepared by keeping a microelectronic system (product) as the physical entity and its prognostics and health management as the purpose.

The digital space can utilise inputs from several lifecycle phases of the product. The text in the 'physical entity' box indicates the features that the Digital Twin can extract from its physical counterpart. A similar approach is utilised in the Reference Architecture Model in Industry 4.0 (RAMI 4.0) for DT [59]. The key differentiation is that RAMI 4.0 includes different terms for the digital replica based on their level of integrity (i.e., the connection type), while the two-branched model keeps a consistent naming scheme for 'Digital Twin' and classifies them based on the connection type (Figure 2). In the two-branched model, the number of features and their combinations included in a digital model can vary depending on their availability and the type of Digital Twin implementation (i.e., DTI, DTP, DTA). For instance, a physics-based Digital Twin can consider loading conditions from the manufacturing stage or the in-use stage. Thus, the two-branched model provides a generalised framework for preparing (product) Digital Twins of different complexities and modelling approaches.

5.3. Product-Specific Monitoring Device

The rapid adoption of electronics across industries has led to a high demand for mission-critical electronics. More electronics per product put forth the need for a fast ramp-up of new electronic components, resulting in high-volume production in shorter periods of time. Consequently, any issues that emerge from non-reliable electronics affect the functionality of the product and can create serious business problems for OEMs in different domains. Thus, PHM must be an integral part of the lifecycle management of electronic products. The increasing importance of electronics and the disadvantage of traditional reliability testing can be overcome by implementing PHM for product-specific monitoring. It can serve as a product-level monitoring device (MonDev), which presents itself as a key enabler for providing performance- and lifetime-on-demand.

