Digital Twin and Product Lifecycle Management: What Is the Difference?

Dmytro Adamenko, Steffen Kunnen, Arun Nagarajah

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Dmytro Adamenko[1[0000-0003-3646-9727]] *, Steffen Kunnen[1[0000-0002-1287-6187]] and Arun Nagarajah[1]

[1] University Duisburg-Essen, Lotharstr. 1, 47057 Duisburg, Germany
dmytro.adamenko@uni-due.de*

Abstract. With the rapid development of modern information and communication technologies as well as infrastructure, the digital twin approach becomes increasingly popular and widely used throughout the industry and research. The digital twin is considered to be the key technology to realize the comprehensive digital description of components, products and systems including the information from all lifecycle phases. The Product Lifecycle Management (PLM) strategy has been present in the industry for many years and is considered as the most effective way of managing the components, products and systems of a company all the way across their lifecycles from the first idea of the product to its disposal. The digital twin is not yet clearly defined. It can be defined as a set of models, linked with each other as well as with the physical product enabling data storage and real-time processing. In contrast to a digital twin the PLM strategy provides a framework, which serves as single source of truth connecting the partial models, that describe the physical product. The models can receive the data stored in a product data management system (PDM).
The aim of the present paper is to distinguish the characteristics of the digital twin and PLM as well to find similarities and differences in the both approaches. The current development of both strategies is presented, and the answer to the question, where is the difference between digital twin and PLM is given.

Keywords: Digital Twin, Product Lifecycle Management.

1 Introduction

The digitization of industry is being driven forward under the term Industry 4.0 and is characterized by two central features such as intelligent components and networking [1]. With increasing globalisation and continually growing individual requirements of customers many companies are coming under increasing competitive pressure. In order to counteract this and improve the industrial competitiveness, companies must offer a broad product portfolio or individual customer-specific solutions due to rapidly changing customer requirements, whereby the quality of the products and the entire process, logistics parameters and costs must not be neglected [2].

The digital existence of products in the network generates large amounts of data over the product life cycle, especially when sensor technologies are used. This data has a value for the user or operator of the product as well as for the developer and manufacturer.

Companies are constantly trying to further optimise the performance of their products or their own processes. The approach of product data management and the strategy of product life cycle management have established themselves as central solutions for the management of data of complex products and assets in the last decades. However, with development of technologies, the terms are being replaced by new ones.

With the technical progress and the continuous development of information, communication and automation technologies, the possibility of networking different components in real time and gaining an insight into current processes or the current status is being developed. The networked components and machines generate a lot of data that can be used for operation analysis. With the development of the Industry 4.0 the usage gets much better perspectives, because the development of such technologies like Big Data, Machine learning and AI provides the optimization of the usage of the existing product data [3].

The flagship of such targeted use of data is becoming widely known as the digital twin approach, a concept that uses the networking of components and the insights into performance available through the data to represent an actual state of the product at any moment of its life cycle. This approach is gaining more and more interest from companies and its importance in industry but has not yet become fully established. For these reasons, the digital twins will be examined in more detail in the following chapters. The concept and construction possibilities of a digital twin will be presented in detail [3], [4].

The similarities and differences of the PLM and Digital Twin concepts will be presented and discussed in the further course of the paper.

2 Product Lifecycle Management Overview

This section introduces the Product Lifecycle Management approach as well as the core component of PLM the Product Data Management (PDM).

2.1 PLM Theoretical Background

Product lifecycle management strategy can be defined as the product-related and cross-company information management, which comprises the planning, control and organization of the processes required for the generation and holistic management of all data, documents and resources throughout the entire product lifecycle [5].

PLM establishes a continuous flow of information so that current product information and also the previous development and operating statuses are available at all times and to all parties involved in product creation, production and use.

Through transparent processes, PLM ultimately leads to improved product quality, cost and time advantages throughout the entire product life cycle. PLM should be considered as a cross-company approach that also takes into account today's globally distributed processes along the entire product lifecycle [6].

The holistic view of the product life cycle includes all phases of an industrial product. The management of product requirements already supports the early phases of the product life cycle. In the area of capital goods or consumer goods, support of the product life phases after delivery and commissioning as well as product recycling is playing an increasingly important role.

