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Digital Twin

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Synonyms

Virtual twin

Definition

A digital twin is a digital representation of an active unique *product* (real device, object, machine, service, or intangible asset) or unique *product-service system (a system consisting of a product and a related service)* that comprises its selected characteristics, properties, conditions, and behaviors by means of models, information, and data within a single or even across multiple life cycle phases.

Theory and Application

The term digital twin (DT) was coined by Vickers and introduced as "Mirrored Spaces Model" concept by Grieves in the first executive Product Lifecycle Management courses at the University of Michigan in 2002 (Grieves 2005, 2014, 2016). The concept of the DT has historically evolved from the aerospace industry and has since then been translated into many areas. This may also be a cause for the fact that there is no uniform accepted scientific definition of the term, yet. Nevertheless, the subject was researched intensively during the last decade. An overview on definitions found in literature is given in Table 1.

Digital Twin Core Components and Dimensions

Digital twins received particular attention in the context of the digitization of all areas of life and the increased use of cyber-physical systems (CPS) and cyber-physical production system (CPPS). All entities in a digitized world can collect, generate, or process data and information in the context of specific operational and use processes. This creates a digital shadow of these entities, that is, a sufficient image to describe the state of the entity abstractly and, over time, a necessary evaluation database to describe its behavior (Schuh et al. 2016).

By incorporating the individual digital shadow of a product with generalized product description models that have been created during product

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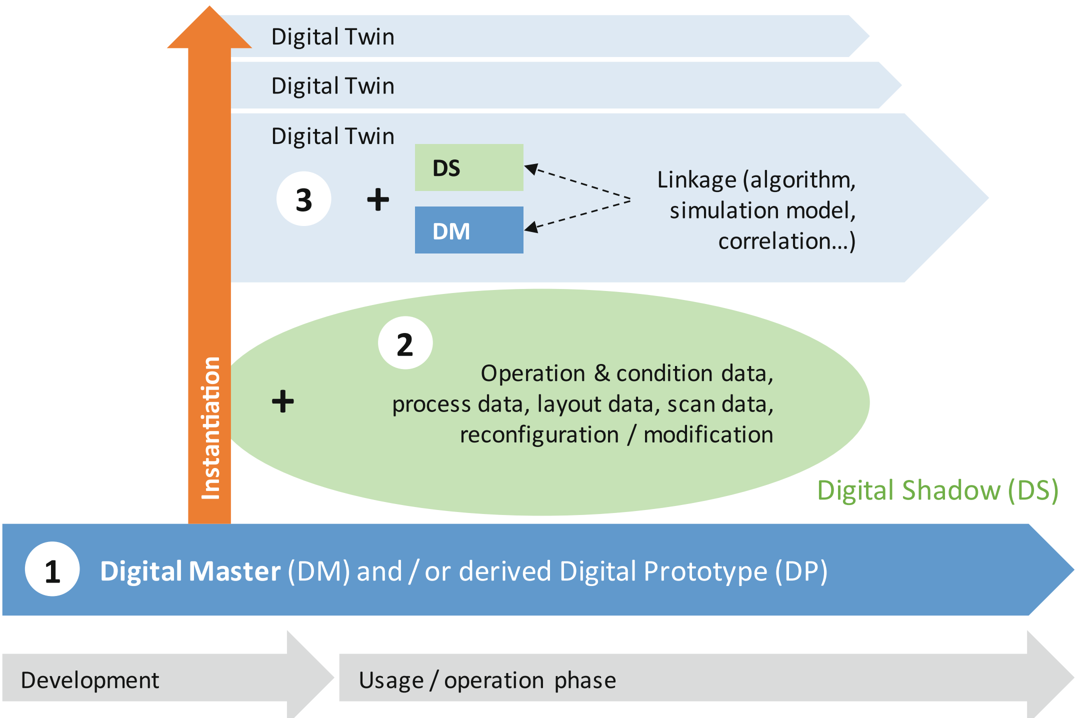
Digital Twin, Table 1 Definitions of digital twin in literature (extend version based on Negri et al. 2017, p. 941)

