Chapter 7
Digital Twins: Definition, Implementation and Applications

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Introduction

The digital technologies accompanying Industry 4.0 have ushered in a new era in the management of industrial economic systems. The concept of the digital twin is at the heart of this transformation. Stemming from the convergence of advanced data analytics, Internet of Things (IoT) technologies, and virtual modelling and domain knowledge (Fig. 7.1), digital twins were conceptualized to create virtual replicas of physical assets and systems.

Digital twin technology allows real-time monitoring, analysis, and simulation of industrial operations, leading to enhanced predictive maintenance, optimized production workflows, and improved product development. It facilitates a comprehensive understanding of complex industrial systems, enabling precise insights into performance, functionality, and potential areas for optimization. Given their ability to simulate and anticipate various scenarios, digital twins have become instrumental in driving innovation and efficiency, providing a solid foundation for the transformative journey toward an interconnected and intelligent industrial landscape. This innovative technology offers a comprehensive understanding of the unique attributes, operational performance, and potential issues of any equipment or system. Notably, the digital twin facilitates the virtual training of operators, eliminating the need for dedicated trainers or simulators.

With the continuous advancement of machine learning (ML) and Artificial Intelligence (AI), the realm of autonomous industrial machines is poised to undergo a significant shift. In this autonomous landscape, the role of the digital twin will evolve, propelling machines toward increased self-awareness and autonomy. Equipped with

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P. V. Varde et al. (eds.), *Advances in Risk-Informed Technologies*, Risk, Reliability and Safety Engineering, https://doi.org/10.1007/978-981-99-9122-8_7

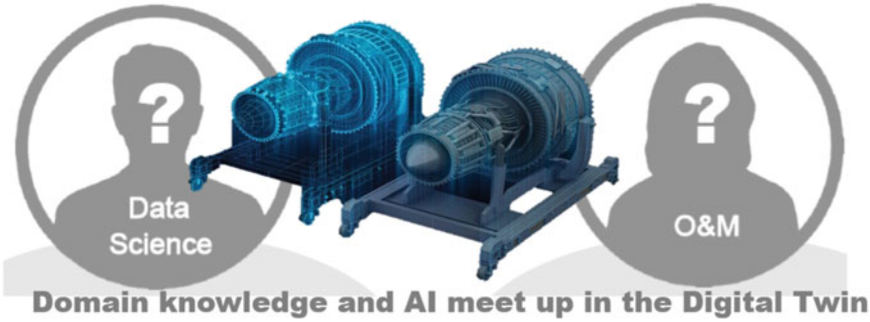

Fig. 7.1 Digital twins as cocreation of O&M knowledge and AI

the capability to optimize their own performance, synchronize with other machines, conduct self-diagnosis, and autonomously rectify faults, machines will necessitate minimal intervention from human operators (Happiest Minds 2021).

The digital twin represents the convergence of the physical and virtual worlds, combining various technologies such as AI, ML, and software analytics to create dynamic digital simulation models. These models continuously update and adapt to reflect changes in their physical counterparts. By providing a precise digital replica of machinery, the digital twin technology enables operators to gain insights into the distinctive characteristics of the machine, its operational efficiency, and potential issues. Real-time monitoring through sensors enables operators to receive timely alerts about potential failures, downtimes, or accidents, allowing them to optimize the machine's performance, monitor inter-device coordination, diagnose issues, and rectify faults with minimal impact on productivity.

This evolving landscape of system development and management is witnessing a significant shift towards making systems and system-of-systems smarter using digital twin technologies. This transformation is driven by the integration of cutting-edge technologies, including IoT and user-friendly interfaces, which have revolutionized system interaction and decision-making processes.

A fundamental aspect of this transformation is Model-Based Systems Engineering (MBSE), a concept that emphasizes system reuse throughout its lifecycle. MBSE facilitates communication among stakeholders and is incorporated early in the acquisition process to streamline system synthesis. A system specification plays a crucial role in defining the requirements of a technical or software system under development. MBSE takes this concept further by formalizing and consistently applying modeling techniques throughout the system's lifecycle, from its conceptual phase to design and beyond. MBSE supports various aspects of system development, including requirements, architecture, analysis, verification, and validation. By employing formal and model-based specification techniques, it simplifies the process of specifying complex systems. The key to MBSE is the creation and utilization of a coherent digital system model, which serves as the central source of all pertinent information, streamlining interdisciplinary specification and development processes.

Formal and semi-formal modeling languages are employed to concisely represent the system's requirements, structure, and behavior.

While some publications explore the use of digital twins within a model-based product development framework or the integration of MBSE into digital twins through diverse methods, the literature does not extensively focus on employing MBSE to manage digital twin complexity or to specify digital twins themselves. Some publications highlight specific advantages of MBSE for digital twin development but may not provide a comprehensive specification technique. They often emphasize the requirements of particular stakeholders or overlook the entire product lifecycle. However, some work is starting to address the need for a holistic framework for digital twins, recognizing research gaps related to considering the full lifecycle and identifying the requirements of various stakeholders throughout the lifecycle (Fig. 7.2) (Rasor 2021).

This concept aligns with the broader digital transformation initiatives pursued by many companies and government agencies. It empowers stakeholders across development, operations, and support with accessible and standardized data, thereby enhancing decision-making processes. In a comprehensive system engineering approach to digital twins, the digital twin itself is treated as a distinct system, resulting in a system-of-systems framework. This approach introduces a new paradigm of integrated system design and modelling.

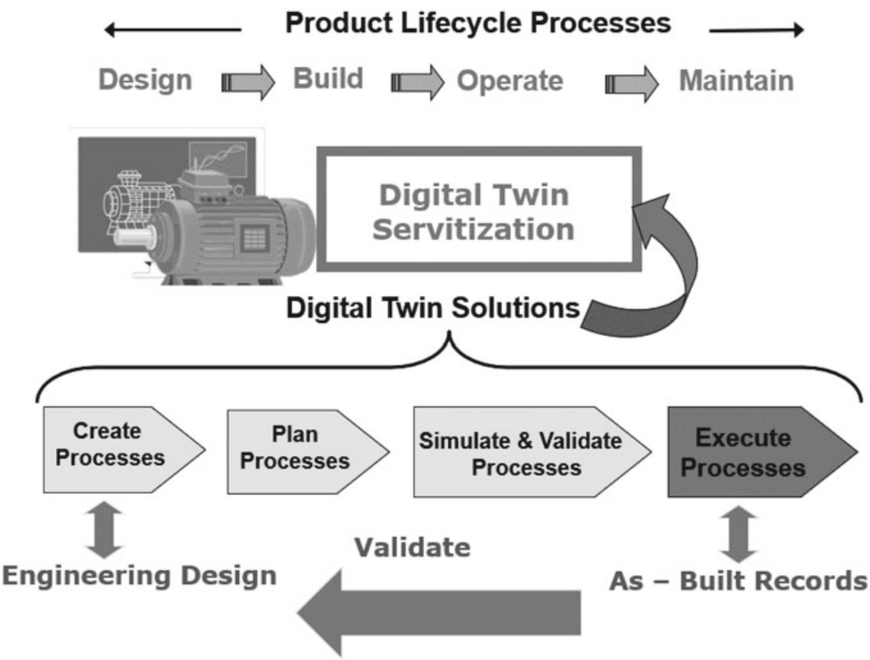

Fig. 7.2 Digital twins and the whole lifecycle dimension

The increasing relevance of Industry 4.0 and the Industrial Internet of Things (IIoT) has expanded the scope of digital twin applications. Notably, digital twin research focuses on creating purpose-oriented virtual models that represent physical systems. Other efforts are directed at establishing bidirectional relationships between physical objects and their virtual counterparts, facilitating data transfer and processing.

