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ScienceDirect

Procedia CIRP 91 (2020) 27–32

www.elsevier.com/locate/procedia

30th CIRP Design 2020 (CIRP Design 2020)

Review and comparison of the methods of designing the Digital Twin

Dmytro Adamenko[a,*], Steffen Kunnen[a], Robin Pluhnau[a], André Loibl[a], Arun Nagarajah[a]

[a]University Duisburg-Essen, Lotharstr. 1, 47057 Duisburg, Germany

* Corresponding author. Tel.: +49-203-379-3431; fax: +49-203-379-4379. *E-mail address:* dmytro.adamenko@uni-due.de

Abstract

Digitization is changing our world and industry. One of the flagships of the current industrial revolution, the so-called Industry 4.0, is the digital twin. The term digital twin is being widely discussed, but it is often unclear to the operators and contractors what added value can be generated from the digital twin and how business models can be shaped in the digital world due to unclear creation and updating procedures and costs. The deterrent factors are the large-scale effort of building the digital twin and synchronizing it with the real object. The partial models as well as the planning, live and historical data have to be integrated into a single framework. The goal of this paper is to analyze different applications and the possible design methods of the digital twin. Another aim is to present the advantages and disadvantages of the respective methods and to suggest suitable design methods for the selected applications.

Keywords: Digital Twin;

1. Introduction

Industry 4.0 and digitalization provide countless subject areas that are constantly evolving. In addition to cross-company system integration, the virtualization of workpieces, components and assets – via digital twins - is a particular driver of the trend towards tight integration. In principle, every component and every process can be virtualized by a digital twin. The combination of both would then enable complex images of entire systems. However, this is only possible if the digital images go beyond traditional simulation models and are capable of permanent feedback with their real counterpart.

The digital twins (DT) will now be deployed throughout the product lifecycle and will be able to develop the new business models for different companies with different functions. So far, there is no company that offers a holistic solution for the digital twin. Also the areas of application and the construction methods differ a lot from company to company.

The digital twin is a concept that uses the networking of components and the insights into performance available from the process data. It is gaining more and more interest from companies and is gaining importance in industry but has not yet fully established itself. One of the reasons is the lacking clarity, how should digital twin be built up.

In the next step, the requirements and the basic procedure for creating a digital twin are described. The basic framework, which is useful for the generation, as well as the most different models are considered. Also the data that must be collected and possible data transfer and storage methods are considered. Therefore different platforms, which can be used to create a digital twin, are examined and compared and the different approaches to create a digital twin are explained.

Finally, the advantages and disadvantages of different construction methods depending on the application and business models are presented.

10.1016/j.procir.2020.02.146

2. State of art

2.1. Definition of the digital twin

There is still no standardized definition of a digital twin. There are many different descriptions for a digital twin that differ depending on the purpose and scope. The comparative analyses carried out by Martinez et. al. [1] and based on the Canvas business model show clear differences in the interpretation of the concept of the digital twin and its use as a business model. For the further course of this work, the digital twin is defined as a digital image of a physical object from the real world. This exact copy contains all properties, information and states of the real object.

Starting as an approach with high commercial impact the added value of the digital twin became significantly higher, and thus gained more and more attention and importance in many companies and industries. Gartner has placed digital twin in the top 10 strategic trends for 2019 [2]. In addition, Gartner estimates that by 2021, half of all major industrial groups will be using digital twin, enabling them to increase effectiveness by up to 10% [2].

With the digital twin, a real object has a digital image that consists of different models. These models have five main functions:

- to accurately reproduce the properties, behavior, and rules of the physical object to create an accurate image.
- autonomous operation of the models thus simulation of different behaviors of the object, which can then be used as guidelines for the operation of the physical object.
- remote condition monitoring of the assets.
- ability to predict problems before they occur.
- validating the performance before the product is even finished [4].

The data flow between the components of the digital twin ensures that the digital twin can be operated continuously. In addition to the data collected by the sensors, the data also includes data from simulations and other knowledge related to the physical object [4].