No.	Author	Year	Definition of digital twin
1	Shafto et al.	2010, 2012	An integrated multi-physics, multi-scale, probabilistic simulation of a vehicle or system that uses the best available physical models, sensor updates, fleet history, etc., to mirror the life of its flying twin. The digital twin is ultra-realistic and may consider one or more important and interdependent vehicle systems (Shafto et al. 2010, 2012)
2	Tuegel	2012	A cradle-to-grave model of an aircraft structure's ability to meet mission requirements, including submodels of the electronics, the flight controls, the propulsion system, and other subsystems (Tuegel 2012)
3	Gockel et al.	2012	Ultra-realistic, cradle-to-grave computer model of an aircraft structure that is used to assess the aircraft's ability to meet mission requirements (Gockel et al. 2012)
4	J. Lee et al.	2013	Coupled model of the real machine that operates in the cloud platform and simulates the health condition with an integrated knowledge from both data-driven analytical algorithms and other available physical knowledge (Lee et al. 2013)
5	Reifsnider, Majumdar	2013	Ultra-high fidelity physical models of the materials and structures that control the life of a vehicle (Reifsnider and Majumdar 2013)
6	Majumdar et al.	2013	Structural model which will include quantitative data of material-level characteristics with high sensitivity (Majumdar et al. 2013)
7	Rosen et al.	2015	Very realistic models of the process current state and its behavior in interaction with the environment in the real world (Rosen et al. 2015)
8	Ríos et al.	2015	Product digital counterpart of a physical product (Ríos et al. 2015)
9	Bielefeldt et al.	2015	Ultra-realistic multi-physical computational models associated with each unique aircraft and combined with known flight histories (Bielefeldt et al. 2015)
10	Bazilevs et al.	2015	High-fidelity structural model that incorporates fatigue damage and presents a fairly complete digital counterpart of the actual structural system of interest (Bazilevs et al. 2015)
11	Schluse, Rossmann	2016	Virtual substitutes of real-world objects consisting of virtual representations and communication capabilities making up smart objects acting as intelligent nodes inside the Internet of things and services (Schluse and Rossmann 2016)
12	Canedo	2016	Digital representation of a real-world object with focus on the object itself (Canedo 2016)
13	Gabor et al.	2016	The simulation of the physical object itself to predict future states of the system (Gabor et al. 2016)
14	Schroeder et al.	2016	Virtual representation of a real product in the context of cyber-physical systems (Schroeder et al. 2016)
15	Kraft	2016	An integrated multi-physics, multi-scale, probabilistic simulation of an as-built system, enabled by digital thread, which uses the best available models, sensor information, and input data to mirror and predict activities/performance over the life of its corresponding physical twin (Kraft 2016)
16	Bajaj et al.	2016	A unified system model that can coordinate architecture, mechanical, electrical, software, verification, and other discipline-specific models across the system life cycle, federating models in multiple vendor tools and configuration-controlled repositories (Bajaj et al. 2016)
17	Abramovici et al.	2017	A virtual twin is a model that integrates interdisciplinary (mechanics, electronics, software, and services) virtual product models and related real-time data of a product instance (physical twin). A virtual twin can be dynamically generated from a model and data space to fulfill a specific task (e.g., dynamic reconfiguration of a smart product during its use phase) (Abramovici et al. 2017)
18	Stark et al.	2017	A digital twin is the digital representation of a unique asset (product, machine, service, product-service system, or other intangible asset) that compromises its properties, condition, and behavior by means of models, information, and data. (Stark et al. 2017)

(*continued*)

Digital Twin, Table 1 (continued)

No.	Author	Year	Definition of digital twin
19	Schleich et al.	2017	In synthesis, the vision of the digital twin describes the vision of a bi-directional relation between a physical artifact and the set of its virtual models. In this context, the virtual "twinning," i.e., the establishment of such relations between physical parts and their virtual models, enables the efficient execution of product design, manufacturing, servicing, and various other activities throughout the product life cycle (Schleich et al. 2017)



Digital Twin, Fig. 1 A digital twin consists of a digital master instance that incorporates the digital shadow of a product

development and have been stored in the digital master or derived digital prototypes, e.g., geometry (e.g., computer-aided design models) or simulation models (e.g., computer-aided engineering models), a digital twin is created.

Hence, a digital twin consists of:

1. A unique instance of the universal digital master (and/or digital prototype) model, tailored to its specific purpose
2. An individual digital shadow of a product, i.e., data measured and acquired during the operation and use of the product, gadget, or machine in the factory, in the field or during logistic transport activities
3. A meaningful linkage of the digital master (and/or digital prototype) instance and a digital shadow using, e.g., algorithms, simulation models, correlations, etc.

Figure 1 depicts this refined definition. While in the development phase different types of digital simulation models are created and used to demonstrate the functionality or behavior of a product under development in the form of generic digital prototypes, the digital twin can be clearly delimited since it designates all types of digital correlation or simulation models which can be used to represent the functionality or behavior of unique real products in operation and interaction.

