Digital Twins for Electronics Packaging and Systems

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1. Introduction

Digital Twins (DT) have become a groundbreaking concept in the field of electronics packaging and electronic systems. In an era characterized by rapid technological advances and increasing complexity in electronics packaging products, digital twins offer a revolutionary approach.

These virtual replicas of physical semiconductor circuits, electronic devices, or systems provide engineers and researchers with invaluable information, enabling real-time monitoring, analysis and optimization. This innovative technology not only improves product development and performance, but also significantly streamlines design and manufacturing processes, ultimately pushing the boundaries of what is possible in the world of electronics packaging and electronics enabled systems.

However, it's worth noting that the concept of digital twins can sometimes vary depending on the context, application field, and one's expertise or experience. In this article, we aim to explore the diverse applications of digital twins in the electronics industry, starting with an examination of various existing definitions.

Digital Twin Definition

Digital Twin was originally defined in the context of the aerospace industry [1] as "*an integrated multiphysics, 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*". Similarly, there are several other definitions of a Digital Twin in the literature. They are highly contextual and application-specific., and thus, contain technical jargon. They also don't necessarily translate well to the other applications.

It's rare to find a fit-for-all definition, primarily due to the fact that the concept continues to evolve. Some of the *generalized* definitions are reviewed below:

Digital Twin consortium [2] defines a digital twin as "*a virtual representation of real-world entities and processes, synchronized at a specified frequency and fidelity*". This definition is a concise description of the Digital Twin concept.

The Heterogeneous Integration Roadmap (HIR) [3] describes a digital twin as "*the 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. 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*".

In the 2022 IEEE EPS Newsletter [4], it is defined as "*a continuously updated virtual representation of an object, system, or process which replicates all phases in the lifecycle of its physical counterpart*".

As the importance of Digital Twins keeps growing, it is crucial to have a generic fit-for-all definition of the Digital Twin, which also includes the technologies involved in it but is also concise. Thus, an updated definition proposed by the authors is as follows:

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

2. Concept of Digital Twin

In the context of electronics packaging, a Digital Twin is an advanced, all-encompassing simulation of an intricate electronic product, integrating multi-physics, multi-scale, and probabilistic virtual models. It leverages the sophisticated physical and AI models, and sensor network to mirror the real-time evolution of its counterpart.

The notion of a digital twin is a composite construct, encompassing the physical product, its virtual counterpart, and a network of interconnected data that bridges the realms of the physical and the virtual spaces. This concept serves as a catalyst for achieving a seamless convergence between the physical product and its virtual representation. Digital twins can be implemented at the unit level (*e.g.*, equipment), system level (*e.g.*, multiple pieces of equipment which cooperate), and factory (or fab) level [5].

Digital Twin Architecture

Initially, a three-dimensional architecture of a Digital Twin was proposed by Michael Grieves [6]. It consists of three fundamental components—the physical entity, the virtual model, and the connection enabling data exchange. A five-dimensional modified version was later introduced in 2018 by Fei Tao et al. [7].

Figure 1 indicates the five-dimensional DT system. It has the following five key components: physical entities, virtual models, data, connections, and services. The new model defines 'data' and 'connections' as independent aspects of the DT system and introduces a new 'services' node.

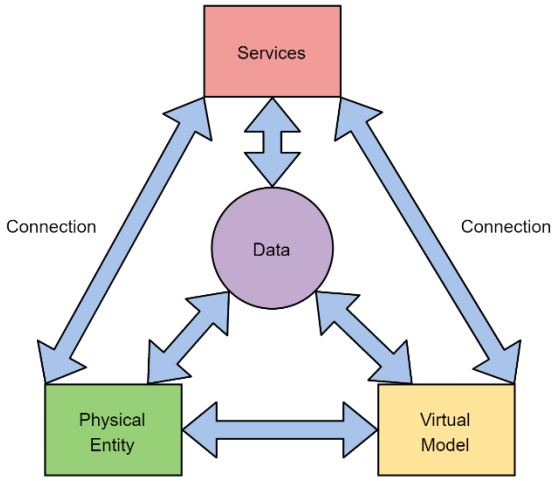

Figure 1: Five-dimensional Digital Twin architecture

The 'physical entity' can be a product, process, or business. It should be equipped with data collection capabilities and device control protocols. For example, an electronic product should be equipped with sensors to collect, process, and transmit data for its condition monitoring.