The connections between the components are necessary to enable the interactions of all elements of the digital twin. These connections can be categorized into three groups:

- connections in physical space
- connections in virtual space
- connections between virtual and physical space.

The interactions between the elements of the digital twin enable iterative changes and optimizations [4]. Through services, the functions and information of the digital twin are prepared for the user in such way that he can access the information and functions easily and without much prior knowledge [4]. All relevant data that is generated during the life cycle flows into the digital twin and continuously develops it further [5].

2.2. Requirements of a digital twin

In order to realize an exact image of a real system with the digital twin, it is necessary to incorporate all available information in single framework. Beside geometrical and simulation models and in addition to environmental conditions and sensor data, this also includes data such as operating settings, inspection and maintenance information. The information can be used to display the relationships between individual components and systems. The data must be continuously transmitted to the digital twin in order to represent an up-to-date image [6]. The collected data must be stored, managed and converted into a format that can be used for algorithms or simulations. Currently, there are no generally accepted standards and specifications. Therefore, it is still a big challenge to combine the data from different sources with different interfaces and data formats in real-time applications [4].

In order to fulfill the continuous transmission of the data, an infrastructure is required that enables a real time interaction between virtual image and physical object. This infrastructure includes, among other things, internet connection and speed as well as sensors and embedded systems. With the infrastructure, it must be possible to transmit and process information in real time. In addition to the required infrastructure for the development and operation of a digital twinT, time is needed to create the various high-resolution models with existing hardware and software. The costs and effort have to be compared to the benefits of digital twin [4].

A digital twin must also be adaptable. This means that if something changes in the object itself or in the environmental or operating conditions, these must be adaptable in the digital twin via the model parameters without great effort. If individual components or systems are replaced during maintenance, this information must be stored in the digital twin and the models adapted to the new component [4].

A digital twin is always unique, it refers to exactly one object in the real world and collects data over the entire life cycle of this one object and not of several.

However, a digital twin can learn from other DTs of the same objects, the experiences of all twins are thus scalable to one. Comparisons between single digital twins can be made. If a malfunction occurs, the cause of the problem as well as the solutions to this problem can be determined more easily from similar cases on another product.

In addition to physical models, artificial intelligence (AI) and machine learning technologies can be used for the digital twin. Using AI, patterns in the data can be identified and possible disturbances or anomalies can be identified. These different physical and analytical models must be linked to each other and exchange data in order to realize an image that is always up-to-date [4].

User interfaces are created for interaction with the digital twin. These user interfaces must be designed in such a way that the user is presented with the results of simulations or other analyses in such a way that he receives the required information and can carry out the required actions without much prior knowledge. A distinction must be made between the different user groups. For each user group a unique surface must be provided. A single interface for all users together would be overloaded with too much information. Accordingly, every employee needs an interface that provides the relevant data and information for one specific task[4].

In addition to the requirements that have to be fulfilled in order for a digital twin to bring an added value, the security of the twin also plays an important role. Since it has all current and historical data and models of the object, it must be protected against unwanted access. In addition, different profiles must also be set up for different user groups so that everyone only receives the information they need and may receive [4].

2.3. Applications of a digital twin

One of the main applications of digital twin is an overarching exchange of information about the value chain of an asset. It requires the ability to represent different systems and information in a common language and bring it to a single platform. In addition, the digital twin is extended by algorithms that describe objects of the real world with a suitable accuracy. Today, there is already a shortage of skilled workers, which will become ever stronger in the future. As a result, asset operators no longer have the ability to constantly track the actual status but must develop strategies for keeping it up-to-date and consistent with as little manual effort as possible. A development of this idea leads to the realization that in the world of digital twin the relationship between plant operators and contractors will change and the digital twin will help to realize the transition from Document Handover to Data Handover.

The digital twin has several advantages. The first advantage is the significantly increased transparency. The various models, which always have up-to-date information make it easier to supervise the product or system. Information is displayed in such a way that the user can see the current status directly and clearly. Among other things, there is the possibility of 3D visualization of current states [4].