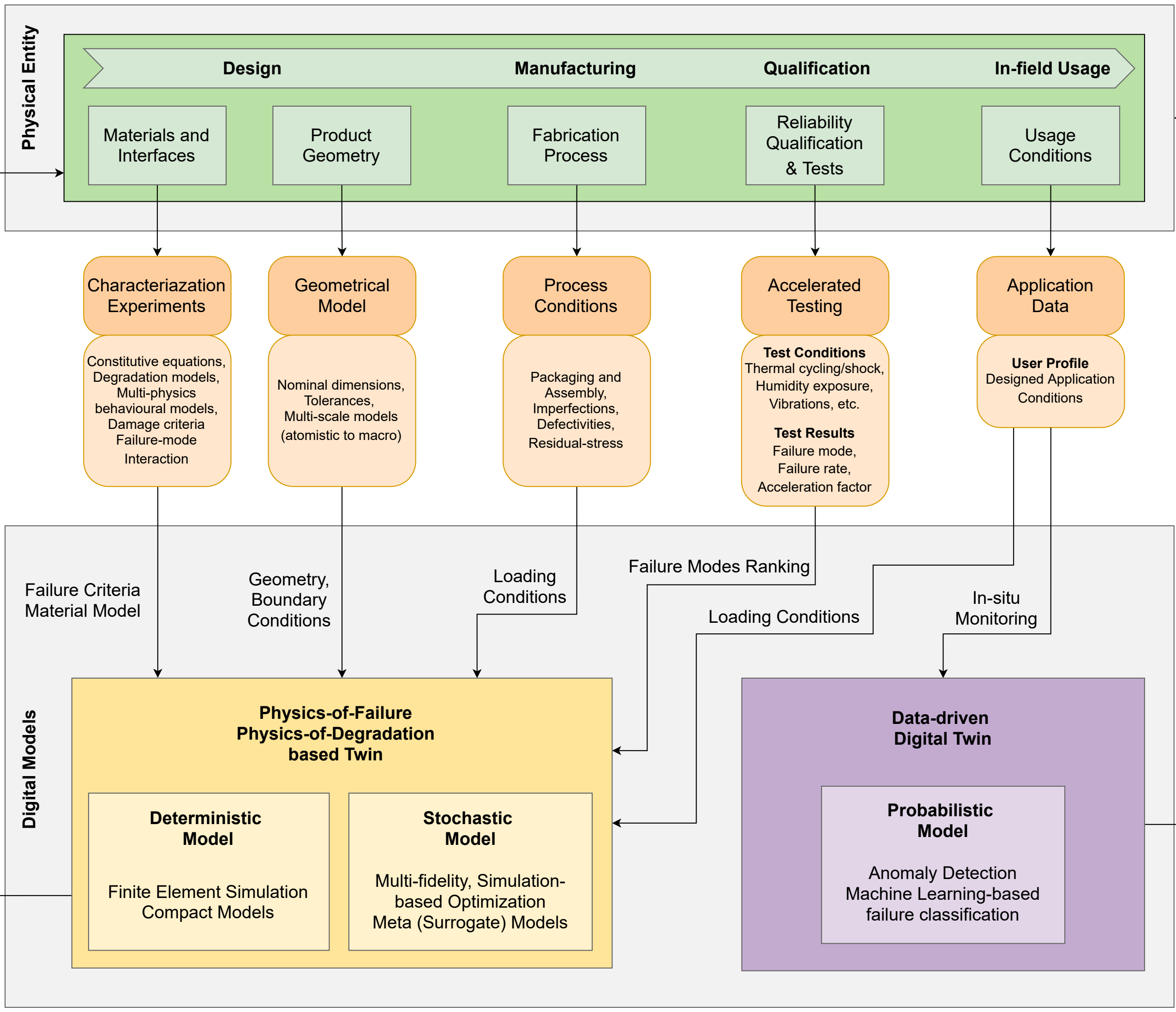

Figure 5. The expanded version of the 'generalised two-branched' Digital Twin model. In this description, the physical entity is a product (e.g., a microelectronic system) and its PHM is the key purpose. Along with the different phases within the product lifecycle, a select number of specific inputs that the digital models can draw from different aspects of the product are also indicated.

New IoT options, combined with edge and/or cloud computing possibilities, can run real-time analysis when reliability-specific parameters are measured and recorded at the system level. Such system-level prognostics help avoid failures by detecting them beforehand, thus reducing the residual risk [79]. It is important to note that the MonDev is not necessarily only a physical device but is more of a conceptual term. It includes both physical (dedicated hardware and sensors) and digital (data and software) components. It can take any form of shape depending upon the application (e.g., automotive industry) and the subdomain (e.g., perception, propulsion, connectivity). The project ArchitectECA2030 [80] explains the implementation of an in-vehicle MonDev for an electric, connected and automated vehicle [81,82], which is able to indicate and measure the health status and possible degradation of the functional electronics and electronic systems, enabling the predictive diagnosis, maintenance, and re-configuration of embedded software.

A Digital Twin is one of the models/implementations of a MonDev. Digital Twin-based health monitoring of microelectronic components and systems can be achieved by adopting the architecture described in Figure 5. It requires developing both Physics-of-Degradation (PoD) and data-driven models. An example of a PoD-based Digital Twin that models the thermomechanical degradation of electronic packages due to the thermo-oxidative ageing of moulding compounds has been presented in the article [83]. Another example of in situ monitoring has been investigated in the paper [84], which shows a specialised degradation-monitoring sensor that can serve as an input to the data-driven models as well as be used for the validation of physics-based simulation models. Moreover, the Reduced Order Models (ROMs) are key in edge-computing (for an 'embedded connection' of a DT). The integration of thermomechanical ROMs with full-order physics-based models has been explored in the publication [85].

Such examples plug into the DT framework as various aspects of the virtual space and form the building blocks for the two-branched architecture (Figure 5). The developed models are then utilised for the fault detection, diagnosis, prognosis, and quantification of Remaining Useful Life (RUL), based on the current state of component degradation. Thus, a Digital Twin-based MonDev promises to be a key tool for the next-generation reliability estimation and PHM of electronics.

6. Implementation—PHM Workflow

PHM is a relatively advanced methodology that allows the reliable assessment of a system/component based on its *individual* working conditions. It leverages condition monitoring, which allows for evaluating a system's current state of health based on its load history and keeping track of all its historical health statuses. Prognostics refers to the prediction of the future state, performance, and RUL of a system based on its current state of degradation. Health management is the process of making decisions and planning actions on the basis of the evaluated state of component health. The prognosis can be of a particular failure mode in a critical component, estimating the progression of a fault, or even evaluating the RUL of the whole system, whereas the actions could be issuing a warning, stopping a system function, or even scheduling maintenance (i.e., predictive maintenance) or a component replacement.

