

DIGITAL TWINS: WHAT NDT PROFESSIONALS NEED TO KNOW

BY JOHANNES VRANA

The concept of the digital twin has moved rapidly from a theoretical idea into a central element of modern engineering, manufacturing, and asset management. It is frequently discussed in the context of Industry 4.0, artificial intelligence (AI), and advanced analytics, yet its practical meaning is often unclear, particularly in the context of nondestructive testing (NDT). For NDT professionals, the digital twin is not simply a virtual model or a data platform. Its value depends fundamentally on the quality, reliability, and interpretation of data describing the actual physical condition of an asset. What that means in practice becomes clear through an examination of the twins' conceptual origins, functional architecture, and the role of inspection data in ensuring predictive capability and trustworthiness.

Conceptual Origins and Evolution

The modern concept of the digital twin can be traced back to the work of Michael Grieves in the early 2000s, developed in the context of product lifecycle management (PLM) [1–3]. Grieves proposed a framework based on the idea of “mirrored spaces,” in which a physical product is continuously linked to a virtual representation. The underlying motivation was economic as much as technical: to shift effort from the domain of physical experimentation, costly in terms of materials, time, and energy, to the digital domain, where design, testing, and optimization can be performed more efficiently [3].

Grieves formalized this concept into three essential elements: physical entity, virtual entity, and the connection between them [1–3]. The physical entity represents the actual asset, whether a component, structure, or system. The virtual entity is its digital counterpart, capable of representing geometry, material behavior, and operating conditions. The connection, often described as a cyber-physical link, enables continuous and bidirectional data exchange between the two.

The term “digital twin” was later popularized in the aerospace sector, notably through work at NASA, where it was used to describe integrated systems capable of supporting lifecycle management from design through operation and maintenance [1, 2]. Over time, the concept has evolved beyond a simple mirror of physical reality. It now encompasses predictive modeling, simulation, and decision support, with increasing integration of data-driven methods such as machine learning.

A widely cited contemporary definition describes a digital twin as a set of virtual information constructs that mimics the structure, context, and behavior of a system, is dynamically updated with data from its physical counterpart, possesses predictive capability, and informs decisions that create value [4]. A key aspect of this definition is the emphasis on bidirectional interaction. The digital twin is not a passive repository of data but an active system that both receives information from and influences the physical world.

Functional Architecture of Digital Twins

Despite variations in terminology, most digital twins can be understood as three functional components that together form a continuous information-to-knowledge cycle (see figure on the next page) [5, 6]. These include the information layer, the data-processing layer, and the visualization and action layer.

- **Information layer.** This component comprises data collected from the physical asset, including sensor measurements such as temperature, strain, and vibration, as well as NDT inspection results. In this context, it is essential to distinguish between raw data and usable information. Raw signals must be processed, interpreted, and contextualized before they can contribute meaningfully to the digital twin. Equally important is characterizing data quality. For NDT applications, this includes not only measured defect characteristics but also metrics that describe the reliability of those measurements, such as probability of detection (POD) [7]. Without such information, the digital twin cannot properly account for uncertainty.
- **Data-processing layer.** In this step, information is transformed into knowledge. This involves deterministic algorithms such as signal reconstruction and filtering, as well as statistical evaluation and physics-based simulation [8]. Increasingly, this layer incorporates data-driven approaches, such as machine learning and deep learning models, that can identify patterns and relationships that traditional models may not easily capture. The purpose of this layer is not only to

describe the current state of the asset but also to predict its future behavior.

- **Visualization and action layer.** The resulting knowledge is presented in a form that supports interpretation and decision-making; for example, through dashboards or advanced visualization tools [8]. In some cases, the output of the digital twin is used directly to trigger actions, such as maintenance interventions or operational adjustments, thereby closing the loop between the digital and physical domains [2, 5].

These three components are not independent but tightly coupled. Data flows continuously from the physical asset into the digital system, is processed into actionable knowledge, and then influences decisions that affect the physical asset. This continuous cyber-physical loop is a defining characteristic of a true digital twin [5].

Lifecycle Perspective and Digital Twin Types

Digital twins can also be classified by their role in the lifecycle of an asset [2, 5, 6]. At the earliest stage, a digital representation exists as a design model, often called a digital twin prototype. This model incorporates design intent, including geometry, material properties, and expected operating conditions. At this stage, the model is not yet linked to a specific physical instance.

Once a physical asset is created and linked to its digital representation, the

system becomes a digital twin instance. This is a unique, continuously updated representation of a specific asset that incorporates as-built geometry, inspection results, operational data, and maintenance history. For NDT professionals, this is the most relevant form of digital twin, as it directly integrates inspection data into the evolving understanding of the asset's condition.

At a higher level, multiple digital twin instances can be combined into a digital twin aggregate. This enables analysis across a population of similar assets, supporting applications such as fleet management, probabilistic lifing, and trend evaluation [6].

The Role of NDT in Digital Twins

The effectiveness of a digital twin depends fundamentally on the accuracy and reliability of the data it receives from the physical world. In this context, NDT plays a central role. While sensors can provide quasi-continuous nondestructive measurements of certain parameters, they are often limited in their ability to detect and characterize defects. NDT methods, by contrast, are specifically designed to identify discontinuities, measure their size and location, and assess their significance.

Within a digital twin framework, NDT serves as a primary source of ground truth. It provides the information needed to validate and update the asset's virtual representation. For example, the detection and sizing of a crack during an ultrasonic inspection can be used

to update a fracture mechanics model within the digital twin, which in turn can predict future crack growth under expected loading conditions.