The 'digital model' is a comprehensive model of the physical entity capable of multiscale multiphysics simulations. The digital model is continuously updated to replicate the current (degraded) state of the physical product based on the collected sensor data and inputs from the 'data' node. The digital model can provide additional data using simulation-based virtual sensors, especially where it's not practical or possible to have a physical sensor placed/measurement done.

The 'data' node collects, stores, and processes the data coming from real and virtual sensors. It handles the data-driven aspect of a Digital Twin and can run algorithms (on the cloud, at the edge, or as a combination of both) for failure classification, Remaining Useful Life (RUL) estimation, and optimization problems. Based on the results generated by the 'data' and 'digital model' nodes (data-driven and physics-based approach, respectively), services such as anomaly detection and reliability prediction can be built.

The prediction 'services' serve as an input for making design modifications to the physical product and for improving the other two nodes. Lastly, the 'connection' node ties the other four nodes together. It serves the same role as in the three-dimensional DT architecture, but a distinct definition underlines the importance of efficient communication and interoperability of the exchanged information between the rest of the nodes.

Digital Twin Workflow

The concept of a digital twin operates through a three-step process that involves data association, forecast, and control, utilizing relationships derived from physics-based or (data-driven) AI models along with statistical characteristics of diverse collected data. Digital twin technology embodies several key characteristics that distinguish it as a powerful and dynamic tool in various industries [8]. The following characteristics are intricately woven into its functionality, enabling it to provide valuable insights and drive continuous improvement:

(1) Real-Time Reflection: It captures data from physical systems, such as sensors and devices. The choice of sensors depends on the complexity of the Digital Twin, mainly on which (degenerative) changes the virtual models are capable of reflecting. Using the collected data, a DT promptly mirrors these inputs in the virtual environment. This real-time reflection ensures that the digital twin's representation remains current and aligned with the actual state of the physical counterpart, enabling up-to-the-minute analysis and decision-making.

(2) Interaction and Convergence: Digital twins enable interaction and convergence on multiple fronts including between historical data and real-time data, and between the physical space and the virtual space. In order to trust the real-time data, the sensors should be robust to withstand application-specific operating conditions as well as capture the environmental loads and their effects on the monitored components. Specialized sensors would be either embedded on the same chip/in the same package, or accompanying on the same board, or even externally placed near the monitored components. Extensive calibration of the sensors using experiments and virtual models is crucial prior to their deployment for prognostics and health management (PHM).

(3) Self-Evolution – Continuous Improvement: Digital twins possess the capability of self-evolution. This is achieved by continuously comparing the virtual representation (simulation, model) with the real-time data streaming from the physical counterpart. Discrepancies between the two are identified and analyzed, enabling the digital twin

to adapt, learn, and improve its accuracy and predictive capabilities over time. This self-evolution mechanism drives ongoing refinement, making the digital twin increasingly adept at predicting behavior and suggesting optimal courses of action.

Digital Twinning Approach

Digital Twins can be built based primarily on two approaches – physics-based and data-driven. A physics-based twin relies on the knowledge of physics-of-failure or physics-of-degradation models to represent accurate thermal, electrical, chemical, and mechanical behavior of materials. This approach is good for accurately representing (only) known physical phenomena using mathematical relations but may not capture all aspects of the physical reality.

A data-driven approach relies on the sensor data from the physical product, *i.e.*, real in-situ measurements. At the same time, the inherent black-box structure cannot describe the mapping between the input data and prediction. A hybrid approach combines workflows of both physics-based and data-driven approaches and can overcome their individual limitations.

What is NOT a Digital Twin?

The term Digital Twin is often used freely and interchangeably with different digital representations of a physical entity. This, however, misrepresents the actual concept. Thus, to avoid confusion and keep consistency, it is crucial to understand and clearly define what a Digital Twin is *not*.

A multiphysics multiscale model is commonly referred to as a Digital Twin. Although such a model accurately represents its physical counterpart (*e.g.*, with a high fidelity Finite Element model), it cannot be classified as a Digital Twin, unless it can be continuously updated through the information exchange with its physical counterpart to represent its current (aged) state. Bilateral communication is the key to differentiate a model (essentially just an instance of a Digital Twin) from a Digital Twin.

A physical entity can be represented in the form of a control system flow diagram. Such a representation also cannot be called a Digital Twin, unless it can be updated based on the physical entity. Even when it satisfies the criterion of continuous update, a control diagram by itself does not suffice in entirely representing the physical entity. Thus, at the most, it can be classified as one aspect of the (data-driven) Digital Twin.

