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An Ecosystem for Digital Shadows in Manufacturing

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Abstract

Digital Shadows are data structures precisely tailored to support decision making in domain-specific real-time that promise tremendous potential to reduce time and cost in the smart manufacturing of Industry 4.0. Digital Shadows are often engineered ad-hoc, for single specific applications, without considering their aggregation, combination, or reuse. This lack of foundations hampers a joint understanding of Digital Shadows that prevents joint research as well as collaboration and exchange of Digital Shadows across enterprise boundaries. Based on interdisciplinary research, we conceived a conceptual model of Digital Shadows that can guide their engineering, combination, and reuse. This not only supports researchers and practitioners in better understanding each other when discussing Digital Shadows but also eases the engineering of compatible and exchangeable Digital Shadows.

Keywords: Digital Shadows; Smart Manufacturing; Digital Twin; Cyber-Physical Production System; Industry 4.0

1. Motivation

Research on Digital Twins often produces exaggerated definitions that are near-impossible to achieve. For instance, Digital Twins are expected to be "the exact mirror of the real system" [2], "an exact copy" [21], a "complete virtual representation" [16], a "complete virtual prototype" [14], or a "complete mirror in the cyber space of the physical prototype" [6]. Of course, being "digital", a Digital Twin must be subject to abstractions (*e.g.,* to digitally represent continuous processes), hence "complete" Digital Twins are a highly idealistic vision. Other research produces ambiguous definitions that, without further details, are little helpful. These, *e.g.,* define a Digital Twin as a "digital replica" [15], a "digital counterpart" [4], a "virtual counterpart" [24], or a "virtual representation" [1]. Without detailing what a replica, a counterpart, or a representation means in these definitions, these, in fact, explain very little. Consequently, much research on the foundations of Digital Twins is necessary. Digital Shadows, on the other hand, are less of an idealistic vision but a necessity to optimize the use of cyber-physical assets [28]. To reduce material consumption, downtime, reject, and waste, the wealth of available machine-level data must be put to better and more timely use.

To this effect, collecting, relating, and exchanging this data in a structured fashion that links it to its origins, is properly abstracted and aggregated, and precisely tailored to the design making challenges at hand is crucial. Such Digital Shadows can enable smart Digital Twins that monitor, control, and optimize the assets of interest. Based on interdisciplinary research in the Internet of Production[1] excellence cluster, we devised a conceptual model of Digital Shadows and their ecosystem that can be applied to a variety of domains to better structure, understand, exchange, and exploit manufacturing data.

In the remainder, Sec. 3 introduces our concept of Digital Shadows, before Sec. 4 details the components of their ecosystem. Sec. 5 then illustrates the use of Digital Shadows with a real-world example and Sec. 6 concludes with a roadmap on smart decision making with Digital Shadows.

2. Background

Digital Shadows [20, 23] are a concept of collecting, aggregating, and abstracting manufacturing data for specific purposes to enable decision making based on this data while still being computationally efficient through domain-specific

[1] Internet of Production `https://www.iop.rwth-aachen.de/`

data reduction. For this purpose, Digital Shadows need to comprise various kinds of data (*e.g.,* measurement data, simulation data, models) from different sources that are abstracted and aggregated in application-specific ways and augmented with necessary metadata to fulfill their purpose. Through their specific abstraction and aggregation, Digital Shadows serve as a basis for, *e.g.,* process optimization and data mining.

The Internet of Production is a DFG excellence cluster at RWTH Aachen University that pursues the vision of interdisciplinary manufacturing based on continuous horizontal and vertical exchange of data, integrated development of specifications, efficient processing of domain-specific tasks, and cross-domain validation. For a first conceptual model of Digital Shadows, their use, and capabilities, we conducted a survey in the Internet of Production through which we reached out to its 200 researchers of 25 departments who conduct research in a variety of domains, including artificial intelligence, computer science, innovation research, labor science, mechanical engineering, and manufacturing technology.