Various terminologies are used to describe digital concepts, such as the Asset Administration Shell in the context of Platform Industry 4.0. Related terms include Digital Model, Digital Master, and Digital Shadow, each serving distinct purposes in connecting physical and virtual realms.

The multitude of digital twin research approaches has led to diverse understandings and use cases, often lacking explicit specifications of required resources. Moreover, there is a growing need to determine the added value of implementing specific use cases. At the moment, there is no holistic framework for the conception, development, and implementation of digital twins; thus, there is a need or further exploration and standardization (Rasor 2021).

Digital Twin Definition

The concept of the digital twin has gained significant traction in the era of Industry 4.0, but there are a number of different definitions and interpretations. Some view digital twins as digital representations of physical objects or systems from the real world, while others consider them realistic digital depictions of physical entities. In essence, a digital twin encompasses a comprehensive description of a component, product, or system, containing all relevant information for its current and future lifecycle phases.

A digital twin is essentially a virtual model intricately integrated with its real-world counterpart. However, digital twins can vary significantly in terms of detail, technical focus, and scope. They have emerged as a critical technology in modern design and production engineering workflows, driven by advancements in sensor technology, information systems, and simulation technologies like Cyber-Physical Systems (CPS) and the Industrial Internet of Things (IIoT). Different interpretations and definitions of digital twins have arisen in both research and industry due to their diverse application areas.

Digital twins are closely linked to several emerging technologies, with simulation systems, communication technologies, and CPS playing pivotal roles. CPS, in particular, represent a fundamental concept in Industry 4.0 and are a technical evolution of mechatronic systems that blend mechanics, electronics, and computer science. CPS are equipped with sensors for data collection, actuators for interacting with their surroundings, and embedded systems, which are microcomputers with computing capabilities and unique identities. They can communicate and coordinate with each other via data infrastructure, typically the Internet, creating cyber-physical production systems (CPPS) when deployed in a production environment (Bauer 2015).

Creating a digital twin relies on decentralized data collection and processing by CPS, using data from multiple CPS. This process involves addressing challenges related to data acquisition, transfer, storage, security, and analysis, and it requires a combination of dedicated hardware and software solutions. The adoption of the 5G communication standard is anticipated to address current limitations in terms of bandwidth, latency, resilience, and scalability, particularly when supporting multiple devices.

Once data from CPS are gathered, digital twins facilitate the running of simulations to explore various scenarios, aiding in predicting the behavior of CPS. Some experts have even asserted that from a simulation perspective, the digital twin approach represents the next significant advancement in modeling, simulation, and optimization technology.

In summary, CPS comprise a conceptual framework and technology for smartness, and digital twins underpin the infrastructure of Industry 4.0. CPS serves as a fundamental framework that combines computing elements and physical processes, enabling the seamless integration of the digital and physical worlds. This integration forms the backbone for the development of intelligent and interconnected technologies, known as smart systems, which encompass automation, data-driven decision-making, and adaptive functionalities. Digital twins, in turn, leverage the capabilities of CPS to create virtual replicas that mimic the behavior of physical assets or processes in real-time. By utilizing data collected from a network of sensors and IoT devices, digital twins facilitate real-time monitoring, analysis, and optimization of complex industrial systems. The interwoven relationship between CPS, smart technologies, and digital twins fosters enhanced operational efficiency, predictive maintenance, and overall system resilience, driving the transformation of modern industries towards an interconnected and intelligent future (Fig. 7.3).

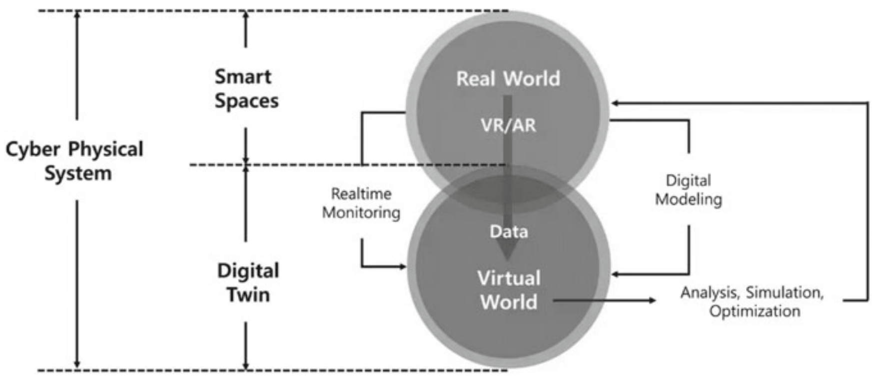

Fig. 7.3 Digital twin as natural outcome of CPSs

Simulation, in general, involves replicating the operation of real-world processes or systems, typically focusing on the evolution of physical quantities or entities of interest over time, across various physical domains. Simulation models describe mathematical, logical, and symbolic relationships among these entities, and these relationships can vary based on the intended use of the model.

Throughout the product lifecycle, different stages can be identified, and numerous simulation technologies have emerged over the years to address each of these stages. These simulation tools continue to evolve, offering increased fidelity and enabling a deeper understanding of how design decisions impact product behavior in real-world use. It's important to note that a digital twin isn't a single, all-encompassing model but rather a collection of interconnected operational data artifacts and simulation models. These models must be chosen with the appropriate level of granularity for their intended purposes and evolve throughout the product lifecycle. For example, simpler models may be suitable for conceptual product decisions, while more sophisticated simulations support detailed product design and manufacturing processes.

Digital twins generate vast amounts of data, necessitating robust data processing methods. AI models, which leverage ML techniques like neural networks, have become increasingly powerful thanks to enhanced computing capabilities. AI models can be deployed in cloud or distributed computing environments or embedded directly in physical objects like robots and vehicles to ensure data security and enable local processing of sensitive information. In distributed systems, ensuring data integrity is paramount, and blockchain technology can provide solutions for data protection and traceability of events throughout the product lifecycle. Blockchain can also facilitate the use of smart contracts, small software components that can automate actions such as maintenance or supply chain transactions within the digital twin ecosystem (Dittrich 2019).

Origin and History of Digital Twins

The concept of the digital twin has intriguing historical roots in NASA's Apollo project. During this project, a physical space capsule on Earth was used to simulate the behaviour of a similar capsule in space. While this example involved a physical representation, it captures the essence of having one object mimic the effects of another. However, the space capsule on Earth was not a digital representation.

Following NASA's lead, the US Air Force embraced digital technology for various purposes, including design, maintenance, and failure prediction. The goal was to use digital twins to simulate the physical and mechanical properties of aircraft to predict issues like fatigue or cracks, ultimately extending the remaining useful life (RUL) of these assets. As the concept of digital twins gained momentum, it found applications in sustainable space exploration and the design of aerospace vehicles, marking its continued evolution and relevance in various industries (Singh 2021).