3. Examples of Digital Twin Implementations

The generalized Digital Twin workflow and architecture can be adopted for different applications of electronic packaged components and associated electronics enabled systems. This section delves into examples of DT implementation in six different application fields.

a. Manufacturing

Semiconductor manufacturing has become more complex over the past two decades. Test and Validation sit at the natural crossroads between product Design and Manufacturing. Test data helps guide the design by providing performance and quality feedback based on real-world operational conditions, and Test provides feedback to the manufacturing process to ensure product defects are properly screened and product performance is optimized.

In the manufacturing of chiplet-based heterogeneous-integrated product packages, we are rapidly approaching in this decade a critical time where our packaged product quality levels will be unsustainable and therefore eventually unsellable. This is driven by the fact that the composite yield of any chiplet-based package is the product of each of the individual chiplet yields and the overall package assembly yield. As a result, sellable products require very high-quality characterized known good die (cKGD) coming out of wafer test.

Chiplets have to be known-good, which is a quality metric, but we also need to have an accurately characterized assessment of their behavior and performance when placed into a package with other chiplets. In order to guarantee full-package performance and reliability, intelligent die pairings are needed based on this characterized data from wafer-test. However, since wafer-test and final package test conditions are vastly different in terms of operating environments (RF, thermal, electrical, mechanical), making all wafer-test characterization data inadequate.

A digital twin of the chiplet die and packaging behavior across process and environmental conditions offers a way to bridge the gap between the inadequate wafer-test data and the predicted behavior that the chiplet will exhibit under final package test conditions. For example, a digital twin final-test model could accurately predict during real-time package assembly that placing two high-leakage CPU chiplets directly adjacent to one another would raise junction temperature by 5C, thus rendering overall package performance thermally challenged. The model could then make recommendations for assembly to make better die pairing choices to optimize overall final-test package performance and yield, and allow for product configurations that would not otherwise be possible.

High-Mix Low-Volume (HMLV) production of 3D Heterogeneous Integration (3DHI) systems presents

several challenges including demand variability, resource allocation, production scheduling, inventory management, supplier coordination, supply chain complexity, changeover and setup times, quality control, workforce flexibility, and lead time management. The fab level digital twin that consists of sub-components such as physical fab, virtual fab, and the service system including supply chain management (SCM), enterprise resource planning (ERP), manufacturing execution system (MES), and product lifecycle management (PLM) can significantly contribute to solving the challenges faced in a HMLV production environment. Some of the manufacturing challenges in HMLV and corresponding Digital Twin-based solutions are as follows:

(1) Demand variability – The digital twin can enhance demand forecasting accuracy. This enables better resource allocation and production scheduling to accommodate demand variability effectively.

(2) Resource allocation, utilization, maintenance – By linking the digital twin with ERP and MES systems, the fab can optimize the allocation of resources based on real-time production requirements and product mix, reducing underutilization and overutilization of resources. The digital twin's simulations can identify opportunities to optimize production processes, minimize waste, and reduce production costs per unit by testing various scenarios virtually. Semiconductor fabrication facilities are equipped with numerous complex machines and equipment. Digital twins can be used to create virtual replicas of these devices and monitor their real-time performance. By analyzing data from sensors, maintenance teams can predict equipment failures, schedule proactive maintenance, and minimize downtime.

(3) Production scheduling; Changeover and setup times – The digital twin can simulate and optimize production schedules considering changeover times, minimizing downtime and maximizing efficiency. Real-time data from MES and virtual factory can guide adaptive scheduling based on actual production conditions.

(4) Inventory management – Integration of the digital twin with SCM, ERP, and MES systems allows for dynamic inventory management, ensuring that the right components are available at the right time, minimizing stockouts and excess inventory.

(5) Supplier coordination/Supply chain complexity – Real-time data exchange between the digital twin and SCM system enables better coordination with suppliers, ensuring timely delivery of materials and components for different products. By integrating SCM data, the digital twin can analyze supply chain performance and identify areas for optimization, such as selecting alternative suppliers or optimizing transportation routes. The digital twin can simulate potential disruptions in the supply chain or production process, enabling proactive risk management and resilience planning.