Conceptual modeling [13] is an abstraction technique in which complex systems are represented through their quintessential concepts and relations to improve understanding of the subject that the model represents. Conceptual models can describe structure, behavior, or a combination thereof of the system under investigation and often use corresponding modeling techniques, such as UML Class Diagrams (CDs) [22] for the description of structural aspects or BPMN [26] for behavioral aspects. In the following, we will use CDs and UML Object Diagrams (ODs) [22] to describe our conceptual model of Digital Shadows.

3. On the Nature of Digital Shadows

Digital Shadows always refer to an underlying system, the system of interest. A system is a set of elements that interact with each other and form a whole; the original system could be technical or biological, material or non-material, real or theoretical. At the moment of observation, it can exist in parallel, no longer or not yet (in the considered state). Digital Shadows are created with a specific purpose, *e.g.,* representations, regarding the system of interest. We specifically focus on the production domain, thus, considering especially Digital Shadows of production machines. A Cyber-Physical Production System (CPPS) is a composition of human resources, production equipment, and aggregated products towards which it establishes one or several cyber-physically formulated interaction interfaces [19]. In the context of the (Industrial) Internet of Things, this is referred to as an *asset* [25].

Digital Shadows

Digital Shadows are sets of contextual data traces, their aggregation and abstraction collected concerning a system for a specific purpose with respect to the original system. Digital Shadows combine data from various sources. Consequently, a Digital Shadow may contain historical information about the system that the system itself has cleared in the meantime because it does not necessarily remember all its historical behavior, activities, and structural changes. A Digital Shadow does not have to reflect the observed system entirely but can include abstractions that reduce the available data to a limit that can be processed in time. One CPPS can have many different Digital Shadows describing various aspects of the system in different detail and at different times. Digital Shadow instances, which we call "Digital Shadows" for short, are defined by Digital Shadow Types.

Digital Shadow Types

Different Digital Shadow types prescribe different Digital Shadows for different purposes, *e.g.,* predictive maintenance or adaptive control. Therewith, each Digital Shadow Type encapsulates a subset of the required data for the specific information need driven by its purpose. Depending on the asset's status when the Digital Shadow is created, the encapsulated data differs, but the structure remains; the type defines which data and from which origin should be part of the Digital Shadow. The Digital Shadow Type thus serves as a construction plan for Digital Shadows. Digital Shadows can be enriched with contextual information (such as metadata about time, location, and purpose). Since the necessary metadata is purpose-oriented, it cannot be defined generically but must also be part of the Digital Shadow Type.

A Conceptual Model of Digital Shadows

To characterize the Digital Shadow components more precisely, we devised the conceptual model for Digital Shadows illustrated in Fig. 1. Our conceptual model (Fig. 1, top), specifies which concepts and relations a data structure requires, such that it can serve as a Digital Shadow. A Digital Shadow consists of a set of contextual `DataTraces`. These can encapsulate various values, *e.g.,* changing over time. The `DataPoint` class is not further restricted, thus, also allows extensions for storing image data or a 3-dimensional vector representing a location. Each `DataTrace` has a `Source` that can be further described by properties. Sources of data traces can be measurements, processings for *e.g.,* filtering data, and also humans. Assets can also serve as sources for data traces, *e.g.,* a camera that provides images of a produced part. `MetaData` can contain any information about data that is relevant for further data usage. This may include the point in time when a measurement was performed, the location or information about data precision. The Digital Shadow always refers to an `Asset`, *e.g.,* a component of a CPPS, that is described by this Digital Shadow or for which the encapsulated data is relevant. The `Purpose` describes why the Digital Shadow is created. For instance, a Digital Shadow's purpose may be to optimize a production process in terms of resource efficiency. Digital Shadows also rely on models for gaining domain knowledge about *e.g.,* the CPPS, its behavior, or further information about the application context. These are