The digital twin concept and solution can be applied in numerous fields and for different purposes. Concerning use cases, digital twins can realize capabilities of visualization, interaction, or simulation. On the product side, the scope of a digital twin might address a certain component, whole products, or even systems of products. Furthermore, digital twins can be created for a singular instance of a product as well as accumulating digital twins, e.g., for product families or fleets. Therefore, digital twins need to be tailored under consideration of its specific business context.

A structured approach for planning the scope and type of digital twins is the "Digital Twin 8-dimension model," as depicted in Fig. 2. One can distinguish the dimensions with focus on digital twin environment and context, marked in orange, and the dimensions with focus on behavior and capability richness marked in green. The area of *digital twin environment and context* is represented by the four dimensions integration breadth, connection mode, update frequency, and product life cycle. *The* digital twin behavior, respectively, *capability richness* comprises the other four dimensions, i.e., the CPS intelligence, the simulation capabilities, the digital model richness, and the human interaction. Each one of the dimensions has three or four levels: a higher level is not necessarily better than another but depicts a different and/or unique realization space. Four out of the eight dimensions, dimension 1 (*integration breadth*), dimension 2 (*connectivity mode*), dimension 7 (*human interaction*), and dimension 8 (*product life cycle*), however, do express with their increasing levels also an increasing degree of richness (dimension 2 and 7) and of breadth and extent (1 and 8).

The model explains to which major "behavior capabilities" a specific twin is designed for by allowing multiple target levels in each of the eight dimensions. Those eight dimensions are not exclusive or exhaustive but represent the most likely dimensions which are of importance to support the individual business context situations of the specific digital twin in scope.

The model is not to be understood as a strict maturity model. The "Digital Twin 8-dimension model" can be used:

As guidance in the development of a completely new product with the help of an already existing digital twin

To extend existing products with the knowledge gained from a digital twin

To further develop digital twins as a product or service by its own (i.e., as a template), adding new functions along the eight dimensions as necessary

1. Integration breadth	2. Connectivity mode	3. Update frequency	4. CPS Intelligence	5. Simulation capabilities	6. Digital model richness	7. Human interaction	8. Product Life cycle
Level 0 Product/ Machine	*Level 0* Uni-directional	*Level 0* Weekly	*Level 0* Human Triggered	*Level 0* Static	*Level 0* Geometry, kinematics	*Level 0* Smart Devices (i.e. intelligent mouse)	*Level 0* Begin of Life (BoL)
Level 1 Near Field / Production System	*Level 1* Bi-directional	*Level 1* Daily	*Level 1* Automated	*Level 1* Dynamic	*Level 1* Control behaviour	*Level 1* Virtual Reality / Augmented Reality	*Level 1* Mid of Life (MoL) + BoL
Level 2 Field / Factory environment	*Level 2* Automatic, i.e. directed by context	*Level 2* Hourly	*Level 2* Partial autonomous (weak AI supported)	*Level 2* Ad-Hoc	*Level 2* Multi-Physical behaviour	*Level 2* Smart Hybrid (intelligent multi sense coupling)	*Level 2* End of Life (EoL) + BoL + MoL
Level 3 World (full object interaction)		*Level 3* Immediate real time / event driven	*Level 3* Autonomous (full cognitive-acting)	*Level 3* Look-Ahead prescriptive			
Digital Twin (DT) environment			Digital Twin (DT) behavior & capability richness				DT Life Cycle context
Living Digital Twin							

Digital Twin, Fig. 2 The "Digital Twin 8-dimension model" for planning digital twins according to their purposes

The first dimension, *integration breadth*, describes the scope and extensions of the digital twin and the environment to be considered within the digital twin. The second dimension, *connectivity mode*, distinguishes the capabilities needed to realize a digital twins' communication capabilities. While *uni-* and *bi-directional* connectivity are self-explaining, *automatic* connectivity features a context-aware self-directed communication capability.

Dimension no. 3, *update frequency*, refers to the questions on how often a digital twin needs to be updated with data from the digital shadow. However, countless update frequencies in the range from continuously to event driven are imaginable. Hence, these levels proposed are understood as an orientation and do influence heavily data acquisition and associated data analytics and reduction operations with the help of information technologies.

