Making the Digital Twin work for Mission Critical Electronics

Adwait Inamdar[1], Przemyslaw Gromala[2], Willem van Driel[1], GuoQi Zhang[1]
[1]Delft University of Technology, The Netherlands
[2]Robert Bosch GmbH, Reutlingen, Germany

Introduction

Digital Twin has become a commonly used phrase in the context of products, processes, businesses, and more. It was first introduced in 2003 by Dr Michael Grieves, but the term was first defined in the *NASA Modelling, Simulation, Information Technology & Processing Roadmap* in 2010 (revised in 2012). Thus, the concept primarily evolved in the context of aerospace and manufacturing applications and was later embraced by many other industries such as healthcare. Among the newer technologies, it currently lies on the peak of the expectation curve according to a report by Gartner in 2018. A recreated chart of the hype cycle, highlighting a few other related emerging technologies, is presented in Figure 1.

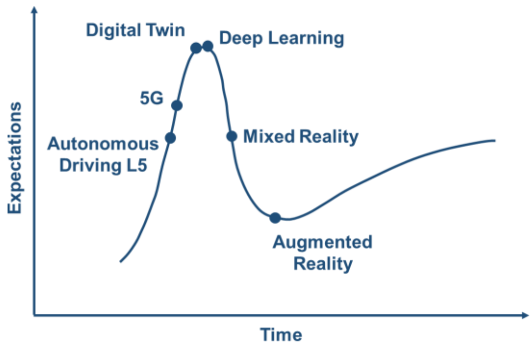

Figure 1: Hype cycle for emerging technologies by Gartner (recreated)

The primary reason behind the adoption of Digital Twin technology is digitalization of industries, which has been accelerated by the newly emerging information technologies (IT) enabling incorporation of more and more electronics such as sensors into the conventional products and systems. A good example of this is the automotive industry, which is progressing towards developing a framework for fully electric, connected, and automated (ECA) vehicles. Every step towards higher level of automation requires additional electronic systems and their integration into various functions of an automobile. Considering exposure to harsh environments, electronics are a crucial component of an automobile with respect to its functionality, cost, and overall safety.

Overall, adoption of electronics is growing at a fast pace. Application fields like intelligent manufacturing, autonomous driving, smart city, and smart services are built around connectivity and artificial intelligence (AI), and thus, require mission critical electronics (MCE) on a large scale. Therefore, reliability of electronic products and their subsystems has become highly critical. In this scenario, performance and lifetime on demand become essential, and Digital Twin presents itself as a key enabler for providing it.

What is a Digital Twin?

Digital Twin is a continuously updated virtual representation of an object, system, or process which replicates all phases in the lifecycle of its physical counterpart. The definition sounds like a virtual model of a system, but it is actually much more than that, virtual model being just one facet of it.

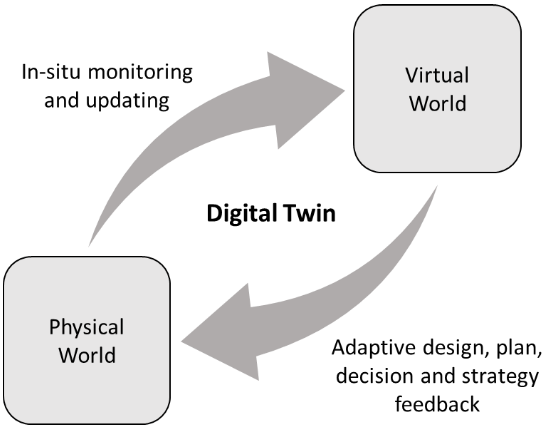

Figure 2: Structure of a Digital Twin system

Figure 2 shows schematically the structure of a Digital Twin system. It consists of three parts – the physical entity, its virtual representation (model), and the connectivity between these 2 islands for data and information exchange.

The physical entity can be any object, system, or process. It can be implemented on different scales – product, machines and tools, processes, a control-volume, or even a business. In the context of microelectronic systems, product-specific implementation is the most relevant.