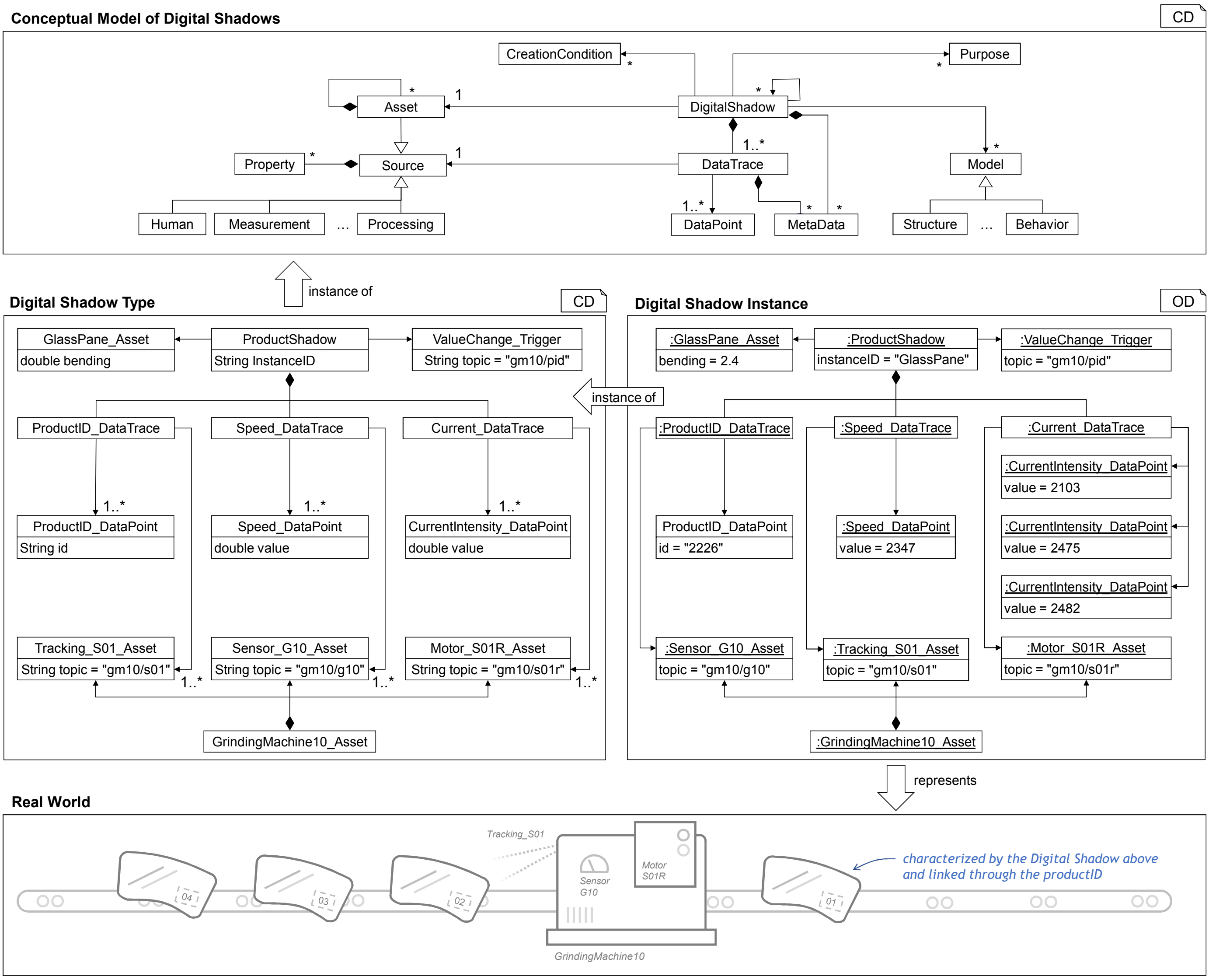

Fig. 1. Conceptual model of Digital Shadows and exemplary utilization for describing the Digital Shadow of a glass pane.

represented by the `Model` class. The `CreationCondition` describes when the Digital Shadow should be created. Possible triggers could be a human operator querying the production state, a clock indicating that it is time to create a new Digital Shadow, or an event within the CPPS or its context, *e.g.,* exceeding a threshold in some measured value.