However, NDT's contribution extends beyond the provision of measurement data. It also involves quantifying uncertainty. No inspection method is perfect, and all measurements are subject to limitations in detectability and accuracy. Metrics such as POD are therefore essential [7]. By incorporating POD into the digital twin, it becomes possible to account for the likelihood that defects may be missed or mischaracterized. This allows predictions to be expressed probabilistically, improving their robustness and credibility.

The integration of NDT data into digital twins also highlights the importance of data standardization and semantic interoperability [9]. Inspection results must be stored and communicated in a way that allows them to be interpreted correctly by different systems and models, including metadata describing inspection conditions and uncertainties.

Predictive Capability and Decision Support

One of the defining features of a digital twin is its ability to predict future states of an asset. By combining current condition data with models of material behavior and loading conditions, the digital twin can estimate how defects will evolve over time and when they may reach critical thresholds [4, 6].

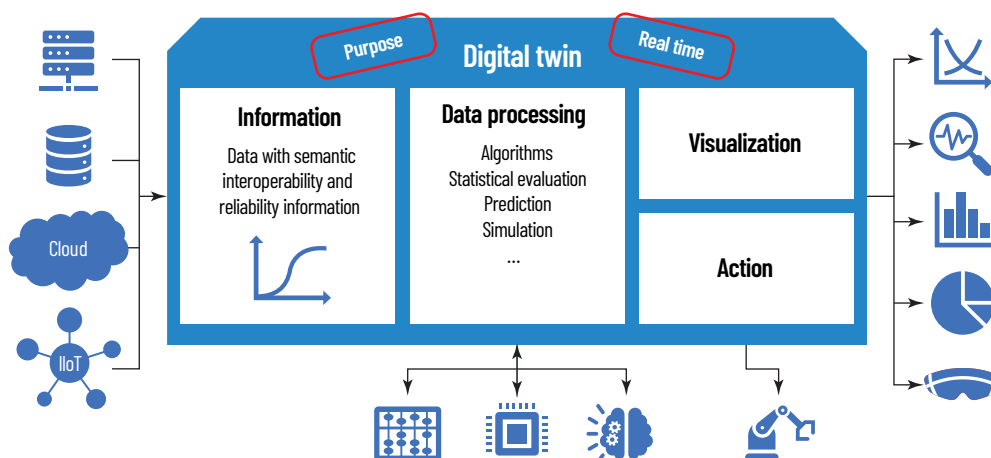


Illustration of the concept of a digital twin (adapted from [5]).

A typical application can be illustrated by considering a structural component subject to fatigue loading. NDT inspections provide measurements of existing defects, including their size and location. These measurements are used to initialize or update a fracture mechanics model within the digital twin. The model then simulates crack growth under expected loading conditions, accounting for stress intensity, material properties, and environmental factors. The result is an estimate of remaining useful life, which can be used to plan maintenance or replacement.

The reliability of such predictions depends directly on the quality of the input data and the validity of the underlying models. If the initial defect size is underestimated or if a defect is missed entirely, the predicted life may be overly optimistic. Conversely, conservative assumptions may lead to unnecessary maintenance. The challenge is therefore to balance accuracy, uncertainty, and practicality.

Verification, Validation, and Uncertainty

The increasing reliance on digital twins for decision-making, particularly in safety-critical applications, raises important questions about trust and reliability. This has led to a growing emphasis on verification, validation, and uncertainty quantification (VVUQ) [4].

In the context of digital twins, these processes are not one-time activities but ongoing requirements. The dynamic nature of the digital twin requires continuous updates and reassessment as new data becomes available. NDT plays a key role in this process by providing periodic validation of the asset's condition. Inspection results can be used to compare predicted and observed behavior, identify discrepancies, and refine models.

At the same time, generating high-quality data can be resource-intensive. Advanced inspection methods and the creation of synthetic data for training machine learning models involve high costs, which remain a practical constraint for many applications [10].

Challenges and Practical Considerations

While the potential benefits of digital twins are substantial, their implementation presents several challenges. Data quality remains a fundamental issue, as incomplete or unreliable input undermines predictive capability. Ensuring data integrity requires careful design of inspection procedures, calibration of equipment, and validation of results.

Another challenge is integrating diverse data sources and models. Digital twins often involve multiple disciplines, and achieving seamless interaction between these components requires standardized data formats and interfaces [9].

Scalability is also a concern, particularly when managing large numbers of assets. Digital twin aggregates and advanced data management strategies are needed to support fleet-level applications [6].

Finally, human interaction remains essential. Many practical digital twin systems include humans in the loop, requiring clear visualization, model transparency, and effective communication of uncertainty to support decision-making [8].

Conclusion

Digital twins represent a significant evolution in the way physical assets are designed, monitored, and managed. By integrating data, models, and decision-making processes into a continuous feedback loop, they offer the potential for improved efficiency, reduced costs, and enhanced safety. However, this potential can only be realized if the digital representation remains firmly grounded in reality.

For NDT professionals, this places their work at the center of the digital twin paradigm. Inspection data provides the essential link between the physical asset and its virtual counterpart. The accuracy, reliability, and interpretation of this data directly determine the quality of predictions and the effectiveness of decisions.

In this sense, digital twins do not replace traditional NDT practices but rather amplify their importance. Ensuring high-quality, trustworthy inspection data and properly accounting

for its uncertainty will be a key factor in the successful adoption of digital twins across a wide range of applications. 

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