Another advantage of a Digital Twin is the reduced time required to bring a product to market. Simulations can be used to predict how the product or system will behave before it is even completed. In this way, weak points and potential sources of error can be eliminated without great effort. On the other hand, the later users of the product or system can interact with the high-resolution virtual models. This allows further customizations after feedback from the customer to optimize the product and system for later use. Iteration steps with prototypes are omitted.

In addition to the reduced time-to-market, the performance of the product or system can always be optimally maintained. Since physical product and digital twin exchange data in real time, the current performance can be analyzed. If environmental or operating conditions change, individual parameters are automatically adjusted so that the product or system always behaves as planned. Process monitoring and diagnosis are also widely recognized as important advantages of a digital twin for improving quality and detecting abnormal behaviour, leading to more efficient approaches for maintenance, which costs and duration can be reduced. Future problems can be identified through continuous data collection, analysis and simulation [4]. The simulations are usually based on the entire data history. Maintenance can be planned in advance as the lifetime of individual components is predicted. Using predictive maintenance, these components can be replaced before faults or failures occur [7].

The asset information model must cover all possible aspects throughout the lifecycle. For economic reasons, it is not feasible to throw away planning models after the end of planning and not continue to use them in the operating phase. It should be emphasized here that information about the asset is an asset that has a certain value for the operator of the asset. An asset needs to be maintained to preserve its value. This applies to a physical asset as well as to an information model.

Since there are already established partial models in different trades, the development of a monolithic overall model is not expedient. Rather, the existing submodels must be combined without contradiction and meaningfully supplemented. This can be realized technically via object links at the data level or via service systems.

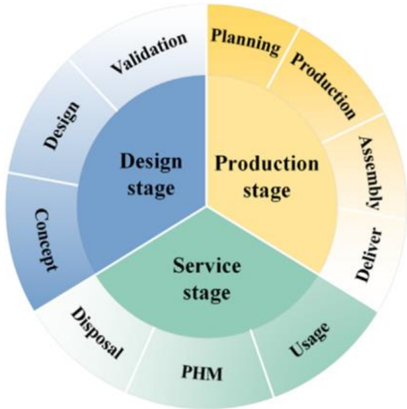

Fig. 1. Product life cycle [3]

Already during the planning and development of an object or a process, simulations with digital twin can be used to predict whether the desired properties and functions can be fulfilled. Optimization of design or performance can thus be carried out in advance [8]. Tests on prototypes can be replaced by simulations on the digital twin which result in a reduction of costs and time [9]. Digital twin can also influence the planning and development of new products by analyzing objects already in use. With the help of the data generated with the digital twin, the user behaviour or operation can be analysed. In this way, improvement possibilities for new products can be identified [4, 10].

The combination of real-time data and simulation models also allows virtual sensors to be placed on the model. This means that data from virtual sensors can be used to generate new insights at locations that would normally not be accessible to sensors [11]. Digital twin can also be used to perform what-if analyses. Changes in environmental conditions or settings can be tested on the digital image [12]. It is also possible to deliberately activate possible errors in the simulation model in order to generate measurement data for these cases, which can then be used for predictions [11].

In summary, the twin serves to analyze the current condition, to predict failures and to identify and eliminate the causes, to minimize downtime, to optimize performance and to help in the development of the new generation of products with the collected knowledge. The digital twin helps to increase efficiency and reduce costs. Therefore it will be used in more and more areas in the future.

3. Building up a digital twin

As the literature review shows, digital twin can be designed in main two different ways. One possibility is to create a system model of the physical object. The other possibility is to create a data structure that organizes and links the sensor data and other information. Independent from the creation method, a digital twin is always application-specific and unique and is being created for a specific task. The holistic description of the asset by models up to molecular level cannot be achieved and used because of big volume and high creation and maintenance costs.