(6) Quality control / Cost of customization – The digital twin can simulate quality control processes and provide training simulations for the workforce, ensuring consistent quality across product variants and facilitating cross-training. The digital twin can simulate the impact of customization requests on production processes, allowing for better decision-making regarding the feasibility and cost of customization.

(7) Workforce flexibility – The digital twin serves as a common platform for communication and collaboration among different departments, suppliers, and partners, enhancing overall coordination and efficiency.

(8) Lead time management – The digital twin can provide visibility into lead times at different stages of the production process, helping in managing customer expectations and optimizing delivery lead times.

b. Optical Networks

Optical networks are transforming rapidly in today's age. Networks are in constant need of monitoring of hardware resource allocation and network virtualization. Due to the architectural complexity of networks in terms of hardware fabric, various modulation schemes, variable wavelength grids and software-defined networks, the need for real-time monitoring and maintenance of networks is crucial. Additionally, ensuring reliable and efficient operation of these systems and intelligent and self-correcting of such networks is indispensable to the reliability and resiliency of the communication infrastructure.

To address some of these challenges, use of a digital twin (DT) has been proposed. DT can potentially integrate data and information among multiple platforms by providing link monitoring capabilities and improvement of overall network connectivity and resilience. Network simulations, hardware configuration and fault management schemes are examples of functions that can be leveraged by DT in networks.

In a network enabled by DT, real time traffic is sensed and monitored. This data is stored in servers and is modeled post data mining and processing. Each digital model is used to address specific requirements in the physical space. These collective virtualized models will enable smart and real time monitoring of the network that is continuously synchronized based on the use.

c. Data Centers, HPC & Hybrid Computing

The massive growth in data centers raised interest and regulations for the management of waste heat and its utilization. This area has seen increased applications of a combination of DT and ML frameworks to optimize the ventilation and cooling of data units and processors in the system. For instance, a model of a data center could include flow rates and air cooling at the multiple ventilation ports and base cooling of processors. A thermo-fluid model, combined with a genomic-based ML algorithm can translate into a DT replica of the system, capable of running in real time or faster than the actual system. As a result, the model becomes suitable as either a design tool or an adaptive controller [9].

Extending DT to other areas such as reliability, fault tolerance, and failure preparedness for data centers and High-Performance Centers (HPC), however, is a multi-disciplinary problem. System architects, software developers, and site operators must have a deep understanding of network reliability at scale, along with the software systems running at these centers. Little has been reported previously on the reliability characteristics of large-scale network infrastructure. Two recent multi-year studies reported the breakdown in failures and the impact on the services provided.

One seven-year investigation carried out by Facebook (Meta) and Carnegie Mellon University [10] reported the reliability of twelve geographical distributed data centers over the world. In this case, only 13% of the failures originated from hardware (from well-established technologies and mature silicon nodes), while the bulk of the incidents came from software configuration, bugs, and maintenance. The corresponding MTBF (Mean-Time-Between-Fail) was about three months. When migrating to advanced technology nodes, however, the picture was reversed.

An eight-year study of HPC (sometimes also called Extreme Scale Supercomputers) conducted by Intel and Oak Ridge National Laboratory [11] on several different systems (0.27 Petaflops to 27 Petaflops) with processor and GPU latest nodes from Intel, AMD, and Nvidia revealed that hardware errors accounted for close to 85% of the incidents, and the normalized MTBF was less than one day! There are many challenges to the application of DT for predicting the reliability of such a system: 1. The likelihood of failures has increased with the ever-larger number of components; 2. With shrinking process technologies, processors have become more susceptible to soft errors, manufacturing defects, and process variation errors; 3. Managing system reliability becomes more complex as the system grows and multi-level redundancy is required.

With the advent of quantum computers, a substantial increase in computational capabilities compared to classical computer architectures becomes available for a range of problems. Quantum computers can make significant contributions to HPC. However, quantum computing (QC) alone cannot achieve this goal as it needs both current and future HPC systems to provide pre- and post-processing to stage operations, and to enable hybrid applications combining computational elements suited for QC with those that are not. Close integration between QC and the HPC ecosystem to form a new integrated HPC+QC framework is required. Quantifying and characterizing the system failures is the first step to improving the performance of this hybrid stack and the development of a DT framework for hybrid computing.

d. Automotive

Digital twins are becoming increasingly essential in the automotive industry, just as they are in other sectors. Various methods for creating digital twins are already available, such as empirical and analytical models, finite element simulations, model order reduction, and regression-based models. While these methods are powerful for linear systems, addressing the challenges posed by highly nonlinear and temperature-dependent systems, especially those operating in harsh environments, remains crucial.