The cycle is closed by the feedback of information from downstream process steps such as product use and product recycling or disposal with the aim of improving product properties. This creates a control loop that enables companies to react more quickly to changing customer requirements and to incorporate experience from product application into the development of new, innovative products [6], [7].

The biggest efficiency with PLM approach can be achieved through so-called top-down strategies involving the company management. The main focus of PLM is the simultaneous, company-wide provision of product data and fast, orderly access to it, as well as the realization of continuous, standardized company processes [7], [8].

PLM provides powerful classification systems for identifying and searching for product data, which facilitate the clear allocation and identification of components and assemblies and support the uniqueness of each component used.

2.2 PDM Systems

The realization of the PLM strategy requires various solution modules, whereby product data management plays a key role in PLM. Product Data Management is considered as essential enabler for PLM and as the technological basis that makes PLM possible [9]. Without a PDM system as the central software component, a PLM strategy cannot be implemented in the company. Conversely, however, a PLM concept is not necessarily required for the productive use of PDM.

The data is collected and linked in a PDM system. PDM systems are used for the management of product-defining data to build a holistic product model, which consists of multiple different linked models in connection with the mapping and management of technical and organizational business processes. Product and process management together allow the complete reconfiguration of any design and manufacturing status over the entire product life cycle [6], [7].

Through the integrated, central view of possibly distributed product data becomes the so-called integrated product model. It consists of the partial models. These models include component information, documents, project-specific configuration data, personnel information, customer data, and much more. A digital product model is defined by logically linking the data with each other. This enables a process-oriented structuring of the data that is generated or required over the entire product life cycle. The most important tasks of the PDM system are to provide the correct data with the correct status and format. Its long-term archiving and support of data exchange via different information channels [7], [12].

2.3 Recent Development of PLM Approach

As technologies evolve, PLM has become a holistic discipline across the entire product lifecycle and across the enterprise - from requirements management to the processing of IoT data. In the classic PLM approach, the document-centered system has been widely used. Modern usage of PLM concept envisions however the data sharing and exchange instead of documents, so that the information out of the documents becomes decomposed and stored as metadata or within specific partial models in database. Critical issue is to ensure that the stored data remains the single source of truth for the product throughout the whole life cycle [10].

Another perspective field is being developed with the evolution of cloud-based data management, which is also emphasizing on information-centered management [11].

This product metadata is defined as the digital information twin of the product and is thus associated with the term digital twin.

3 Digital Twin Overview

There is not yet a standardized definition for 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. [25] and shows clear differences in the interpretation of the concept of the digital twin and its use as a business model. Small overview of existing concepts and definition is presented in this chapter as well as the most common construction methods.

3.1 Digital Twin Definition

The concept of a digital twin has been developed by Michael Grieves in 2003, as a model consisting of three main components; the physical product in the real world, the virtual product in the digital world and the connection between the real and virtual objects by means of data and information [13].

Digital twin is being widely understood in connection with the rapid acquisition, aggregation and analysis of data from networked technologies and allowing the simulation of possible scenarios for predicting results in the virtual without affecting real production. Great strength of the digital twin lies in the visualization of data: data thus becomes insights into processes that are accessible not only to experts but also to a technically less well-versed audience and is also available independently of location. This data visualization promotes learning and decision-making processes at all levels of the "Connected Enterprise", which is the core of PLM strategy and helps to identify critical areas directly.

Digital twin has several meanings in today industry’s context. The digital twin prototype is created within the PLM framework when planning or ordering a physical product, long before the physical twin is even born which is especially crucial for the automation of manufacturing in Industry 4.0 scenarios. With its help, companies can, for example, switch to the individual production of a "lot size 1". The digital twin prototype appears at each production step on the respective machine together with the physical part and controls the processing. At the end of production, the physical twin is born and has all the characteristics of the virtual prototype model.

The digital twin instances, which are created from the image of a finished product and reproduce its continuous configuration or operating data, behave completely differently. In the automotive industry, the DTP reflects the production and the DTI the after-sales processes, such as software updates or operating data such as telematics data [26].