Digital twins have various precursors leading to their modern incarnation:

- Mirror Worlds (1991): David Gelernter proposed the concept of "Mirror Worlds," where software models would replicate reality based on information from the physical world.
- Mirrored Spaces Model (2002): Michael Grieves introduced a model featuring real space, virtual space, and a linking mechanism to exchange data between them.
- Information Mirroring Model (2006): Grieves refined his model and renamed it the "Information Mirroring Model." This model introduced bidirectional linking between real and virtual spaces and allowed for multiple virtual spaces corresponding to a single real space, enabling the exploration of alternate ideas or designs.
- Digital Shadow and Digital Model: A digital model represents a physical object but involves only manual data exchange. It lacks real-time synchronization with the physical object. A digital shadow is a static copy of the physical object's data, with one-way data flow from the physical object to its digital representation. It does not reflect the real-time state of the physical object.
- Semantic Virtual Factory Data Model: The model represents virtual entities within a factory environment, primarily used in manufacturing and industrial contexts. Unlike digital twin, it focuses on data modelling alone and does not offer real-time synchronization with physical objects.
- Product Avatar: Product avatar is a distributed and decentralized approach to managing product information. However, it lacks the concept of feedback and may provide information on only specific parts of a product.
- Digital Product Memory: Digital product memory involves sensing and capturing information related to specific physical parts or products. It was a precursor to the broader capabilities of digital twin.
- Intelligent Product: The concept of an intelligent product incorporates technologies like IoT, Big Data, and ML but lacks the comprehensive integration and synchronization offered by digital twin. Digital twin builds upon the foundation of intelligent products.
- Holons: These are early computer-integrated manufacturing tools that laid the groundwork for subsequent technologies. They contributed to the development of concepts like digital twin.

Despite these early conceptualizations, practical implementation of digital twins faced significant challenges due to limitations in technology. Factors such as low computing power, limited device connectivity to the internet, inadequate data storage and management, and underdeveloped machine algorithms hindered the practical application of digital twins during this period. The concept of the digital twin evolved significantly with the rise of IoT, a fundamental component of Industry 4.0.

Figure 7.4 illustrates the progression of digital twin concepts over time.

Today, there is no universally accepted standard definition for the term "digital twin". Instead, various definitions have emerged based on specific characteristics that stem from different use cases involving digital twins. A common thread among these definitions is the integration of diverse data sources to create a digital representation of

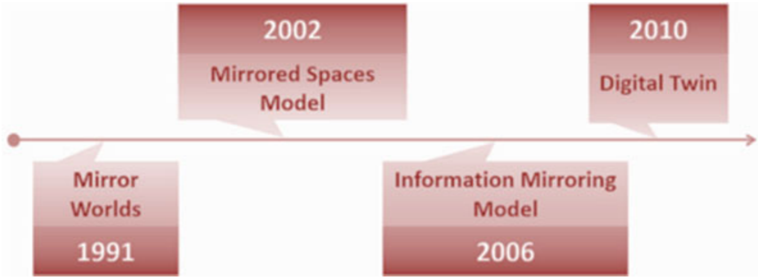

Fig. 7.4 Timeline of evolution of digital twin (Singh 2021)

a physical object or process throughout its entire lifecycle. This digital representation serves as the foundation for conducting various analyses and simulations (Van der Valk 2020).

A digital twin serves as a virtual model of a real-world system, process, or service and can be applied to model products, factories, or business services. It offers the capability for real-time monitoring of systems and processes, enabling timely data analysis to prevent issues before they arise, schedule preventative maintenance, minimize or prevent downtimes, explore new business opportunities, and plan future updates and innovations. While traditional virtual models often represent general concepts of a system or its components, a digital twin is an instance, a specific representation of a real-world counterpart. Digital twin technology can reduce the cost of system verification and testing while providing a real-time assessment of the system's performance.

In summary, the digital twin concept represents a significant advancement over its predecessors. It combines real-time synchronization, comprehensive data exchange, and feedback mechanisms between the physical and digital worlds. While earlier concepts served specific purposes, the digital twin integrates these functionalities to create a holistic and dynamic representation of physical objects, making it a valuable tool across various industries and applications.

Defining the Digital Twin

As mentioned above, the term "digital twin" is relatively new and has various interpretations and definitions depending on the context and organization. Different entities have their own perspectives on what a digital twin represents:

- General Electric (GE) refers to digital twins as "dynamic digital models of physical assets and systems."
- Siemens defines digital twins as "a digital copy that is created and developed simultaneously with the real machine."
- DNV GL describes digital twins as "a virtual image of an asset, maintained throughout the lifecycle and easily accessible at any time."
- SAP defines digital twins as digital representations that use real-time data from sensors to continuously represent a physical reality.

While these definitions vary, they all share common intrinsic characteristics that define what a digital twin is:

> Identity: A digital twin is always associated with a real-world object or system. It represents a one-to-one or one-to-many mapping between the object or system and its digital twin counterpart.

Representation: A digital twin captures the essential physical manifestation of the real asset in a digital format, which can include computer aided design (CAD) or computer aided engineering (CAE) models with corresponding metadata.

(1) *State*: Unlike traditional CAD/CAE models, a digital twin has the capability to render quantifiable measures of the asset's state in close to real-time.
(2) *Behavior*: A digital twin reflects basic responses to external stimuli, such as forces, temperatures, or chemical processes, within its operational context.
(3) *Context*: A digital twin describes the external operating context in which the asset exists or operates, including factors like wind, waves, temperature, and more.

These characteristics ensure that digital twins offer a genuine view of the virtual system and its real-world status. When the model corresponds uniquely to an identifiable object and accurately reflects its state, it qualifies as a digital twin. Furthermore, in some cases, digital twins can even initiate operational changes in the physical object they represent (Makarov 2019).

Benefits of Digital Twins

Digital twins offer several advantages, including:

- Monitoring and inspection: Digital twins enable monitoring and inspection of assets digitally, saving effort and resources compared to physical inspections, especially in challenging access scenarios.
- Data aggregation: Digital twins facilitate high-fidelity data aggregation, such as stress cycle counting in fatigue life utilization calculations.
- Remaining life assessment: Digital twins can assess the remaining life of structures, aiding in maintenance and longevity.
- Early damage detection: Digital twins can detect damage early, enabling pre-emptive maintenance and preventing shutdowns.
- Design feedback: Digital twins provide access to aggregated time series data for design feedback, transitioning from hindsight to foresight.
- Visualization and stress analysis: Digital twins allow visualization and inspection of stresses at inaccessible or hidden locations.

As technology advances, digital twins are becoming increasingly sophisticated, with high-definition maps and detailed mathematical models of physical objects. These digital twins have the potential to revolutionize various industries, from self-driving cars with highly precise maps to regulatory reviews of medical devices based on realistic mathematical models.

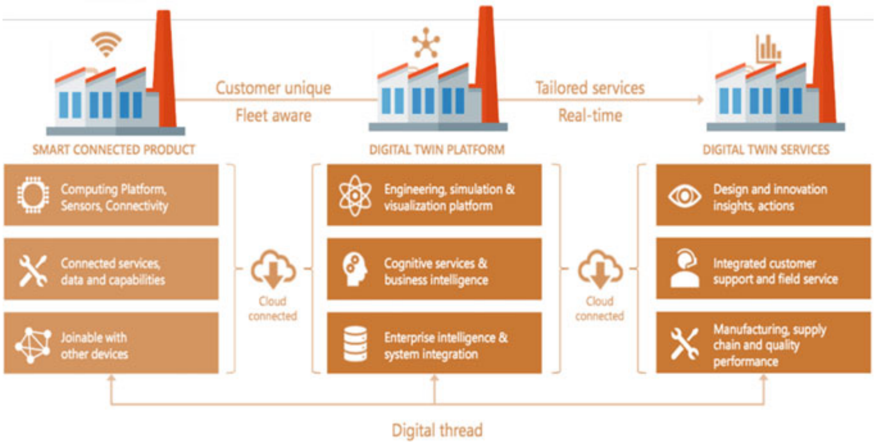

Fig. 7.5 Architecture of digital twins

Digital Twin Architecture

The digital twin architecture links physical and virtual worlds (Juarez 2021):

1. Physical World: This element encompasses the tangible, real-world entities targeted for replication or modeling by the digital twin. In manufacturing, these physical entities may encompass machines, equipment, assets, products, and the entire production environment. The physical world (see Fig. 7.5) includes devices and sensors:

- Devices: These are the physical objects or assets themselves, such as machines or equipment used in manufacturing processes.
- Sensors: Sensors represent physical components directly connected to devices, responsible for collecting real-time data and information from the physical world. Sensors capture essential data, which is subsequently transmitted to the digital world for processing.