The current state of degradation depends on the deviation from the nominal operating conditions. Two identical components subjected to different sets of working and environmental conditions after a certain period of time will have different states of health. PHM facilitates capturing that deviation individually for each system. Therefore, this technique gives a major advantage over traditional reliability qualification tests. PHM can be implemented based on a model-based, data-driven, or even a hybrid (fusion) approach. Various publications focused on reviewing and summarising the PHM concept and its implementations present different flowcharts [86–91], which are usually complex and/or application-specific. Figure 6 indicates a rather simplified and generalised framework for the PHM workflow.

The workflow of PHM begins with condition monitoring, which requires the collection of relevant data using appropriate sensors for capturing environmental loads, operating conditions, and additional measurements (e.g., current or voltage). Thus, the first three steps in the PHM workflow are data sensing, acquisition, and preprocessing. The second phase of the PHM framework is diagnostics. The collected data is processed to provide a preliminary assessment of the component's condition, such as the detection of an anomaly. The state of component health is then evaluated, which requires physics-based validated models for quantifying degradation and fault progression. In the last phase, prognostics and decision-making come into the picture. A prognosis of the component's performance and an estimation of its RUL is made. Based on the prediction, decisive action is chosen, such as scheduling maintenance for repair or replacement.

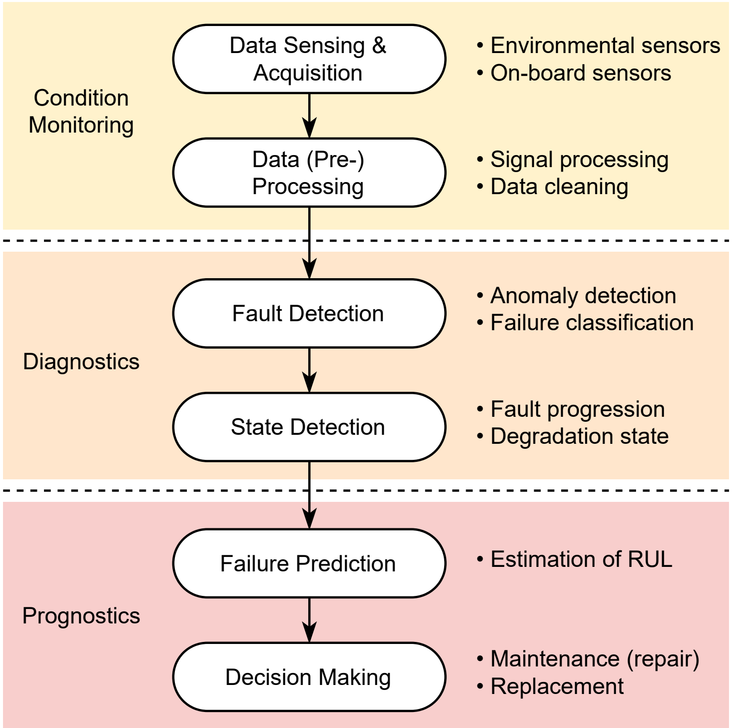

Figure 6. The framework of the PHM workflow and its three main phases—condition monitoring, diagnostics, and prognostics. The flowchart indicates the actions involved in each phase, and their respective functional descriptions are listed as bullet points on the right side.

Building Blocks of Hybrid PHM

The physics-based models play a key role in the PHM workflow, as the later steps in its framework depend on the health-state evaluation. The Physics of Failure (PoF) is a preferred, but not the only, choice for physics-based models. It can be further enhanced when used in conjunction with the PoD-based models. Some notable examples of PoD-based models due to the thermal ageing of different materials and sub-components of an electronic system are solder joints [92], moulding compounds [93], and printed circuit boards [94]. A strong foundation of such validated models is a necessity for building a health monitoring system for electronic components.

The input to the degradation models is the operating conditions experienced by the electronic system. Ambient conditions such as temperature, moisture, vibrations, shock, pressure, and acoustic levels can affect the component's lifetime. Thus, relevant environmental parameters should be continuously measured. In addition, some additional embedded sensing devices or external measurements, such as electric current, changes in electrical resistance, displacement, and strain, can give even more information about the state of component degradation. Thus, the data-sensing needs should be considered in the hardware design of the component; for example, specialised integrated sensors such as a piezoresistive sensor [84,95,96] or measurement techniques such as the DC-resistance measurement, RF-impedance measurement, the multivariate state estimation technique, and the sequential probability ratio test [97–99].