In order to combine the both digital twin meanings in more recent publications, the digital twin is no longer described with the three dimensions already mentioned, but with five dimensions [14]. This model builds on the three-dimensional model introduced by Grieves and adds the data of the digital twin and service as respective dimensions. Figure 2 shows this model in more detail. PE stands for the physical entity, VE for virtual equipment, SS for services, DD refers to digital twin data and CN for the connections [14], [15].

With the digital twin a real object has a digital image that consists of different models. These models have four main functions. The first function is the exact reproduction of the properties, behavior and rules of the physical object to create an accurate image. The second function of the models is that they can be operated autonomously. This means that they simulate different behavior of the object, which can then be used as guidelines for the operation of the physical object. The third function is the ability to predict problems before they occur. The fourth function is fulfilled by validating performance before the product is even finished [15]. The data enables the digital twin to be operated and updated continuously. This data includes information collected by sensors, results of simulations and other knowledge related to the physical object [15].

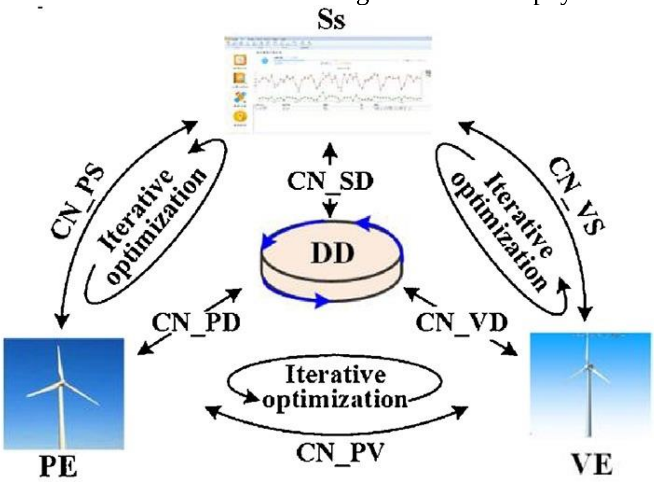

Fig. 1. Five dimensions of a digital twin [14].

Services are used to prepare the functions and information of the digital twin for the general user in such a way that he can access them easily and without much previous knowledge [15]. It can be seen that the digital twin is not a single model, but rather consists of a number of interlinked models [16].

These are based on current and historical information of the object to be depicted [17]. All relevant data generated during the lifecycle are incorporated into the digital twin and continuously developed further [16]. In figure 2 the components of a digital twin are presented. It becomes clear that the digital twin does not only consist of models, but also of data, simulations and analyses. It is characterized by its uniqueness, since each digital twin represents exactly one single object. Through the interaction between the digital twin and the real product, the digital twin it is also possible to control the twin and, if necessary, adjust settings and monitor the current status.

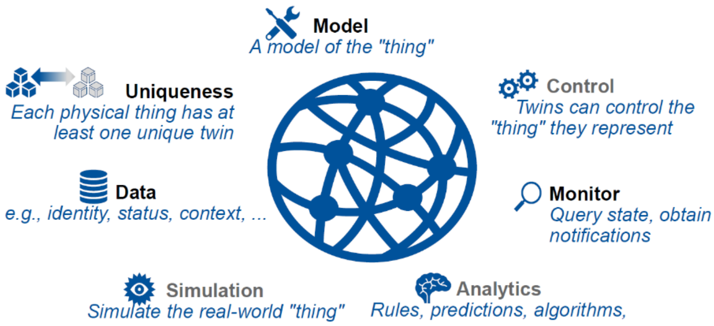

Fig. 2. Digital twin components [18].

For the further course of this work the digital twin is defined as a holistic digital model of a physical object from the real world connected with it. This exact copy contains all properties, information and states of the real object [3].

The general structure of a digital twin first of all includes the question of the complexity of the digital twin. If the complexity and level of detail of the individual models are not high enough, the digital twin will not have any profitable added value for the user. If these are too high, the use of the digital twin becomes too confusing for the system presented [19].

3.2 Digital Twin Construction Methods

Considering actual digital twin construction approaches, digital twin can be built up in main two different ways. One possibility is to create a system model of the physical object to be enriched by real product data. 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 [20].