2. Digital world: the digital world comprises two essential components:

- Virtual environment platform (VMP): The VMP serves as an integrated 3D digital model capable of executing applications and actions to validate various algorithms. It provides the foundation for creating and operating digital twins, offering the requisite models for their effective development and utilization. It can be considered middleware that links (see Fig. 7.5) smartness with delivered services.
- Digital twins: Digital twins are virtual representations of their corresponding physical objects. They faithfully mirror the life cycle and behavior of these physical entities, enabling a wide array of operations, including control, prediction, and analysis.

3. Connections between physical and digital worlds: These connections facilitate the exchange of data and information between the real and virtual domains. The nature of these connections may vary depending on the specific development methodology employed. They are vital for ensuring that the digital twin accurately reflects the state and behavior of the physical object.

These components collectively form the core of the digital twin concept. They enable organizations to create virtual counterparts of physical assets and systems, empowering real-time monitoring, analysis, and informed decision-making. This capability holds substantial potential for enhancing efficiency and effectiveness across various domains, including manufacturing.

Digital Twin Classes and Categories

Digital twins are applied across domains, playing pivotal roles in decision-making, real-time monitoring, and behavior prediction for tangible objects. The primary digital twin classes include:

- Digital twin of products: Originally developed for aerospace applications, this class manages data related to specific product lifecycles. Sensors capture real-time data for simulations.
- Digital twin of systems: This class predicts and reflects the behavior of systems throughout their lifecycles, aiding tasks like real-time monitoring and predictive maintenance in various fields.

Digital twins in Industry 4.0 can be also categorized into types based on their characteristics:

- Plain gadget models: These models encompass current values obtained from sensors and expected values the gadget aims to achieve.
- Embedded digital twins (EDTs): EDTs actively participate in all operations involving their real twins, enabling smart decision-making through bidirectional connections between the physical and digital realms.
- Networked twins: Networking enhances connectivity and information exchange among integrated EDTs in smart manufacturing.

The most relevant feature is the level of integration which reveals the relation of the physical object with the digital instance. Digital twins are classified based on the level of integration of data between real and digital twins:

- Digital model: This virtual representation doesn't use automated data interchange between real and virtual objects. Data may be manually entered, and changes in one twin don't directly affect the other (Fig. 7.6).
- Digital shadow: Involves automatic unidirectional data interchange from real to virtual objects. Changes in the real object directly update the virtual twin (Fig. 7.7).

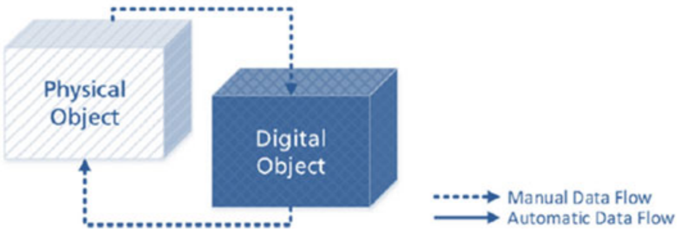

Fig. 7.6 No connection between model and real entity

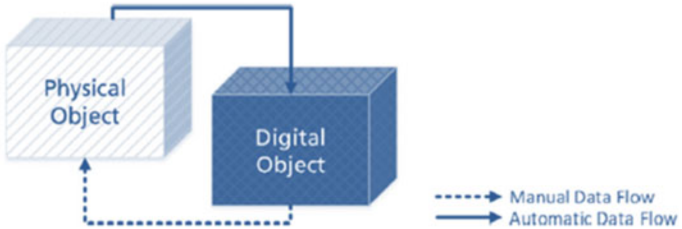

Fig. 7.7 One-way connection from real entity to reflection

- Digital twin: Features bidirectional data interchange between real and virtual objects, with changes in either twin directly affecting the other (Fig. 7.8).

A real digital twin exhibits three key characteristics (Fig. 7.8):

Real-time reflection: Digital twins maintain both physical and digital worlds, allowing synchronization through data exchange.
Communication and confluence: Digital twins involve communication and confluence within the physical world, between stored and current information, and between the physical and digital realms.
Self-evolution: Digital twins can refresh and modify real-time information, leading to positive changes in models and content as current information is compared with the physical world.

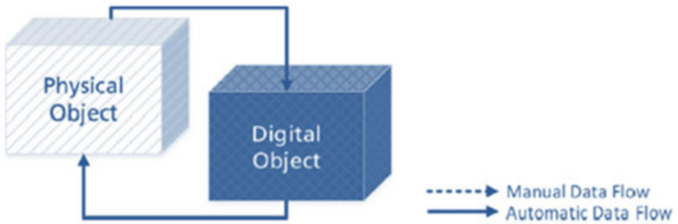

Fig. 7.8 Two-way connection and real twinning

Creating a Digital Twin Model

Creating a digital twin model is a complex endeavor, and there is no one-size-fits-all approach to building these virtual representations of real-world assets and systems. Different authors and practitioners employ different methods, methodologies, and modeling tools to develop these virtual counterparts (Makarov 2019). One of the most popular is the virtual prototyping powered by ALSTOM in energy and rail applications, as shown in Fig. 7.9, where physical models compensate for lack of knowledge extracted from data.

There are several variants to model a twin, but most comprise knowledge about the physics of the failure and the surrounding context of the asset:

(1) Systems Modeling Languages as a Basis for Digital Twins

Systems modeling languages play a crucial role in creating digital twins. These are graphical modeling languages designed to support the analysis, specification, design, verification, and validation of complex systems. They provide a structured framework for capturing essential aspects of systems, components, and objects. These aspects include:

- Structure, interrelation, and classification: Users can define the structural elements of a system, how they relate to each other, and their classification.

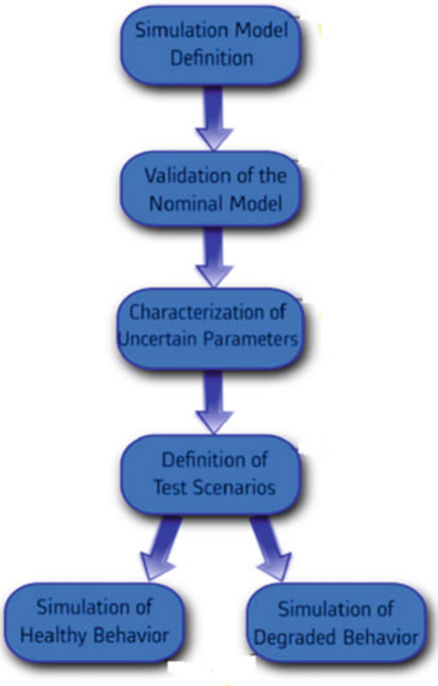

Fig. 7.9 Virtual prototyping process

- Behavior: They represent system behavior using functions, messages, and states, allowing a comprehensive understanding of how the system operates.
- Limitations: They permit the specification of physical and operational properties and constraints.
- Distribution: They help manage the distribution of elements, behavior, and limitations across a system.
- Requirements: They support the documentation of requirements and their relationships with other system conditions, design elements, and test cases.