3.1. Data-based digital twin

With a data-based digital twin, the focus, like the name implies, is on the data. With this approach, the data of the physical object is structured according to certain criteria. A common approach is to sort by different functionalities or assemblies of the physical object. In this way, a simple structure of a data-driven digital twin can support the root-cause analysis which makes it possible to quickly gain an overview of the performance of the object.

A possibility of structuring is shown in Figure 2.

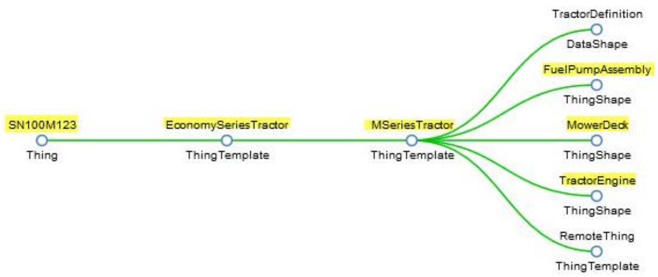

Fig. 2. Data structuring in ThingWorx [2]

Sensors or other data sources are then assigned to these individual properties. The data can be evaluated and analyzed using algorithms and functions combined with machine learning. In this way, forecast models and models for predictive maintenance are created [12]. In order to make data evaluation as easy as possible for the user, data can be displayed visually in diagrams or other display options.

With the IoT platforms, this approach is used. The procedure for creating a data-based digital twin looks similar for every platform presented. In the first step, it is ensured that all required data is accessible for models. For this purpose, a data structure is created that the various models and services can access. In the second step, these models, analyses and functions are created, verified with data and then made available. The results and data are stored. In this way, the behavior of the object over a longer period of time can be understood on the basis of the data. In order to provide the end user with the added value and information of the digital twin, final applications must be created. Through these applications, the user receives the information that is important to him. You can also combine the results of several digital twins [14].

With data-based digital twin architecture categorically related objects are bidirectionally adjusted at any time. Examples for common objects can be technical spaces, equipment or materials. Data-driven architecture links together information generated from across the product lifecycle. Therefore digital twin is gaining traction as a digital communication framework to streamline design, manufacturing, and operational processes in order to more efficiently design, build and maintain engineering products. With data-driven the design process is highly iterative and not all information is available at once. Output design decisions are made not only on what data to collect but also on the costs and benefits involved in experimentation and sensor instrumentation to collect that data.

A data-based digital twin has the advantage that not all technical information is required to create it. Only access to the sensors is required in order to be able to analyse them. How the data is structured can be decided by the user himself.

3.2. System-based digital twin

In contrast to a data-based, the system-based digital twin focuses on the actual physical object. Various models are combined in order to obtain the most accurate possible representation of reality. The system model represents the single source of truth and contains the holistic information with all existing links between the components at logical, physical and functional level.

In order to create a system-based twin, knowledge of all technical details of the object to be mapped is required. In addition to data sheets, this also includes data on the individual components (dimensions, weight, material, etc.). Information on software and electronic components used is also required. If the system's characteristics are mapped using a consistent asset information model, simulation models can retrieve the information needed in a standardized manner. The goal is that each date must be stored in one place only in a digital twin. Such a consistent asset information model is not yet state of art.

A skeleton is required for the creation, which is enriched with further models and data in order to generate a large model comprising all information and properties. This skeleton forms the basis for the digital twin and enables data exchange between the various models and systems.

This model is particularly suitable for simulations. It provides information on why the object behaved exactly in this way under certain conditions. In addition to these simulations, analyses (what-if analyses) can also be performed that show how the object would behave under certain conditions. Various environmental conditions or settings on the object can be simulated in this way without actually exposing prototypes or the object to these conditions. Costs and development time can be saved. Additional rules can be created how the operator or user has to react when certain situations occur. Ideally, human interaction is no longer necessary. Based on the stored simulation results, the object can know at any time exactly what conditions or even malfunctions are present and automatically adjust the settings accordingly.

This method is considerably more complex than the data-based structure, since exact information and specifications are required by the manufacturer in order to be able to generate a model that is as accurate as possible [12].