With a data-based digital twin, the structuring of the data flow is the main focus. Here, the individual instances of the physical object are sorted, for example, according to functionality, in order to gain an insight into the current status and performance of the physical instance. An IoT platform can be used for structuring, for example, which makes various applications for structuring data available to the user. Through these applications the structured data can be stored and analyzed with the tools defined by the user. The advantage of a data-based digital twin is that the physical instance does not have to be virtually visualized for creation and use, but the recorded data sets of the sensors are sufficient for data structuring and analysis. In the building up of such a twin, the data generated from the operation is used (bottom-up). Data-driven models offer less insight into the interior of the system due to their black box type.

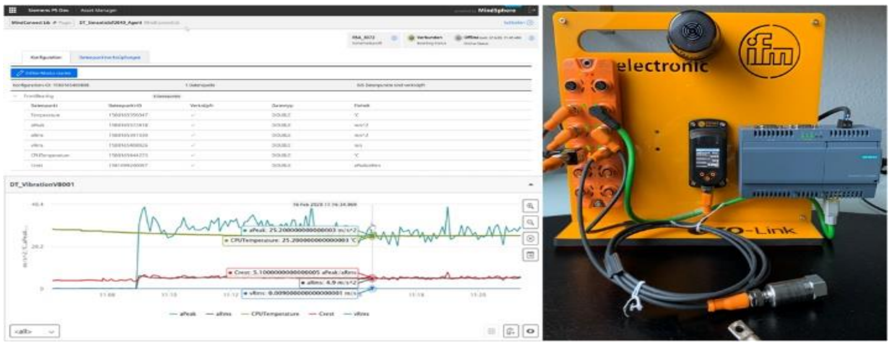

Fig. 3. Data structuring in data-based digital twin [20].

As example a data-based digital twin of a combustion engine constructed in MindSphere can be seen. The data from vibration and temperature sensor as well as alarm switches is being sent in given periods to the IoT platform in order to define the value patterns which lead to alarms and adjust the motor accordingly [3], [20], [21].

The construction method of the system-based digital twin places the physical instance in the foreground. In comparison to the data-based digital twin, not only the data from the sensors are included in the data structuring, but also the entirety of the physical functions of the physical instance.

A PDM system can be used as a skeleton to provide the logic stored in the system model. A complex assembly structure including partial models (geometry, simulation, sensor data models, as can be seen in figure 4) can be set up in the common PDM systems. Each change of the entire system model or a single partial model is also documented within the PDM system.

The digital twin should be able to be used by several users. With the help of PDM system the rights and roles of individual users can be set, so that the necessary know-how protection can be guaranteed.

Top-down 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. For this purpose, for example, a CAD model of the physical instance can be created, which serves as the basis for the data structure. This partial model can then be implemented in the data structure to link the detailed visualization of the physical instance with the entirety of the recorded data. The digital twin created in this way can be used, for example, for simulations of theoretical scenarios to predict and prevent possible failures of the physical instance. The advantage of a system-based digital twin is the possibility to use the created data structures and partial models for simulation predictions, which allows a deeper insight into the performance of the object [3], [20].

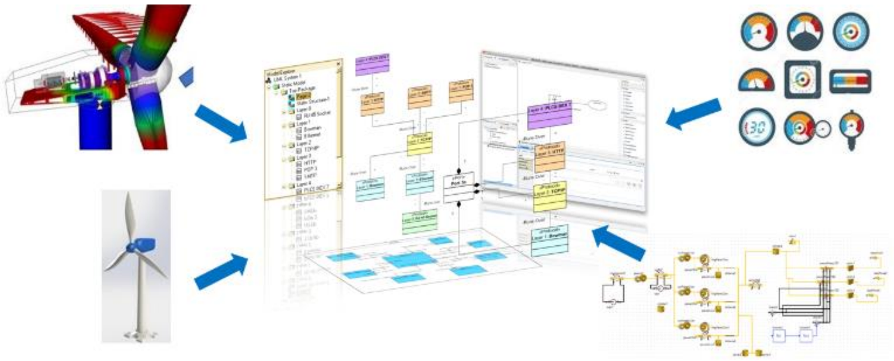

Fig. 4. System-based digital twin [20].