2. Simulation as the digital twin foundation:

Simulation is a numerical method used to study complex systems by developing mathematical models of their elements and connecting these models into an informational representation. Hybrid models that combine AI with multiphysics simulations are becoming increasingly vital in the development of digital twins. These models harness AI's capabilities, including ML algorithms and data-driven insights, to augment the accuracy and predictive power of traditional simulations. One of the remarkable aspects of this integration is its ability to create synthetic data and compensate for the lack of real-world information (see Fig. 7.10). By incorporating AI into simulations, these hybrid models can analyze the complex interplay between various physical phenomena and forecast system behavior under diverse conditions. This integration leads to a more comprehensive understanding of intricate relationships among different variables, resulting in more precise and reliable digital twin models. Through AI-enhanced multiphysics simulations, organizations gain valuable insights into system performance, identify potential issues, and optimize operational strategies to enhance overall efficiency and resilience.

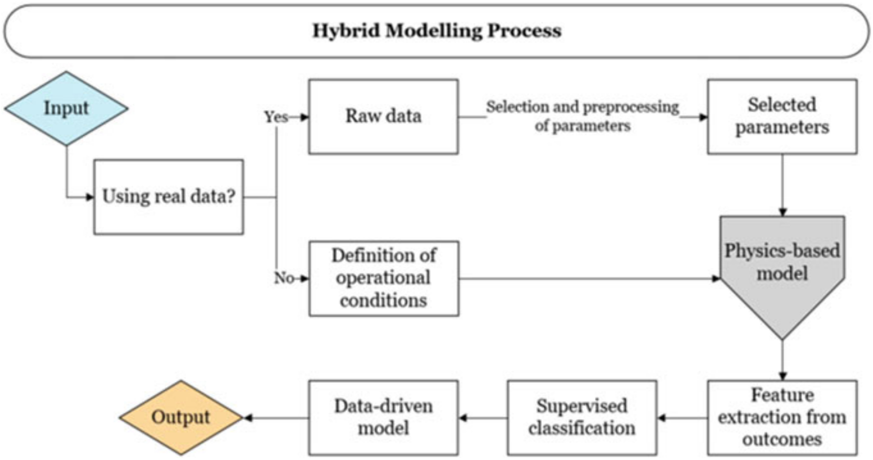

Fig. 7.10 Contribution of hybrid modelling to digital creation by means of simulation

When applying simulation to create digital twins, the following tasks must be addressed:

- Data acquisition: Gathering data from real-world objects is essential to create accurate virtual models that mirror physical objects.
- Software selection: It is necessary to decide whether to use universal simulation software or opt for custom development based on specific requirements.
- Effectiveness of digital twins: Digital twins are most effective in areas where formalized methods and mathematical models are integral.

Applications of Digital Twins

Digital twins play a pivotal role in enhancing the intelligence of operational systems across various industries. By maintaining an accurate and up-to-date representation of real-world operating assets, these virtual counterparts empower enterprises to exercise precise control and optimize both individual assets and the broader operational ecosystem. This representation encompasses not only the current state of assets but also their historical operational data. Digital twins offer a multitude of benefits, including optimization, automation, and predictive capabilities, and their utility extends to purposes beyond standard operations, such as virtual commissioning and the development of next-generation designs.

The key applications of digital twins span several domains:

Operations optimization: Digital twins excel in conducting what-if simulations that assess readiness and recommend adjustments. This capability enables organizations to optimize their operations, reduce risk, cut costs, and enhance overall efficiency. By running scenarios and evaluating potential changes, digital twins provide valuable insights into how to refine operational processes.

Predictive maintenance: Digital twins are invaluable in predicting the RUL of equipment and assets. By continuously monitoring and analyzing real-time data from these assets, digital twins can determine the optimal timing for maintenance or replacement. This proactive approach to maintenance helps organizations avoid unplanned downtime and costly repairs.

Anomaly detection: Operating in parallel with their real-world counterparts, digital twins are equipped to identify operational behavior that deviates from expected, simulated behavior. For instance, in the context of a petroleum company's offshore oil rigs that operate continuously, a digital twin can scrutinize sensor data to swiftly detect anomalies. This early detection is instrumental in preventing potential catastrophic damage or accidents.

Fault isolation: When anomalies are detected, digital twins can trigger simulations aimed at isolating the fault and identifying its root cause. This diagnostic capability empowers engineers or the system itself to take appropriate corrective actions promptly. By pinpointing the source of the issue, organizations can minimize downtime and ensure the safety and reliability of their assets.

In summary, digital twins serve as intelligent companions to real-world assets and systems, offering a range of capabilities that enhance operational efficiency, minimize risks, and optimize performance. Whether used for operations optimization, predictive maintenance, anomaly detection, or fault isolation, digital twins are instrumental in driving informed decision-making and ensuring the reliability and longevity of critical assets.

Some key sectors where digital twins are making a significant impact are:

- Manufacturing: Digital twins are revolutionizing the manufacturing industry by optimizing product design, production processes, and maintenance procedures. This optimization leads to reduced throughput times and enhanced operational efficiency, ultimately resulting in cost savings.
- Automobile: In the automotive sector, digital twins create virtual models of connected vehicles, capturing comprehensive behavioral and operational data. This data analysis aids in evaluating overall vehicle performance as well as individual connected features. Digital twins also enable personalized customer service, enhancing the automotive user experience.
- Retail: Digital twin technology is enhancing the retail industry by offering virtual representations of customers and allowing the modelling of fashion items on these digital avatars. This capability improves customer experiences by enabling personalized shopping recommendations. Digital twins are also used to optimize store planning, enhance security measures, and manage energy resources efficiently.
- Healthcare: Combining digital twins with IoT data has far-reaching applications in healthcare. These applications range from cost-saving measures to patient monitoring, preventative maintenance of medical equipment, and personalized healthcare solutions. Digital twins facilitate better patient outcomes and resource management in healthcare settings.
- Smart Cities: Digital twins, coupled with IoT data, play a crucial role in the development of smart cities. They contribute to economic growth, efficient resource management, reduced environmental impact, and an improved quality of life for residents. City planners and policymakers use digital twin models to access data from various sensor networks and intelligent systems, enabling more informed decision-making for urban development.
- Industrial IoT: In industrial settings, digital twins empower firms to monitor, track, and control industrial systems digitally. Beyond operational data, digital twins capture environmental data, including location, configurations, and financial models. These data enable the prediction of future operations and anomalies, enhancing operational efficiency and cost-effectiveness.

The digital twin concept has a transformative impact on various industries, offering opportunities for optimization, innovation, and data-driven decision-making. Its application extends to manufacturing, automotive, retail, healthcare, smart cities, and IIoT, where digital twins enhance performance, customer experiences, and resource management, while driving cost savings and operational efficiency.

Applications of Digital Twins Through the Product Lifecycle

The application of digital twins is a multifaceted concept that spans various stages of the product lifecycle and industrial processes.