As already described above, a digital twin may include models and algorithms, e.g., from the field of machine learning or, respectively, artificial intelligence, which enable intelligence for automation. Therefore, the dimension *CPS intelligence* distinguishes different levels of intelligence. While level 0, *human triggered*, refers to intelligence provided solely by users, level 3 (*autonomous*) describes human-like intelligence to be provided by future artificial intelligence and cognitive solutions. Between these, *automated intelligence* describes rule-based approaches, while *partly autonomous* stands for advanced solutions, utilizing machine learning and artificial intelligence methods for analytics and decision-making.

Concerning the simulation features of a digital twin, the dimension *simulation capabilities* delimitates four levels. *Static* describes simulations where input parameters and the simulation model are not defined time-dependent. In contrast, the level *dynamic* aims for a time-dependent definition of input parameters and the simulation model, for example, as seen in fluids or deformation simulations. A further level, ad hoc, describes simulations based on behavior models and is executed with current parameter values. This enables real-time digital twins and, for example, the utilization within in-the-loop simulation scenarios. The fourth level, *look-ahead prescriptive*, designates digital twins equipped with predictive simulation capabilities, e.g., used for predictive maintenance services or bottleneck prediction in self-organized nondeterministic Industry 4.0 shop floor environments.

Aligned with the *simulation capabilities*, dimension no. 6, the *digital model richness*, needs to be adjusted accordingly. This dimension describes which characteristics of a product are mapped to its digital twin. Three levels are distinguished: *geometry and kinematics* describe a mapping of the product's current shape, leveled from its abstract representation to an ultra-realistic rendering and degrees of freedom for movable parts. For kinematics the level *control behavior* adds models that describe the behavior of movable parts, e.g., the control code that describes reactions on interactions, inputs, and outputs. Ultimately *multi-physical behavior* models can be mapped: an example is the integration of a signal propagation model for a 5G base station digital twin. While this is actually not mentioned by authors explicitly, it also seems plausible to create digital twins with abstract models that are not directly product-related, e.g., using human behavior, but, concerning the *integration breadth*, represent specific entities of the overall product context.

The *human interaction* dimension refers to digital twin user interfaces. *Smart device* stands for digital twin interfaces tailored to commercialize off-the-shelf hardware, e.g., an intelligent mouse or an app on a smartphone, which utilizes and combines built-in capabilities to enhance the digital twin with functionalities, e.g., for event-related service calls. For higher visual fidelity, in certain use cases, a digital twin can offer *virtual or augmented reality* interfaces for its user. A further level, called *smart hybrid*, enhances the experience via intelligent multisense couplings, e.g., with additional interaction options like haptic technologies.

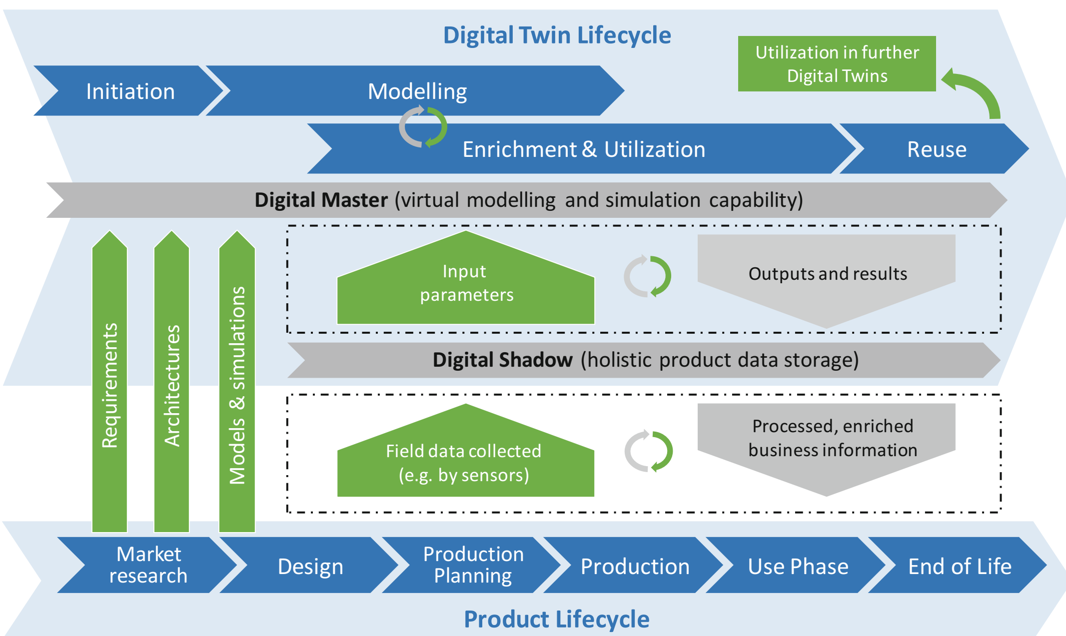
The last dimension, *product life cycle*, is related to the life cycle phases of the product or system in question supported by the digital twin. Based on a simplified three-phase product life cycle model (begin of life, BoL; mid of life, MoL; end of life, EoL), the three levels are distinguished, ranging from one to three phases, whereas the base assumption is to start with BoL and then extend further via the inclusion of the other life cycle phases. This complies with the basic definition that the digital master and its derived digital prototypes are originally established in the BoL life cycle phase.