The CD (Fig. 1, middle left) is an instance of our conceptual model. It specifies an exemplary Digital Shadow Type that characterizes the reformation of window panes and specifies which data should be part of each Digital Shadow conforming to this type. For another glass pane, the values would differ, but both Digital Shadows share a common Digital Shadow Type since the same data is relevant for quality analysis. The Digital Shadow is created every time that the product id changes, as indicated by `ValueChange_Trigger`. The `instanceID` can identify the `ProductShadow`, so each instance of this Digital Shadow Type has a unique id. The Digital Shadow Type contains three data traces: the `ProductID_DataTrace`, `Speed_DataTrace`, and `Current_DataTrace`. Each of these data traces refers to an asset as a data source. The classes describing these assets also contain a topic attribute that has a MQTT topic through which they distribute data as default value. While the `ProductID_DataTrace` contains only one data point, the `Speed_DataTrace` and `Current_DataTrace` can also contain multiple speed and current values.

Fig. 1 also shows a Digital Shadow instance (right) that conforms to the Digital Shadow Type and is represented as an OD. The Digital Shadow is created for one glass pane with the product ID 7776 and contains three current values (2103, 2475, 2482) and one value for speed (2347). Other properties are omitted for clarity.

In the real world, we observe data that can become part of Digital Shadows. This data is collected by sensors within the CPPS or its context, for example, or by software components within the CPPS. Data can also be entered by the operators via user interfaces. The actual data origin depends on the use case.

The values displayed in the Digital Shadow instance in Fig. 1 are values originating from a glass pane's real production process. They are captured via sensors within the CPPS.

Summarizing, the conceptual model of Digital Shadows specifies which concepts and relations are used to describe Digital Shadow Types. The Digital Shadow Type describes the components of one concrete that can be instantiated with different data values at runtime. Thus, it prescribes the structure of a Digital Shadows for one particular use case. The Digital Shadow Type is an instance of the Digital Shadow conceptual model. At runtime, there can be different Digital Shadows conforming to the Digital Shadow Type with different values.

The technical realization of Digital Shadows includes different infrastructure elements. There has to be data acquisition and storage, a communication infrastructure, and a software component that creates Digital Shadow based on the Digital Shadow Type every time the specified trigger occurs. The data acquisition and storage collects the data necessary to create Digital Shadow and also provide historical values. The Digital Shadow caster elevates the notion of Digital Shadow to an actual useful concept that adds value to the production by providing information that would otherwise not have been available to users of the CPPS. This infrastructure is defined separately to decouple the concept of Digital Shadow Type and Digital Shadow from the technical realization.

4. A Conceptual Ecosystem for Digital Shadows

The basic requirement for Digital Shadows is data that sufficiently describes the (production) system in terms of its intended purpose. Such data can be generated and provided by the asset itself, *e.g.,* from the sensors or the control unit. It may also come from other systems that generate data concerning the system of interest; this can be simulations, management software or design tools, as well as humans in various roles providing information. The concept of the Digital Shadow does not prescribe a technical realization of data provision: Data can be fetched directly via interfaces of the individual apps or devices, or it may first be aggregated from various sources in one (or more) repositories such as a data lake. The challenge is to balance data economy with great flexibility for future, even not yet defined, data analysis cases. Fig. 2 illustrates how the Digital Shadow is generated from data.

Digital Shadow Caster. The Digital Shadow caster, a software component, instantiates the Digital Shadow: The blueprint for this task is provided by the Digital Shadow Type, defining which data is aggregated in which way. Additional domain knowledge can be added for this purpose through models; these can be physical correlations, a forecasting model or reference process. Depending on the purpose or the individual scenario, the instantiation of the Digital Shadow can appear in different shapes: The instance of the Digital Shadow can be a live reflection whose content continuously changes with the state of the real asset. This enables the online observation of the asset from a purpose-driven perspective and is usually volatile. However, the caster can also generate individual Digital Shadow instances, initiated (as well as terminated) by a trigger. The trigger can be defined periodically, either time-based (*e.g.,* every 10 ms, every morning or one a year) or event-driven (*e.g.,* when a value drops below a threshold or each time a new item is detected). This instantiation can happen in real-time as well, or - if the data originates from an archive - it can be generated (retrospectively) on-demand, *e.g.,* when a case of damage occurs.