- Product design and optimization: Digital twins are increasingly integrated into the product design stages, offering a quantitative tool for efficient and optimal decision-making. Data from previous product generations are amalgamated to form a comprehensive digital twin, facilitating knowledge transfer and enhancing the early stages of new product development. This approach leverages data from digital twins of past product designs to analyze and optimize new designs, streamlining the design process.
- Production and manufacturing: Digital twins have a significant presence in production systems. They are used to simulate production processes, predict outcomes, optimize operations, correct deviations, and evaluate system performance. By modeling manufacturing steps and entire machine tools, digital twins help determine the effects of tool behavior and process parameters, leading to optimized tool geometries and enhanced product quality. In additive manufacturing, digital twins are employed to evaluate 3D printed metallic components, reducing trial and error tests and shortening the design-to-production timeline. Complex production systems, characterized by interconnected manufacturing, quality control, and logistics processes, also benefit from digital twins. These systems involve stochastic and dynamic processes with non-linear dependencies that are challenging to address analytically.
- Optimization: Simulation models of digital twins are eventually used in combination with optimization programs to achieve various objectives, including selective part assembly, robust production scheduling, and the prediction of countermeasures in response to disturbances.
- Maintenance: Maintenance and refurbishment play key roles in shaping the behavior of assets, introducing new components, and even involving suppliers outside the original equipment manufacturer (OEM) supply chain. Third-party maintenance providers, with the appropriate service-level agreements, can modify assets independently of the OEM. This scenario imposes an obligation on asset owners or operators to maintain an up-to-date digital twin that accurately represents the asset's as-maintained state. Even if operators are not directly connected to the manufacturing supply chain, they must ensure the digital twin remains relevant. This requirement extends to facilitating the seamless handover of digital twin data from the manufacturing process to the operating process owner (Bächle and Gregorzik, 2019).

Despite the evident benefits, current approaches to digital twins often operate within distinct and separate disciplines. This siloed approach can lead to missed opportunities. Product design and specification may occur without considering more efficient production possibilities, and highly precise production processes may not take advantage of previously acquired product knowledge and the interactions of individual features.

In essence, digital twins offer a versatile set of tools that can revolutionize product design, manufacturing, and production systems. Their ability to simulate and optimize processes, predict outcomes, and facilitate human-robot collaboration holds immense potential for industries seeking to enhance efficiency, reduce costs, and accelerate development timelines. However, to realize these benefits, there is a need for greater integration and collaboration across disciplines to ensure that knowledge and insights from digital twins are leveraged holistically throughout the product lifecycle.

Digital Twins and Predictive Maintenance

A digital twin is a dynamic digital replica of a physical entity, bridging the gap between the physical and virtual worlds. It leverages IoT, AI, ML, and software analytics to create simulation models that continuously adapt to changes in their physical counterparts. Maintenance analytics is a crucial component within the context of digital twins and Industry 4.0. By integrating data-driven insights and analytics, maintenance processes can be optimized for efficiency and cost-effectiveness. Maintenance analytics leverages historical and real-time data to identify patterns, anticipate equipment failures, and schedule preventive maintenance tasks. This proactive approach ensures potential issues are addressed before they result in costly downtime or disruptions to production. With the integration of maintenance analytics, organizations can make informed decisions based on data-driven predictions, leading to improved asset performance, extended equipment lifespan, and overall operational resilience (Fig. 7.11).

Essentially, a digital twin evolves and updates itself based on multiple data sources, offering real-time insights into its present and future states.

Industry 4.0 has ushered in a strategic shift from reactive to predictive maintenance. Predictive maintenance assesses equipment conditions through periodic or continuous monitoring. The objective is to perform maintenance at the most cost-effective moment, just before equipment performance falls below a certain threshold. Digital twins have the potential to elevate predictive maintenance to the next level.

Analytical solutions for predictive maintenance empower organizations to proactively prevent unforeseen events and monitor asset conditions or entire production processes. When combined with the capability to simulate behavior, digital twins enable companies to optimize operations comprehensively and efficiently. They also facilitate testing of production developments and planned investments. Collaboration between predictive maintenance platforms and digital twins becomes crucial.

By simulating asset behavior and maintenance scenarios, digital twins inform decision-makers about critical maintenance Key Performance Indicators (KPIs) such as cost, downtime, RUL, end of life (EoL), and mean time between failures (MTBF). These simulations empower enterprises to plan future maintenance, enhance preventive and condition-based maintenance processes, and minimize unscheduled downtime (ReliaSol 2021).

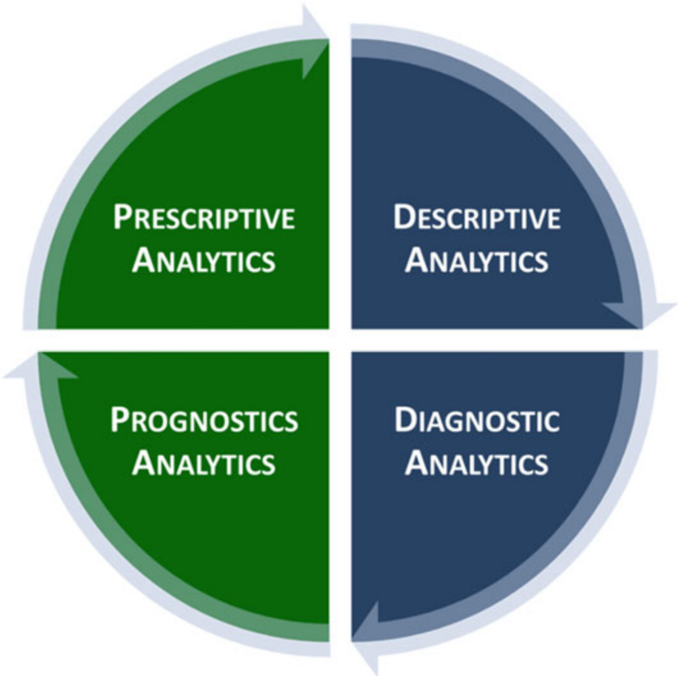

Fig. 7.11 Maturity stages in maintenance analytics

How Are Digital Twins Used in Maintenance?

Digital twins find significant utility in maintenance in the following areas:

- Digital simulation: Digital twins provide essential data for realistic asset behavior and maintenance simulations. These simulations consider risk factors, failure modes, operational scenarios, and system configurations. They yield maintenance-related KPIs like cost, downtime, RUL, EoL, and MTBF. Simulations support predictive maintenance planning and improve preventive and condition-based maintenance processes, minimizing unplanned downtime. Indeed, reliability, availability, maintainability, and safety (RAMS) knowledge during design is crucial to cover all the ways an asset might fail and therefore increase the digital twin detectability or predictability of such failure modes as depicted in the flowchart in Fig. 7.12.
- What-if analysis: Organizations leverage digital twins to simulate various maintenance scenarios (Fig. 7.13), aiding in the selection of the most effective strategy. These analyses contribute to long-term planning decisions, such as choosing between predictive and preventive maintenance strategies, and short-term choices like asset replacement.
- Maintenance system configuration: Digital twins synchronize with the status of their physical counterparts. Changes in the asset's status reflect in the digital twin