In summary, it can be said that the system-driven digital twin provides a significantly more comprehensive insight into the performance of the asset. This can not only be used to better understand the current state and predict possible faults and problems. Another possibility is simulation, which can take place independently of the physical object. With these simulations possible scenarios can be simulated and analyzed.

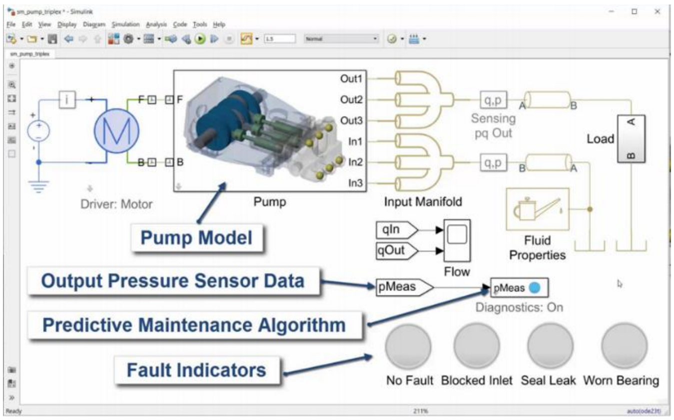

Fig. 3. System-based digital twin [31]

The example in Figure 3 shows what a possible system-based digital twin can look like. In the example, a digital twin was created for a pump in Matlab. For this purpose, the individual system elements are simulated and linked to each other.

3.3. Other methods of building up the digital twin

Another possibility to create a digital twin is the combination of both approaches. In this approach, the data model of the data-based approach is combined with the system model of the system-based approach. In this way, the advantages of the approaches can be combined. In addition to prediction models with artificial intelligence or machine learning based on the data model, the individual models of the system-based approach can be used to visually represent the current state or to perform analyses. The data sets used for machine learning for prognosis can be enriched with the simulation results of the what-if analyses. This allows the predictions to be significantly improved, since they are not only based on historical data, but also on data that may occur but have not yet occurred.

4. Advantages and disadvantages of the building up methods

Basis and most important component of the data-based digital twin is the IoT platform.

Despite the rising trend, the development of data-based product design faces major challenges/core issues:

- How can a large amount of data be effectively transformed into a small selection of useful information that can be queried, found and supplemented directly?
- How can a multitude of different product, customer, environment and production data be collected from different sources to discover the hidden dependencies and patterns?
- How fast can such a complex system react to an event from real operation and predict a result of this event based on real data and simulation models?

In order to answer these questions, the data-based approach to building the digital twin must be described in more detail.

In the building up of such a twin, the data generated from the operation is used (top-down). Data-driven models offer less insight into the interior of the system due to their black box type. Although they can be integrated into the system, they are easier to develop and provide a suitable basis for online prediction and control in situations where data acquisition exceeds the speed of analysis.

To create the digital twin in an IoT platform, the data structure must normally be stored so that the parameters and variables can be grouped together and the templates for components of the object can be created. The data sources are individually assigned to the corresponding variable ones.

The data-based digital twin will be built up for very complex systems with large amount of sensors and data sources. The other aspect of using the data-driven digital twin is if cross-impact between different components is not in the foreground und must not be investigated within the scope of the digital twin.

Data collected and updated throughout the life cycle of a product, including design, manufacture, operation, maintenance and recycling.

The great advantages of building up the data-driven digital twin are achieved by mastering technologies such as IoT and Big Data Analytics. The function of IoT technology is ensured by sensors, actuators, software, electronics. This means that the degree of automation, accuracy, efficiency and productivity can be significantly increased. The data can thus be retrieved directly from the physical objects products and stored structured in real time on the IoT platform. Thus, a physical product integrated into the IoT platform can interact with the virtual service (model) and thus be monitored, controlled and updated if necessary (in the case of software).