Moreover, in the automotive domain, having a suitable platform for performing these calculations is paramount. Presently, cloud-based solutions offer the capability to deploy digital twins, allowing for the execution of any type of model, including a full 3D finite element method (FEM)-based digital twin. This flexibility proves invaluable during the development phase. However, challenges emerge when contemplating field applications.

The smartSTAR project [12], for instance, has focused on developing a compact digital twin tailored for the automotive industry. Its primary objective was to estimate the thermo-mechanical load on solder joints, a common source of fatigue and creep damage in automotive electronic components. Creep typically arises from isothermal storage conditions, while fatigue occurs during thermal cycling loading, both of which are encountered in the field.

In our example, a fully verified and validated FEM model was used as a reference. Time-temperature load profiles, incorporating parameters like T_{max}, T_{min}, dwell time, and ramp rate, were analyzed. These profiles were divided into test and validation datasets. Based on the reference FEM model, data were generated for an artificial intelligence (AI) and machine learning (ML)-based compact digital twin. In total, 30 pseudo-field profiles were created, with

20 utilized for training the AI/ML model and 10 for validation.

The degradation criterion employed in this context was the accumulated creep strain in the solder ball. The objective was to predict this strain with 80% accuracy concerning the reference value. Figure 2 illustrates the results for both the reference and AI/ML-based digital twin. The light blue curve represents the time-temperature loading profile, while the red curve signifies the results from the FEM reference case, showing the accumulated creep strain. The dark blue curve represents the results of the compact digital AI/ML twin, with an impressive accuracy rate of 96%.

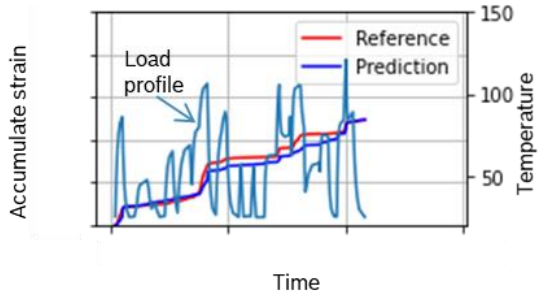

Figure 2: Accumulated creep strain calculated for solder joint

In summary, electronic components and systems in the automotive sector necessitate the development of compact digital twins based on AI/ML to address thermomechanical loading conditions in critical design elements. These compact digital twins should be deployable on low-computing platforms, such as microcontrollers, while producing results comparable to those of high-performance FEM workstations. This advancement promises to significantly impact automotive engineering, enhancing both efficiency and accuracy in electronic component design and analysis.

e. Lighting

Lighting industry is another example where products need to withstand harsh environments. LED-based products are ubiquitous. They are installed in a variety of surroundings – from indoor controlled conditions to outdoor harsh weather conditions, which can drastically vary across various locations on the whole planet and different seasons throughout the year. In addition to extreme temperature and humidity (or moisture), chemical exposure is yet another challenging environment for a lighting product installed at paint or chemical factories.

Lighting products are complex systems consisting of LEDs, peripheral electronic components, and protective materials for covering/packaging them. They need to be robust to withstand aforementioned conditions. Standard reliability and qualification tests are traditionally used to determine the lifetime of LED products. However, they are resource intensive and expensive. Moreover, they use accelerated tests which may not be sufficient to replicate the real-life aging of the products.

The first challenge is partially overcome by adopting a simulation-based analysis in addition to the traditional reliability tests to save on resources. This is, however, not sufficient to tackle the second one. An in-situ data driven solution must be in place for condition monitoring of the deployed LED products. It can enable localized and part-specific condition monitoring for a set of identical products installed in different ambient conditions. In addition, it can aid the simulation-based approach by providing real-time data coming from one or several active products. This can be achieved by utilizing a Digital Twin-based lifetime monitoring solution.

Several steps of creating a Digital Twin of a luminaire, which is the baseline physical entity of a lighting product, is presented in the article [13]. A luminaire consists of five key components – LED device, PCB, secondary optics, driver, and enclosure. Each component serves a unique role and thus could be represented differently with different complexity in their respective digital representations. Figure 3 illustrates the component wise aspects considered to build a Digital Twin of a luminaire.