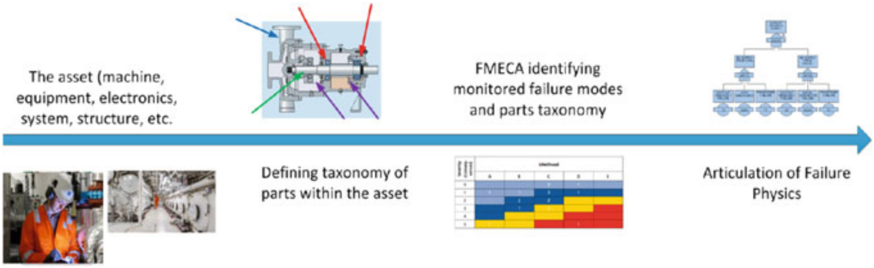

Fig. 7.12 Digital twin creation based on design information and RAMS parameters

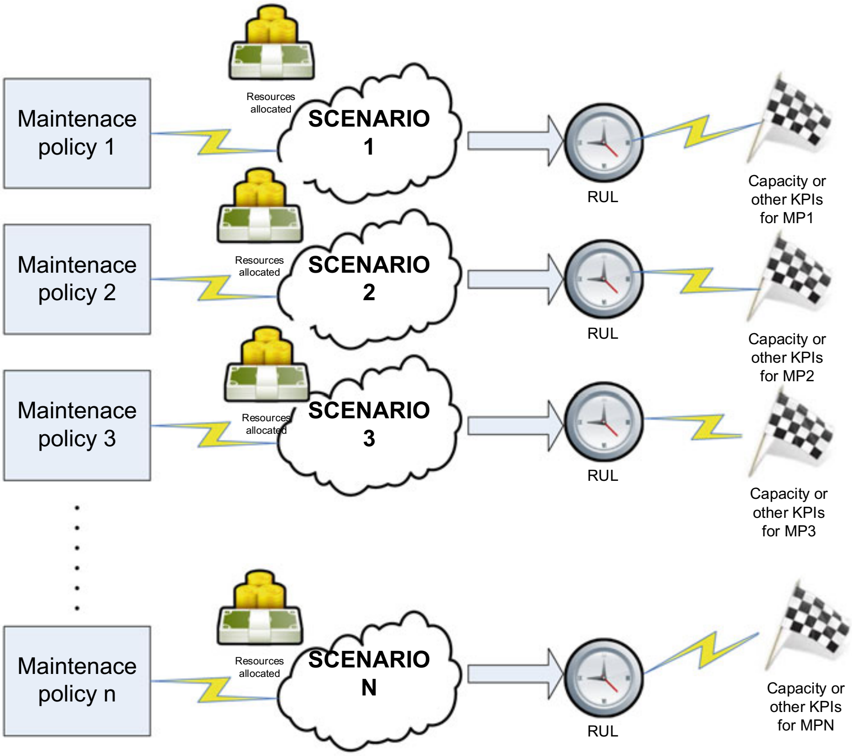

Fig. 7.13 Prescriptive analytics for maintenance performed in a digital twin for the optimal decision support system (DSS)

and vice versa. This synchronization allows digital twins to configure asset operation and related physical systems. Systems can adjust their physical components based on information and commands from their digital counterparts.

- Innovation: Digital twins serve as innovation catalysts in maintenance. They facilitate the testing, validation, and evaluation of innovative maintenance concepts without disrupting operations.

In fact, digital twins are transformative tools in maintenance, enabling data-driven decision-making, scenario analysis, and improved asset performance throughout the lifecycle.

Digital Twin Implementation Considerations

Digital twin technology represents an advancement in numerous industries, offering a holistic approach to enhancing operational efficiency and informed decision-making. This innovation allows organizations to create digital replicas of physical assets, enabling profound analysis and real-time monitoring. However, successful implementation requires careful consideration of multiple factors, including reference models, regulatory compliance, implementation phases, and organizational approaches.

Regulatory requirements: Digital twin technology serves as an invaluable tool for organizations aiming to conform to regulatory requirements. Particularly in industries subject to strict environmental regulations, such as automotive, marine, and aerospace, digital twins enable engineers to redesign components, significantly reducing emissions and helping organizations avoid regulatory fines and expenses (Altair 2019).

Timeline considerations: The timeline for implementing digital twin technology varies significantly based on factors such as the type of asset, accuracy requirements, feasibility, cost considerations, and technology readiness. At its core, a basic digital twin implementation necessitates:

- Edge capabilities, which encompass observing key aspects of the asset's real-time state and behavior. This typically involves deploying sensors with associated edge processing capabilities and enhancing data quality through processes like calibration, filtering, and time synchronization.
- Digital twin core runtime, which utilizes the data stream from the edge to create a (near) real-time digital representation of the asset's state.

The application layer integrates with the digital twin's data streams, becoming an integral component of various business processes, including user applications for monitoring and control, legacy applications for maintenance and asset management, and data analytics and ML stacks for pattern recognition and decision support (Erikstad 2017).

Practical considerations in implementation: A well-structured approach is crucial to the success of digital twin implementation (Roundy 2020). This organization involves four essential steps:

- Involving the entire product value chain: Collaboration across the product value chain is vital. Different departments within an organization face distinct business

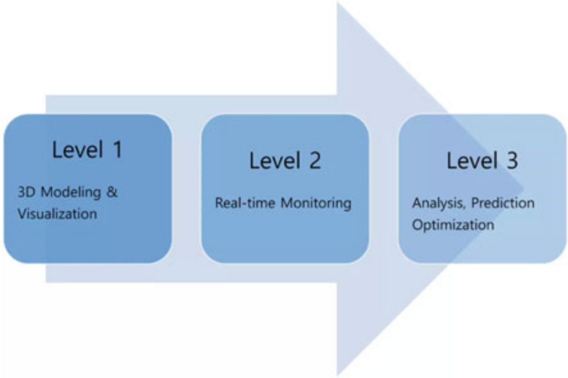

Fig. 7.14 Evolution from 3D models to predictive engines

challenges in their daily operations. A digital twin offers solutions to issues such as cross-functional collaboration, data-driven decision-making, and supply chain coordination. Gathering insights and inputs from stakeholders at all levels ensures a more efficient digital twin design.

- Establishing well-documented practices: Employing standardized and well-documented design practices enhances transparency and simplifies collaborative work. This approach fosters the communication of ideas across departments and regions, allowing multiple users to build or modify digital twin models without disrupting existing components.
- Incorporating data from multiple sources: A rich dataset from various sources, both internal and external, is fundamental for creating realistic and insightful simulations. While 3D modeling and geometry are sufficient for representing how parts fit together and how a product functions, predicting faults and errors requires extensive data and advanced analytics. Figure 7.14 shows the evolution of digital twins from 3d representations to analytic engines.
- Ensuring long access lifecycles: Avoiding vendor lock-in is crucial when implementing digital twins using proprietary design software (Roundy 2020). Assets with long lifecycles, such as buildings and industrial machinery, often outlast the software used to design them. To mitigate this risk, IT architects and digital twin owners should establish terms with software vendors to ensure ongoing data compatibility and avoid dependency on a single supplier.

In conclusion, digital twin technology offers immense potential when organizations pay close attention to reference models, regulatory requirements, structured implementation phases, industrial applications, and the broad range of benefits. The success of digital twin implementations is closely tied to embracing an inclusive approach, fostering standardized practices, leveraging diverse data sources, and ensuring long-term sustainability in the deployment of this transformative technology.

Cost of digital twin implementation: When implementing digital twin technology, various factors contribute to the overall costs, and the expected returns on investment (RoI) largely depend on the specific application and the scale of the asset systems.

The cost of implementing and starting up digital twins can vary significantly based on asset type, size, complexity, and the level of detail required by the client (Lengthorn 2021). Not all sectors have a quick payback in terms of ROI. The benefits and RoI of digital twins are particularly pronounced in the maintenance sector. The application of DTs in maintenance yields several positive impacts:

- Insights into asset management: Digital twins provide insights into asset management processes, enabling the optimization of maintenance strategies by identifying non-obvious failure or degradation patterns.
- Optimal maintenance decisions: Simulations enabled by digital twins facilitate optimal maintenance decisions, leading to improved Overall Equipment Efficiency (OEE) and better RoI.
- Automation and cost-effectiveness: Digital twins increase the automation and cost-effectiveness of maintenance processes, enhancing their flexibility.
- Transition to predictive maintenance: Digital twins aid in the transition from traditional maintenance approaches to more effective ones, like predictive maintenance, with minimal disruption to operations (Edge4industry 2018).

However, the design and construction of digital twins for maintenance applications remain costly and complex. To harness the benefits, various aspects must be considered:

- Understanding assets' physical properties, including electrical and mechanical specifications.
- Identifying failure modes, their criticality, and degradation patterns.
- Incorporating statistical information, such as failure probabilities and distribution functions.
- Aligning digital twins with maintenance and business goals, including cost targets, spare parts inventory, OEE, and risk management (Edge4industry 2018).