Connectivity between the physical entity and its virtual representation is what sets a Digital Twin system apart from just a model. The connections facilitate exchange of data, which enables continuous update of the model rather than remaining static. Similarly, the results generated from the updated model can be used as feedback for improving the physical product. Thus, a bilateral connectivity is the key to build an effective Digital Twin system. The connections can be categorized into three types based on their levels of complexity –

(a) Weak connection: this utilizes connection in only one direction, i.e., from product to model, with no closed loop. Thus, modelling serves as a supporting tool, and it can be mainly used for virtual prototyping, and product/process design.

(b) Cloud connection: this allows real-time monitoring of product, data filtering and transmission. A cloud-based platform is utilized to process the collected data using complicated simulation models. This data can be then utilized for product or process improvement with a closed-loop connectivity. A caveat of this implementation is that the closed loop is external to the product. But the advantage is the capability to run bigger and complex models on an external computational node.

(c) Embedded connection: an embedded connection allows the model to run locally. It also incorporates real-time monitoring and data collection but processes it on the edge. This saves the cost and energy of transmitting data to an external server, and thus, is more efficient. In this way, an integrated close-loop control and decision-making can be achieved. Only shortcoming of this approach is the limited computational power at the edge, e.g., of a microcontroller. Therefore, only simpler, and computationally lighter models such as compact models or meta-models can be used.

Each of these above three approaches is suitable for different kind of applications and use cases.

Digital Twin for Microelectronics

Different stages in the lifecycle of an electronic product are: (1) product design, (2) material selection and characterization, (3) production, (4) usage, service, maintenance, and repair, (5) recycle. Figure 3 (first appeared in *Heterogeneous Integration Roadmap 2021*) elaborates on its wider landscape, where each stage requires its virtual representation. Thus,

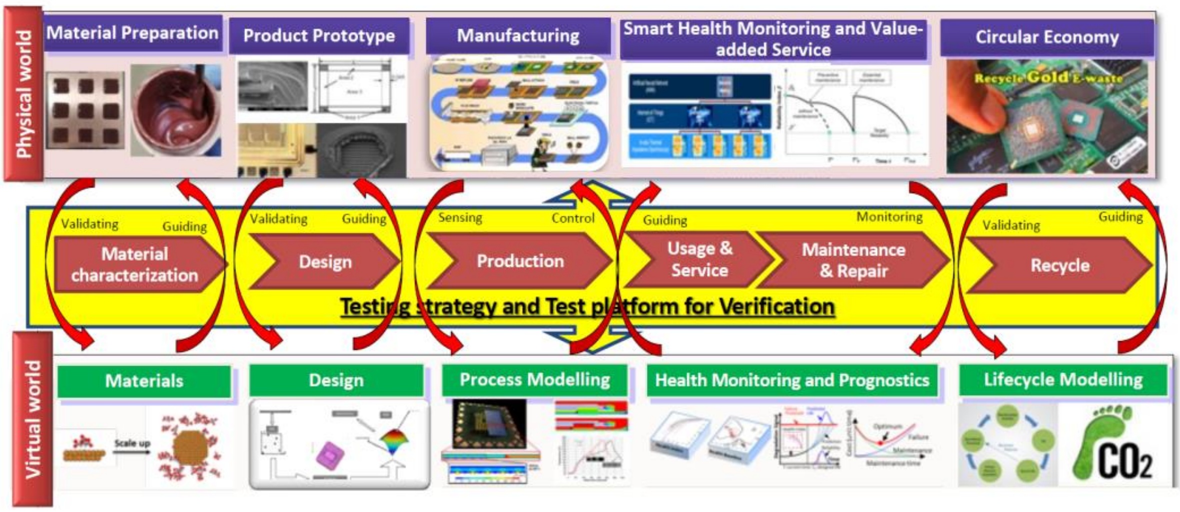

Figure 3: Landscape of product lifecycle and Digital Twin implementation

Digital Twin is multi-layered and multi-scale in nature. The goal is to have an end-to-end Digital Twin implementation for all the stages of product lifecycle, but the complexities involved to achieve it are not addressed by the current state of the art. However, each one of the stages can have its individual Digital Twin implementation.