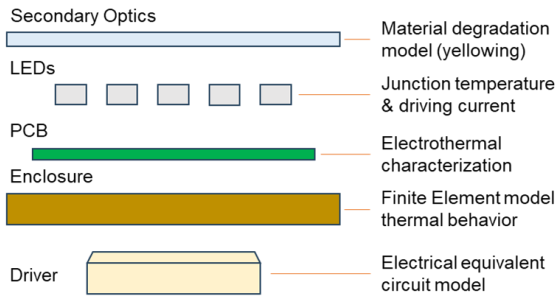

Figure 3: Components of a luminaire and corresponding relevant aspects for building a Digital Twin

LED device operation mainly depends on the PN-junction temperature (T_j) and the driving current (I_f). They affect the forward voltage drop on the device, its output radiant flux and spectrum. A mathematical relationship mapping these parameters to the governing factors T_j and I_f, along with 'cumulative stress' coefficients (scalar functions) to compensate for the aging is sufficient for the digital representation.

On the other hand, the enclosure needs to be modeled with a full Finite Element simulation, as it directly affects thermal performance of the whole luminaire. Its digital representation needs to have an accurate 3D geometry model with thermal behavior of the system. Similarly, PCB modeling involves electrical and thermal characterization. The secondary optics is modeled with physical

mechanisms like photodegradation and chemical reactions, since 'yellowing' is the primary aging effect.

This example clarifies how a Digital Twin representation of a system (here, a luminaire), consisting of different components, can have different types of models with different levels of complexity based on their respective functional relevance.

f. Power & Energy

Power and energy systems for electrification and renewable energy generation (wind solar, wave, etc) are adopting power electronics semiconductors. These solid-state electronic devices are used for the conversion and control of electrical power. The packaging of these power devices – diodes, transistors, and thyristors – can be accomplished for a single power device (a discrete package) or an assembly of power devices (a module). Devices within a module (or a single device in a discrete package) are then interconnected to perform the required function of power conversion. The design and materials used for these packaging architectures is important as it aims to address the following requirements:

(1) Electrical: Reducing parasitics, for example, inductances, and conduction and switching losses that cause electromagnetic interfaces problems and produce heat.

(2) Thermal: Ensure that heat generated within the module is extracted and the power devices and surrounding packaging materials do not become too hot. For a module this is achieved through a baseplate and possibly a heatsink.

(3) Mechanical: Providing protection to the power devices from the environment (dust, moisture, etc) and to ensure that any stress developed due the mismatch in material thermal expansion coefficients is minimized to meet reliability and robustness requirements.

Physics-based models using solvers such as the finite element method [14] and reduced order model equivalents [15] have been used extensively to support design optimization for both Silicon and Wide-Band Gap devices and their packaging. Examples of failure modes that need to be assessed include wire-bond lift-off, die-attach cracking, and delamination of metallization on the substrate, as illustrated in Figure 4 for a traditional power module.

Similar to the 5D model for digital twins, using digital twins for the lifecycle management (design, control, and maintenance) of power electronics-based energy systems (PEECS) requires technologies for each layer such as (a) physical entity (power module, system), (b) data (sensors, communication, data fusion, etc), (c) virtual twin (3D physics models, data driven models, etc) and (d) algorithms (AI, etc). Developments in each of these areas when combined will form the digital twin of the power electronics-based energy system (PEECS) [16].

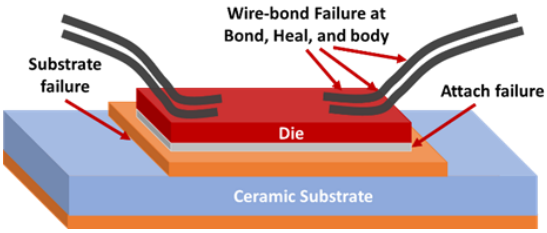

Figure 4: Traditional interconnect structure and prominent failure modes for a semiconductor die in a power module.

Real-time predictions using fast analysis (e.g. model-driven, data-driven, or a fusion of both), sensors for data gathering, and identified metrics for monitoring module degradation are key requirements for successful adoption of digital twins for the life cycle management of PEECS. For example, Neural Networks have been used to create digital twins that can run on a converter digital controller where training data for the NARX-ANN network is obtained from simulations and is then used for fault detection, prognostics, and risk assessments [17]. Linking the virtual twin to data gathered from the physical system requires sensors. For example, condition monitoring using thermal data gathered from a power module is a critical aspect in assessing the overall performance degradation of a power module. Numerous techniques are available for this, including contact-based fibre optic temperature sensors which can provide real-time data for analysis [18].