A phased approach, starting with simpler models and gradually incorporating more sophistication, is a practical way to implement digital twins while minimizing risks and gaining confidence in their use maybe less costly and a right approach for quick wins.

Digital twins have a significant impact on maintenance indicators by optimizing processes, improving decision-making, and increasing automation. They can lead to substantial cost savings, particularly in maintenance costs, by identifying and addressing issues proactively (Edge4industry 2018). Furthermore, digital twins have a substantial impact on the income statement of organizations. By integrating technologies like artificial intelligence, machine learning, and software analytics with real-time data, digital twins create simulation models that optimize development cycles, anticipate downtime, and enable real-time performance assessment (TWI 2021). However the ROI should be considered before deciding the adoption of such technology and the timing to design and deploy.

Conclusion: Advantages of Digital Twin Technology for Maintenance and Ongoing Issues

1. Advantages of digital twins in maintenance

Many companies across diverse industries are actively investing in digital twin technology, offering digital twin software solutions, or applying digital twins within their own operations (Sharma 2020). The adoption of digital twin technology has compelling benefits for enterprises, including:

- Continuous asset tracking: The ability to monitor assets, components, and processes in real-time.
- Efficient problem understanding: Quick identification and understanding of issues as they arise.
- Enhanced product and operation improvement: Opportunities to refine products, processes, and services based on real-time insights.
- Facilitation of innovation: Reduced risks associated with high-cost investments.
- Advanced planning through simulations: Improved planning and decision-making through the use of simulations.
- Effective problem tracing: The ability to pinpoint and address issues that traditional methodologies may miss.
- Predictive maintenance: Anticipating failures in terms of their type and timing, enabling proactive maintenance (ReliaSol 2021).

The latter point is especially important. Many assets, especially complex and long-lasting ones like aircraft, ships, locomotives, and wind turbines, undergo substantial changes throughout their operational lifespans. This necessitates efficient maintenance decision-making to prevent unscheduled maintenance, as it can lead to increased costs and operational delays. Predictive analysis has emerged as a key strategy for improving reliability and reducing unscheduled maintenance. Organizations are increasingly turning to predictive analysis to anticipate potential failures before they occur, addressing long-standing issues related to asset failures.

The digital twin plays a pivotal role in enabling effective predictive analysis. It serves as an exact replica of a physical asset, offering the essential context required for accurate predictions. This context encompasses the entire history of an asset, capturing its configuration and managing changes over time. The digital twin integrates data from various sources, including computer-aided design (CAD), simulation models, IoT data, time series data, and maintenance records, to provide a comprehensive and detailed picture of an asset's condition.

However, it's crucial to distinguish between digital models and digital twins. While there is a growing trend to use simulation or CAD models as digital twins, this approach can be problematic. These models may not accurately reflect the final as-built configuration of an asset, as changes often occur during manufacturing, modifications, and defect rectification. As assets undergo maintenance and upgrades over time, they may deviate significantly from the original models.

To maintain the effectiveness of predictive maintenance, it is important to continuously update the digital twin to reflect significant changes in an asset's configuration. This includes capturing alterations made during maintenance, such as component replacements. This constant updating ensures the digital twin configuration provides the necessary context for accurate predictive analytics. For example, it allows different maintenance approaches based on specific asset configurations, even if two assets have logged the same number of operating hours.

Predictive maintenance, powered by context-rich digital twins, relies on real-time data from IoT sensors. These data are sent to the digital twin configuration, where they are analyzed against OEM specifications. Multi-physics simulation models are then applied to interpret the data and predict potential component failures proactively.

Challenges and Barriers to the Adoption of Digital Twin Technology

Despite the promise of digital twins, their implementation can be challenging. Several common errors and pitfalls should be avoided to ensure success. These include repurposing a digital twin platform for different applications, attempting to implement digital twins across an entire production line or facility too quickly, neglecting data quality control, overlooking the importance of device communication standards for IoT devices, and failing to secure buy-in from users across the product value chain. Addressing these challenges and avoiding common pitfalls is essential to maximize the effectiveness and value of digital twin implementations across various industries.

- Digital twins focus on providing insights into physical systems. This limits their applicability in certain fields that require a more holistic understanding. For example, when used in urban planning, digital twins cannot address underlying sociopolitical issues, such as social inequality or housing crises. Thus, their use may not directly impact broader societal challenges (Kshetri 2021).
- Digital twin adoption may be hampered in developing economies, primarily due to the computational power required to create high-fidelity models, which can often exceed the available resources (Kshetri 2021).
- Cost is another issue, especially for projects with short lifespans. Implementing and maintaining digital twins can be prohibitively expensive, potentially undermining their viability (Sharma 2020).
- The intricate nature of digital twin technology further complicates matters. It demands seamless integration of various components, real-time tools, algorithms, and vast amounts of Big Data, a process that can be time-consuming and resource-intensive (Sharma 2020).

  Digital twins require continuous updates to remain aligned with advancements in related technologies and remain fit-for-purpose throughout their lifecycle (Sharma 2020). Correctly designing a DT to carry out its intended purpose and evaluating its performance are non-trivial tasks.

- Digital twins need an extensive and reliable data supply to function effectively. They produce copious amounts of data of various types, and users must be able to swiftly access and extract meaningful insights from this data. System knowledge often proves incomplete, inconsistent, or erroneous, posing challenges to data quality. Furthermore, issues related to sensitive data, such as privacy concerns and the protection of business secrets, can complicate digital twin development. Differing stakeholder perspectives on data quality, based on their unique purposes, add further complexity to the challenge. Accountability and transparency in data usage are essential to foster user confidence in the results (Pileggi 2021).
- In the realm of model fidelity, the challenge lies in determining which features of the system are most salient and relevant. Striking the right balance between too much detail, which can be costly and complicated, and too little detail, which may be insufficient, requires careful consideration. As the purpose of the digital twin evolves, the model, data infrastructure, and applications must be continually evaluated and adapted (Pileggi 2021).
- Maintaining the reliable operation of digital twins is another technical challenge. Digital twins are designed to be used throughout the lifecycle of a real-world object or system, which entails managing a complex blend of software, hardware, measurements, and simulations. This complexity escalates when various stakeholders from different organizations are involved concurrently. Maintenance, encompassing software upgrades, hardware component changes, and model adjustments, is crucial to ensuring that a DT continues to deliver value efficiently (Pileggi 2021).

  Effective use of digital twins necessitates the careful allocation of computational resources, often distributed across private and public clouds, vendor platforms, and high-performance computing resources. Security considerations must be integrated, and the system must be designed to prevent computational overload (Pileggi 2021).
- The absence of standardized definitions, common language, and established best practices in the industry poses a significant technological challenge. This lack of standardization can make it difficult to identify and address specific requirements for digital twin implementations.
- Dgital twins often require data related to product lifecycle management, which may come from a company's suppliers and even their suppliers' suppliers. Obtaining access to data on products and processes outside an organization can present challenges, including issues of data sharing and integration (Lawton 2020). To foster the development and widespread acceptance of digital twins, the industry needs to create standards and best practices. Establishing common definitions, language, and guidelines can facilitate smoother implementation and interoperability across various digital twin systems. These standards will play a crucial role in realizing the full potential of digital twins across diverse sectors.

In summary, the practical application of digital twins faces myriad challenges encompassing technical, knowledge-based, and organizational aspects. Overcoming these barriers is essential to fully leverage the potential of digital twins while recognizing their inherent limitations.

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