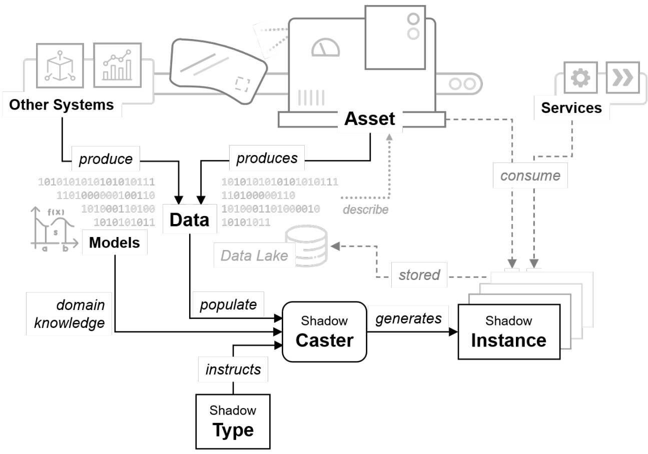

Fig. 2. Workflow of the Digital Shadow system to create and consume Digital Shadow instances.

The Digital Shadow instance created by the caster can be consumed directly by the asset itself or by other services. Depending on the system architecture, both publish-subscribe concepts as well as querying of a concrete shadow by the consumer are applicable. There is a wide range of applications that can be considered as consuming services, including a device in the CPPS, software applications, or humans, either in the role of a worker or a data analyst. If the caster generates instances on a continuous schedule, these might also be stored in the data store to be available for their use.

Asset. An asset in our conceptual model is a system that "has a value for an organization" [25]. As such, it could be a cyber-physical production system or a pure software system as long as data relevant to the purpose of the Digital Shadow can be collected. Purely physical systems consequently need to be accompanied by another system able to provide that data, *e.g.,* through measurements.

Data Lake. Data lakes are big data repositories that store raw data of heterogeneous data sources and provide functionality for on-demand integration with the help of metadata descriptions [10]. Data lakes combine data objects of structured and unstructured form. In addition to data from relational databases they may contain, *e.g.,* emails, images, PDFs but also semi-structured files like CSV, XML, and JSON. One advantage of data lakes is that they are designed to store different types of data and can also handle large amounts of data. In addition, data lakes also provide mechanisms for searching and structuring the data they contain. They are therefore well suited for storing data and engineering models of CPPS and making them available when needed. A well-known realization of the data lake concept is available from Apache Hadoop [2]. MongoDB also offers a Data Lake realization [3] which in contrast to HDFS is not open source. In the infrastructure we envision, a data lake will store historical data, engineering models, metadata, and generated digital shadows, if their generation was computationally intensive.

Services. A software service refers to a software solution, providing a functionality or a set of software functionalities such a data retrieval or controlling a CPPS with a specific purpose and that is also reusable through different users. In the field of smart manufacturing, many domain-specific services are being developed, such as automated execution of experiments, process monitoring, and predictive maintenance. All of these services require information about the underlying CPPS which they can obtain in the form of Digital Shadows. The Digital Shadow caster will produce these Digital Shadows and make them available to the services via an (open) interface.

Engineering Models. Model-based Systems Engineering is the formalized application of modeling to support system requirements, design, analysis, verification and validation activities beginning in the conceptual design phase and continuing throughout development and later life cycle phases [7]. As such, the resulting engineering models store information about the CPPS structure, geometries, and intended behavior. This information is relevant as metadata for Digital Shadow, as it can provide additional information about the origin of measurement data. In addition, parts of the Digital Shadow infrastructure can be derived from these models. For example, databases, communication infrastructure, or monitoring Digital Shadow Types that combine information about the predefined activities of the CPPS and can serve to detect malfunctioning can be generated from a well-formed engineering model.

5. Real-World Digital Shadows Examples

In the case of an automotive supplier, the data in the production plant, such as the current and speed, but also the tracking of individual products are recorded. Via edge devices, the data from the control system is published via an MQTT broker and stored in a database. The data is initially stored without further modeling to maintain flexibility for different processing strategies. The annotation of the data is realized by an ontology, the MQTT topic of the data endpoint is used as a reference. This metadata describes the type of measured value and physical quantity, information about the sensor and the controller, its position in the plant, and the process.