Further advantages of data-based digital twins include the possibility to use the machine learning algorithms automatically in the IoT platforms, so that predictive maintenance can be realized with the self-learning system implemented. For this purpose, the data can be structured according to a given data structure before the digital twin is built up and can be directly addressed and read out. The IoT platforms offer the possibility to develop own applications and to adapt the digital twin directly to the requirements. Clear structuring of data and built-in functionalities are the prepared building blocks for the visualization of the digital twin. Furthermore, the coupling to the PDM system is possible using the example of ThingWorx and PTC.

One of the disadvantages of the data-driven digital twin is the difficulty in predicting the exact cost of the digital twin based on the poorly estimable volume of data at the beginning of the product's life cycle. In the case of fees based on data volumes, the costs for the digital twin increase disproportionately with ongoing operation. In addition, app creation on some platforms can only be achieved through the

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IoT platform developers, and not by the user company itself possible. Also the data structures of some platforms are tailored to special models (e.g. service model for GE Predix platform).

For the use of the digital twin as a service, it becomes more complex to get the release of data-driven systems (black box approach), since the dependencies are defined by iterative data analytics algorithms and not by humans.

In addition, results from a data-based model often cannot be extrapolated and transferred to cases outside the original data scope. once developed data model cannot also be used for the complex system as a template to develop further twins of a similar kind when changing large numbers of parameters.

Bottom-up or system-based concepts offer better insights into the system to be developed and support the maximum possible (and maximum meaningful) parameterization of the system, they are associated with considerable expenditure of time and thus high development costs, since the interfaces between all virtual and real components must be clearly structured and defined.

According to Zweber's approach [15], the digital system model is necessary for the construction of the digital twin. This model is a digital representation of a system that is defined by all stakeholders and includes the relevant technical data and associated artifacts that define all aspects of the system for the specific activities and behaviors throughout the system life cycle. The structure is built on a data model for the system and is considered the basis of a data instead of document-centered model. The amount of data and the types of data that the system receives are collected and evaluated throughout the lifecycle.

The system-based digital twin should be built up for the systems with defined logical, functional and physical links between the components, so that the cross-impact between different components can be not be investigated within the scope of the digital twin.

The digital twin is built on the basis of the developed system model as a skeleton that brings virtual models together in different domains. The data is fed to the stored simulation models from the existing sensors. If there are large differences between the simulation results and real data, the boundary conditions of the simulation models are adapted. The components of the system with the respective requirements, and ports can be stored in the library and used by building up another digital twins.

With increasing maturity and precision of both the overall system model and each virtual model, predictions will increasingly be based on data models.

Another disadvantage of this concept is the difficulty in supplying the model with operating data in real time. Furthermore, the complexity of the processes in the components and systems is too high to describe them completely with a system model or a similar structure.

The integration of data- and system-based approaches for the construction of the digital twin can offer an efficient "framework".

5. Conclusion

Using Digital Twins offers a number of benefits that justify the implementation into the digital environments of industrial companies. Asset models enable consistent documentation throughout the life cycle of the plant. This provides a better starting point for simulations, optimizations, expansions or replanning. Through the integration of historical data, planning and live data and their simulation, preventive maintenance is possible. In addition, the maintenance personnel must have all the information they need in one place, step by step, of the test and maintenance plans to be performed. The cost savings at this point outweigh the costs of creating and maintaining the Digital Twin. For complex systems and for the systems, that are already in operation, it is highly expensive to create a system-based digital twin though the connections between the components and data can not be explored.

When creating a digital twin, two different approaches can be followed. The first approach is the data-based digital twin.

The other approach is system-based digital twin. The greatest added value and functionality is achieved through a combination of both approaches.

For both approaches there are various software tools from different providers. The solution to be chosen depends on which specific functions are to be realized with the digital twin.

Another crucial criterion is access to sensor data or access to the system.

The possibilities and application of the digital twin are additionally limited by the infrastructure and software used, including computing power. With poor infrastructure and poor computing power, high-resolution models are not possible. It is to be expected, that design process of digital twin will be further standardized.

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