As an example, consider the stage 4 – usage and service. The primary goal of the Digital Twin of this stage is to establish individual per-product in-situ health monitoring for failure detection and lifetime prognosis. A logical workflow to achieve that is indicated in the flowchart in Figure 4.

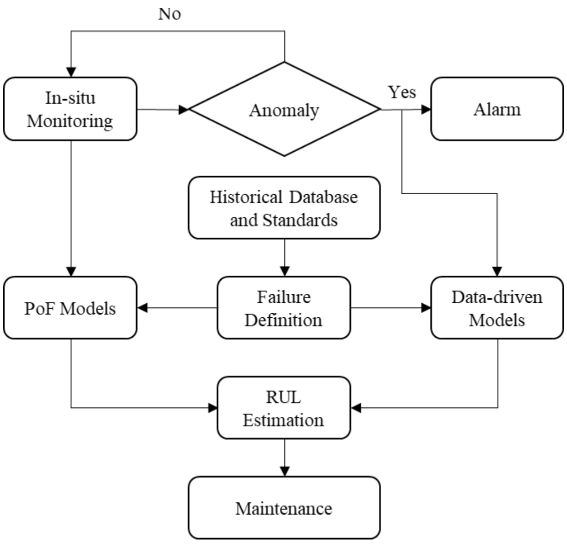

Figure 4: Health Monitoring and RUL Prognosis

In-situ monitoring of products is achieved using advanced sensors. The collected data is used for anomaly detection on the edge. Anomalies are reported, and otherwise, data is utilized for data-driven algorithm for remaining useful life (RUL) estimation, which can either be on the cloud (bigger and complex models) or on the edge (compact/meta models).

Simultaneously, the sensor data is utilized to identify current state of degradation based on the total exposure to harsh environmental conditions and using material degradation models. Accordingly, the physics-of-failure based (e.g., finite element) model of the product is updated, and possible failure modes and resulting RUL is estimated based on the multi-scale/multi-physics simulations, historic database, and standards. The simulations run mostly on an external computing node.

In this way, edge + cloud computing can be utilized for a Digital Twin implementation for predicting RUL. Based on the estimation, a condition-based maintenance can be suggested, which forms a closed loop of connectivity between physical and virtual world.

This implementation has the potential to facilitate individual monitoring of every single product from a batch, while they are in-use. With the combination of edge and cloud computing per-product health monitoring and failure prognostics can be achieved. This would result in better insights about product degradation, and eventually, failure risk mitigation.

Challenges and Roadmap

One of the primary challenges is to develop proper definition, boundaries, and standards around the concept of Digital Twin. The challenges related to the hardware aspect, i.e. the physical twin, involve developing advanced, low cost, and reliable sensors for in-situ monitoring, and embedding these sensors in products to make the system capable of self-monitoring.

The Digital Twin needs to have accurate and efficient multi-scale multi-physics simulation models, which consider non-linearity as well as time and temperature dependency. Some of the key milestones in the context of failure criteria are – definition of accurate failure threshold and multi-failure modes interaction; while for the modelling aspect, they are – simulation-driven design and optimization, accurate compact models, automation for model generation, and transition from a deterministic to a probabilistic /stochastic simulation methodology.

The connectivity aspect needs to solve the challenges with cloud platform and wireless connection, low cost and reliable real-time monitoring, smart sensing and IoT, computational power at the edge, big-data management – collection, storage, smart filtering, processing, and lastly, a closed loop control algorithm.

The roadmap for solving the above challenges is laid out for next 5-10 years, and the key goals to achieve can be simplified as the following 6 points: smart in-situ sensing and transmission, edge computing capable hardware, accurate compact/meta-models embedded in a dedicated highly reliable Digital Twin chip, robust multi-scale multi-physics (nonlinear, dynamic, probabilistic) simulation models, robust data-driven models, and lifetime (RUL) on demand.

prediction of anomaly and failure. This purely data-driven ML-based approach is still a black-box implementation and thus, is difficult to completely rely on.

Digital Twin proposes a combined approach, integrating physics-of-failure (PoF) based models with ML and data-driven models. This ensures that the simulation model of the product is continuously updated for its current degraded state using in-situ data and ageing models.