The Digital Shadow enables a view of this data from different perspectives: For example, the data of a single plant may be relevant over time, or a selection of quality-determining variables may need to be mapped to individual products. This mapping is defined in the Digital Shadow type. For this purpose, a selection of relevant data is made with the help of the metadata. This selection is specified: Which variable triggers a new shadow? For what purpose does this shadow serve? How are the instances of the shadow further used? This type definition is described in the form of a JSON document with which the Shadow Caster, a service, creates concrete instances of the shadow. The instances themselves are then published via the MQTT broker to be consumed by applications such as tools for data analysts.

6. Towards Smart Decision Making with Digital Shadows

This section discusses five research challenges towards the vision of semantic Digital Shadows that are automatically gathered, abstracted, and aggregated in the most suitable granularity for a specific purpose.

1. Semantic integration of engineering models. Giving semantics in the sense of meaning [11] to the data of Digital Shadows demands understanding them first. The data gathered from production systems always exists in the context of its sensors, the surrounding system, and the environment. In Industry 4.0, this context is increasingly often modeled explicitly [27]. Consequently, properly understanding the data demands relating it to the (AutomationML [5], OWL [17], Simulink [3], SysML [9], UML [22] *etc.*) models of its context. To make these relations explicit and comprehensible, modeling itself can help. For instance, UML class diagrams, OWL ontologies, or SysML blocks can relate models to data (sources) and describe their context through additional (meta) data, such as employed units, precision, and more.

2. Automated generation of (minimal) Digital Shadow Types. Currently, Digital Shadow Types are crafted manually to describe semantically relevant integrated data. For large systems of systems, collecting and properly connecting the data structures is challenging due to the sheer amount of data structures involved. Where a system leveraging Digital Shadows is reified, data acquisition, *e.g.,* through SPARQL [18] queries, and the underlying data structures can be derived automatically. The data parsimony of the resulting data structures then depends on the precision of the reified data collection requirements.

3. Data pursuing Digital Shadows. Currently, a Digital Shadow is a snapshot of system data collected, abstracted, and aggregated for a specific purpose. While each Digital Shadow may link to its predecessor, the latest Digital Shadow can neither be retrieved easily nor reliably if the predecessor link is not implemented. Providing services for each Digital Shadow Type that always make their respective latest Digital Shadows and their predecessors accessible, *e.g.,* as MQTT [12] topics can mitigate that. Using technique from model-driven development [8], such services could be generated. However, regularly publishing a Digital Shadow with all its predecessors may not be data parsimonious. Similar to the former challenge, means

[2] https://hadoop.apache.org/docs/current/hadoop-project-dist/hadoop-hdfs/HdfsDesign.html

[3] https://www.mongodb.com/atlas/data-lake

to automatically derive the minimal frequency, history, *etc.* of such data pursuing Digital Shadows need to be conceived.

4. Composing and integrating Digital Shadows. Digital Shadows are data structures linking to models, data traces, assets, and data sources. For parsimonious data collection, Digital Shadows and Digital Shadow Type need to be reusable in different contexts. For instance, a Digital Shadow representing the power consumption of different parts of a manufacturing system could be integrated into a Digital Shadow representing the power consumption of a factory containing that manufacturing system. Consequently, Digital Shadow must support comprising other Digital Shadows, including their models, data traces, assets, and data sources. Where Digital Shadows include data of different quality, from different time frames, or collected at different intervals, they need to be integrated, merged, composed, or embedded carefully to retain the semantic integrity of the result. Otherwise, composing incompatible Digital Shadows might lead to making flawed decisions based on their data. Consequently, also the notion of Digital Shadow compatibility needs to be investigated.

5. Connecting Digital Shadows to data sources. Digital Shadow Types describe logical data structures that refer to data sources. They do not explain how the data shall be obtained, *e.g.,* the technical realization of data access. This separation of concerns serves the purpose of reusing Digital Shadow Types with different systems and in different contexts. This, however, demands connecting the platform-independent Digital Shadow Types to platform-specific data sources. Currently, this mapping needs to be established manually. In a future where systems are modeled holistically, the information about technical access to data sources will be part of the system models and the mapping of Digital Shadows can be derived from these accordingly.

All of these functionalities can be used in the future to create context-aware Digital Twins that optimize the production process in CPPS based on data encapsulated in Digital Shadows.

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