The presented approaches can be combined in the design of the digital twin, which allows the advantages of both approaches to be used.

The biggest challenges of constructing the digital twin are IT infrastructure, data handling, defining a necessary fidelity of a system as well as privacy and security.

The rapid growth of AI needs to be met with high-performance infrastructure in the form of up to date hardware and software, to help execute the algorithms. The challenge with the infrastructure currently is down to the cost of installing and running these systems. From a data point of view, it important to ensure the data is not of inferior quality, it needs to be sorted and cleaned, thereby ensuring the highest quality of data is fed into the AI algorithms. Digital twins can quickly become overloaded and will then never be finished or will not be able to provide the required added value. Therefore, digital twin cannot be provided and held up to date for every application for the smallest element in it. Important is to define the necessary fidelity so that the maintenance of the digital twin does not exceed the added value of its use. Privacy and security are an important issue for anyone concerned with the computing industry and is no different when performing data analytics. Laws and regulation are yet to be established fully because of the infancy of AI. The challenge is more scrutiny, regulation and measures concerning AI in the future as the technology grows. Future regulation ensures the development of algorithms that take steps to protect user data.

3.3 Applications of Digital Twin

The digital twin can map a single element as well as a complete system. The digital twin of a complete system usually consists of several digital twins of subsystems and individual components. Ideally, the digital twin serves several applications that interact with a physical product. However, synergies are only achieved if different physical products also share a twin infrastructure.

The essence of the digital twin is the establishing of connection and real-time synchronization between the data from physical product and the information contained in virtual product model [22].

The digital twin has several advantages. The first major advantage is the significantly increased transparency. Thanks to the various models, which always have up-to-date information, the product or system can be better monitored. Information is presented in such a way that the user can directly and clearly see the current status. Among other things, there is the possibility of 3D visualization of current statuses. Furthermore, maintenance costs and time can be reduced. By continuously collecting and analyzing data and using simulations, future problems can be identified [15]. The simulations are usually based on the entire data history. Maintenance can be planned in advance by predicting the lifetime of individual components. By means of predictive maintenance, these components can be replaced before malfunctions or failures occur [23].

Another advantage of a Digital twin is the reduced time needed to bring a product to market. Simulations can be used to predict how the product or system will behave before it is even finished. In this way, weak points and potential sources of error can be eliminated without much effort.

In addition to the reduced time-to-market, the performance of the product or system can always be maintained at an optimum level. Since 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.

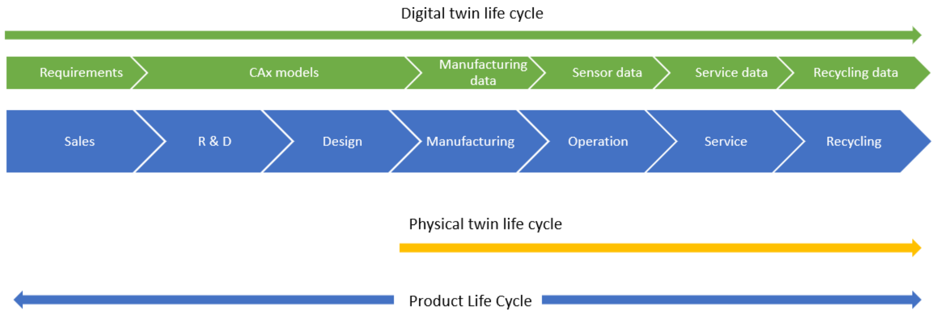

Fig. 5. Product and digital twin life cycle.

The digital twin can be used in different phases of the product life cycle or across different phases. Figure 5 shows the product life cycle. Already during the planning and development of an object or a process, it is possible to predict whether the desired properties and functions will be fulfilled using simulations with the digital twin. Optimizations of design or performance can thus be carried out in advance [3], [24]. Prototype testing can be replaced by simulations on the digital twin, saving costs and time. Digital twin can also influence the planning and development of new products by analysing objects already in use. The data generated by the digital twin can be used to analyse the usage behaviour or operation of products or systems. In this way, improvement possibilities for new products can be identified [15].