A robust data processing pipeline needs to be in place to utilise the collected data in data-driven approaches, e.g., lifetime prediction, failure classification, and anomaly detection. The PoF models should identify relevant failure modes associated with the electronic system of interest. The PoD models should be able to translate the loading conditions into an effective aged health state of the component, including the changes in the behaviour of its constituent materials. In addition, PoD should also reflect the effects of all the manufacturing steps (semiconductor processing, die-bonding, electronic packaging, moulding, solder reflow, component assembly, etc.) until the electronic system is ready to be used in the field. Lastly, the decision-making logic should consider the criticality of the role of an electronic component in the function of the entire system, such as an autonomous vehicle or a manufacturing line. The described PHM workflow utilises a combination of physics-based and data-driven approaches and, thus, fits perfectly well with the two-branched model of the Digital Twin.

7. Conclusions and Outlook

The Digital Twin is a key technology in Industry 4.0. It has evolved from its conceptualisation in aerospace application to its adoption in manufacturing, automotive, healthcare, and several other industries. The literature shows a big fragmentation in the definitions and the models of a Digital Twin. This is largely due to the deep contextualisation of DT and application-specific publications. This article addresses three main aspects of the Digital Twin technology—the definition, the architecture, and the framework for (electronic) product-specific DTs. Along with a detailed review of different kinds of DT definitions, a generalised, information-rich, and yet, concise definition is presented.

Furthermore, the existing three-dimensional and five-dimensional models of the DT architecture are analysed. To overcome their disadvantages, a new two-branched model is proposed along with its expanded version for a product-specific monitoring device. A simplified PHM workflow for electronics-enabled systems is outlined, and its integration into the proposed two-branched DT model is described. Three different categories of classifying Digital Twins are defined based on the (i) type of connection (viz., weak, cloud-based, embedded), (ii) computational infrastructure (viz., cloud and edge), and (iii) modelling approaches (viz., physics-based, data-driven, and hybrid). A combination of aspects within these categories gives three main scales of DT implementation in a product lifecycle: DTP, DTI, and DTA.

A Digital Twin-based approach facilitates the next-generation reliability assessment and PHM of microelectronics. At the same time, there are some important challenges to be addressed. To enable DT implementation in different aspects of a complex ecosystem (e.g., a manufacturing facility), industry-wide standards need to be established and adopted; for example, for the data exchange formats, interoperable IoT connectivity and cyber security. Moreover, it is crucial to have more advanced, low-cost, and reliable sensors, and to have different measurement techniques for in situ monitoring and integrate them into products to make the system capable of self-monitoring.

The cloud-based digital models need to be multi-scale, multiphysics-based, and should consider complex non-linear and ageing effects. On the other hand, more efficient compact models (ROMs, meta-models, response surfaces, etc.) and AI-based techniques (unsupervised learning, ML-based classification, etc.) need to be developed for edge-deployment and local data processing. The key milestones in the context of failure criteria are the definition of accurate failure-threshold levels and the know-how of multi-failure-mode interactions. A push towards simulation-driven design and optimisation and a transition from a deterministic to a probabilistic/stochastic simulation methodology is crucial. More robust collection, storage, filtering, and processing of big data and increased edge-computing capabilities are also essential.

Thus, the overall roadmap for addressing the challenges associated with the Digital Twin technology can be summarised in the following six points: (1) smart in situ sensing and data transmission, (2) edge-computing capable hardware, (3) accurate compact/meta-models integrated into products, (4) robust multi-scale multi-physics (non-linear, dynamic, probabilistic) simulation models, (5) robust data-driven models, and (6) lifetime (i.e., RUL) prediction on demand. Working towards these six goals would push forward the current state-of-the-art of Digital Twins.

Finally, Digital Twins are also instrumental in realising the next phase of the industrial revolution (Industry 5.0), which would be an extension of Industry 4.0 and focused on human-centric development, sustainability, and resilience [100,101]. It has been identified by the European Commission as one of the six key technology pillars of Industry

5.0 [102]. DTs enable health monitoring and the preventive maintenance of products and systems, which can help extend their lifetime, taking a step towards a more sustainable and circular economy.

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