While the presented eight-dimension model is suitable for planning digital twins, further research is needed toward a reference model, considering the digital twin model itself in terms of abstraction, representation, and properties. First thoughts were suggested by Schleich et al. (2017).

Digital Twin Business and Life Cycle Considerations

Having designed and understanding a digital twin as a self-contained digital product, considerations of the interdependence between the business intention and the life cycle of a product (machine, object, gadget, etc.) as well as its linked services and the life cycle of an associated digital twin are crucial. Furthermore, since a digital twin does have a physical twin along its entire life cycle, it is necessary to separate digital twin and physical product life cycles in order to differentiate what life cycle data can be requested for the definition of the digital twin (Abramovici et al. 2017).

Figure 3 describes a principal four-phase model of a digital twin life cycle and depicts its correlations with the product (and service) life cycle. In the earliest phase of the digital twin life cycle ("the birth of a digital twin"), it is essential to recognize and understand the business acumen which should be driving the digital twin business role: requirements toward the operational needs and opportunities like "intelligent and data-driven operational monitoring with integrated model learning" or "opportunity for development staff to allow for new functional and behavioral execution during specific use pattern" need to be analyzed and detailed out in close conjunction with the intended operational product or service. Subsequently, the digital twin architectures and the appropriate digital twin design elements are to be identified and engineered. The target conditions of the digital twin operation require certain digital



Digital Twin, Fig. 3 Relation between the product and digital twin life cycle. Updated version based on Halstenberg and Stark (2018, p. 18) models and simulations which partly might already exist due to the virtual product creation work of the products and services themselves. Additional ones are to be determined and will drive certain data and information acquisition capabilities. The digital twin start of operation might already be triggered during the phase of physical prototyping in the product creation process, but at latest it will be triggered on a specific instance level at the start of use of the machine or production line in the real factory ("digital production twin") or by sampling product data as part of the "digital product twin" before it will further get enriched by the digital shadow of the product during its field operation. The output results have to cater for the intended business goals of the twinning operation as determined during the requirements and architecture phase.

It should be pointed out that a digital twin does not necessarily require a full smart product. Even for simple products, i.e., individual components, digital twins can be implemented. They need, however, at least sensor and IoT capabilities which both represent a subset of a smart product. Alternatively, data of such simple products/components may also be an integral part of a superordinate digital twin of a bigger system. For example, the operating data of a production system can be combined with data of components to be assembled from quality and geometry assurance perspective. This would allow for both, the in-line optimization of production but also a new level of traceability in component production beyond the batch number approach.

Outlook on Digital Twin Perspectives of the Future

Digital twins are not yet fully established, neither in engineering and applied information technology nor in production and maintenance business. Due to a deeper understanding of the difference to an ordinary digital master and to traditional operational data in factories and in the operational field of products and due to new potentials in information technologies, it will now be possible to conduct further research and engineering work on the following challenges moving forward:

How to best represent a (living) digital twin?

Which digital master (and prototype) models allow for a good fit with which type of digital shadows (operational data and information sets)?

Which business models lend themselves the best foundation for the operational use of digital twins?

Which technology mix is crucial to minimize the IT footprint for live and history digital twins?

How to drive new engineering curricula in order to provide the right skill set to develop, operate, and effectively use digital twins in business?

Another open question is whether digital twins are a mandatory prerequisite/enabler for the implementation of smart factories and Industry 4.0. Since human cognitive abilities are limited, it is believed that as system complexity increases, the need for DT solutions to foster autonomy will increase, whether it is for managerial task or the control of detailed processes.

Cross-References

▶ Cyber-Physical Systems
▶ Product Life Cycle Management
▶ Simulation of Manufacturing Systems
▶ Smart Products

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