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 in places that would not normally be accessible to sensors on the object. Digital twin also allows what-if analyses to be carried out. Changes in environmental conditions or settings can be tested on the digital twin. However, it is also possible to deliberately activate possible errors in the simulation model to generate measurement data for these cases, which can then be used for predictions [3].

4 Comparison of PLM and Digital Twin Approaches

As showed in literature review, core idea of both PLM and digital twin concepts is a holistic product model, which consists of multiple interlinked models to provide different views on the real product. A storage of data, describing the product at any time is also one of important aspects of both approaches.

In order to distinguish the differences between the both approaches, their characteristics according to selected criteria are provided in Table 1.

Table 1. Comparison of PLM and digital twin characteristics.

Criteria	PLM	Digital Twin
Data structure	• Data is stored in the PDM system • Mainly document-centered storage • Model-centered storage evolving • Multiple partial models interlinked	• System-based or data-based structure • Data-centered storage • In case of system-based structure multiple interlinked partial models • In case of system-based structure, a PDM system can provide a platform for models and data storage
Data exchange	• Mainly document exchange • Collaborative access to the documents	• Microservices • Via the IoT-platform
Real-time data usage	• Storage • Simulation within the linked models	• Machine learning within IoT-platform

	• Hardly possible in document-centered structure	• Cross-impact analysis within system model in case of system-based structure • Integration of Big Data algorithms
Product lifecycle coverage	• Whole lifecycle covered	• Coverage of production and service product lifecycle phases • Integration in the development phase only possible for future products
Tracking of individual products	• Big effort in document-centered structure	• Great transparency • Individual for every product in production / in use
Product control	• Defined workflows with defined roles and activities • Defined notification and validation workflows	• Defined workflows, roles e.t. within system-based digital twin via PDM system • Defined roles, notifications and workflows within IoT platform for data-based digital twin
Collaboration possibilities	• Full cooperation within a single enterprise • Cooperation between the enterprises mainly limited due to access issues	• Communication between developers, operators and service

5 Conclusions and Outlook

As can be seen in comparative table, both approaches have common characteristics and can be regarded as complements to each other, where having good capabilities within PLM can be applied on a virtual product model and a physical product. Both concepts describe a complete virtual product model from different points of view through integration of different partial models. Both the PLM and digital twin concepts can include process frameworks, so that the different states or life cycles of the products can be processed within firm workflows with integration of defined departments or vendors. The main goal of the digital twin concept is the real-time data processing and exchange between the virtual product model and its physical twin, whereas the PLM concept defines the data processing and exchange in general.

The evolution of PLM approach has led to a migration from document-centred information storage to data-centred and this is a great step towards combination with digital twin approach due to the possibility to use data processing algorithms through the stored data in real time. The digital twin can exist at any stage of the lifecycle and aims leverage aspects of the virtual environment (high-fidelity, multi-physics, external data sources, etc.), computational techniques (virtual testing, optimisation, prediction, etc.), and aspects of the physical environment (historical performance, customer feedback, cost, etc.) to improve elements of the product (performance, function, behaviour, manufacturability, etc.) over it lifecycle. Usage of digital twin approach is at the time suitable for not all the product lifecycle phases (for example sales) but can serve as a value adding service in combination within the defined PLM strategy of an enterprise.

The greatest benefit can be achieved by cleverly combining both approaches. The structure of the digital twin can be built up within the PDM system. The system model can still be used as the "skeleton" of the digital twin with the defined logical links between the partial models stored in PDM system. Also, sensor and simulation data can be stored and linked continuously. Due to the usage of PDM system each adjustment of the entire system and each individual partial model is also documented. The digital twin should be able to be used by several users. With the help of PDM system the rights and roles of individual users can be set, so that the necessary know-how protection can be guaranteed.

For the processing the data in real time and used integration of PDM system with IoT platform is needed. Many of the data platforms also offer interfaces with PDM systems, making it easier to assign data and simulation results to a concrete plant status. Based on the existing data and simulation results, recommendations the benefits of both approaches can be united in single framework.

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