Digital twins will continue to evolve and be adopted for PEECS. Future trends will see advances in modelling platforms (multi-physics/scale), data gathering and its fusion, faster compute engines and data processing, encryption for data security, and prognostics and health management for life cycle management of PEECS. These techniques will evolve as packaging techniques for power electronics module change with adoption of wide-band gap devices and need to reduce volume and weight of power modules whilst ensuring their reliability and robustness in challenging environments.

4. Technological Requirements & Challenges

A Digital Twin utilizes real-time data to assess the system's health, such as electrical and mechanical integrity, with the aim of predicting the overall reliability of the product in service. The electrical signals acquired through service operations can be

effectively channeled as inputs to virtual sensors embedded within the Digital Twin.

The DT prognosticates the thermal and mechanical behaviors intrinsic to the complex packaging such as a 3DHI system, predicting the reliability and maintenance plan. This real-time monitoring and prognostication also requires multi-physics and multi-scale simulation tools that can give high accuracy and fast results. However, the simulations of 3DHI design and operation conditions involve complex multi-physics and multi-scale models that often come with prohibitively high computational costs.

The inherent constraints of physics-based simulations present challenges when it comes to achieving real-time data interaction and seamless convergence between digital models and physical systems. Utilizing a DT enhanced by advanced deep learning architectures, which can provide rapid computational solutions, offers a potential solution for implementing DT in electronic design and manufacturing. These advanced techniques could serve as the fundamental building blocks of 3DHI digital twins, but they also face numerous challenges, particularly within the context of multi-physics and multi-scale scenarios.

The designs of these neural networks and the associated training methods are of utmost importance, not only to ensure satisfactory generalization performance but also to enable their practical application. Addressing optimization challenges within multi-physics and multi-scale systems can lead to the discovery of optimal strategies for thermal management, power distribution, signal distribution, and mechanical stress design, ultimately enhancing the reliability of microelectronic systems.

5. Future Scope

Digital twin as of today is at the very early phase. Today, we estimate that DT will play an important role in electronics industry, specifically in the following aspects:

- **Simulation and Modeling:** DT will allow for more efficient analysis and optimization of electronic components and systems, reducing the risk of design flaws, enhancing product performance and cost optimization.
- **AI and Machine Learning Integration:** With advancements in AI and machine learning, digital twins will enable development of new materials, calculation of highly non-linear and temperature dependent responses of materials.
- **Electronics Manufacturing:** Digital twins will find extensive use in electronic manufacturing, such as predictive maintenance, process optimization, and quality control.
- **Industry 5.0:** Digital Twins are instrumental in realizing Industry 5.0, which is the next phase of industrialization [19], emphasizing sustainability, human-centricity, and resilience.
- **Cross-Industry Collaboration:** Federated learning will enable collaboration between electronics companies (supply chain) and those in other industries (OEMs) like healthcare, automotive, and energy.
- **Predictive Maintenance:** Continuous condition monitoring paired with PHM (prognostics and health management) workflow will help in allowing timely scheduled product maintenance, risk mitigation, and minimized system downtime.
- **Integration with IoT and Edge Computing**: Digital twins are becoming an integral part of the Internet of Things (IoT) ecosystem that enables real time monitoring, predictive maintenance and pave a way for new data driven business model.
- **Lifecycle Management, Sustainability and Green Initiatives:** Digital twins can be used throughout the entire lifecycle of an electronic product, from design and manufacturing to operational use and maintenance. This will help in enhancing the efficiency and durability of electronic products, and to make more sustainable choices and reduce electronic waste.

6. Summary

Digital Twin has evolved as a concept in the past several years and has been adopted across several industries. The available definitions for DT are, therefore, highly contextualized and application-specific. Highlighting the need for a generic fit-for-all description, this article reviews a few and proposes an updated definition for the Digital Twin. A five dimensional architecture is elaborated on along with the workflow and modelling approaches.

Implementation of Digital Twin for electronic packaged components and associated electronics enabled systems has been discussed for six diverse applications fields – manufacturing, optical networks, data centers & HPC, automotive, lighting, and power & energy systems. Considering these examples, the technological requirements and challenges are also discussed. Finally, nine aspects of the future scope of DT technology are presented.

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