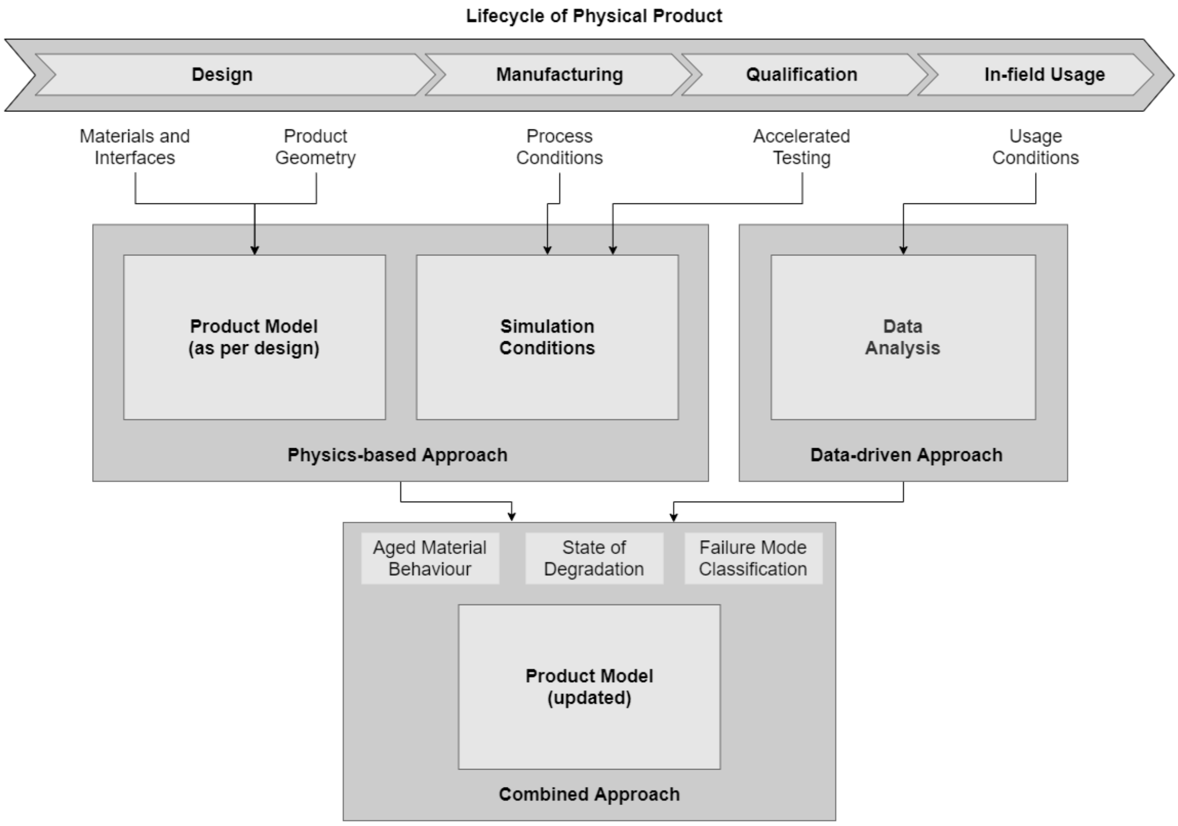

Figure 5: Overview of product-specific Digital Twin Implementation

An overview of how a product-specific Digital Twin system would work is indicated in Figure 5. It shows how the current physics-based modelling approach is limited to consideration of product model as per the original design. It does not get updated for its degradation due to exposure to operating conditions. Thus, the simulations of all later stages do not consider the changes in product due to ageing, making the 'simulation conditions' block completely separated from the product model.

On the other hand is the data-driven approach. It monitors operating conditions through sensors and uses machine learning (ML) for

This allows consideration of 'aged material behaviour', making the virtual representation of the product more realistic. Thus, the simulations are also closer to reality, giving better results and predictions.

In summary, the Digital Twin implementation utilizes best of both approaches. It enables the ability of system optimization, monitoring, diagnostics, and prognostics using integration of AI, machine learning, and big data analytics with the traditional PoF based methods. It serves as a powerful tool for scheduling strategic maintenance by predicting failures and estimating lifetime of electronic components.