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# Digital Twin data architecture for Product-Service Systems

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#### Abstract

The digital representation of physical products by Digital Twins has been increasingly perceived as a relevant enabler for Product-Service Systems (PSS). Digital Twins concentrate product data that can be applied to generate insights and thus support value-added services. However, the literature on the intersection between Digital Twin and PSS has only recently started to receive more attention. There are still research gaps related to the required data and systems integration. In this context, this research aims to propose a Digital Twin data architecture to support Product-Service Systems operation. A Design Science Research (DSR) approach is applied, and the proposed architecture has been implemented and tested. Assessment results indicated that the proposed Digital Twin architecture fulfills the four requirements established from the literature: 1) facilitate and support the service offering; 2) acquire and transmit field operation and customer data; 3) integrate design and manufacturing data; 4) guarantee real-time monitoring, data integration, and data fidelity. The presented results provide an original contribution to the research area and can serve as a reference for applying Digital Twin to support PSS in practice.

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## 1. Introduction

A Digital Twin provides a digital representation of an individual physical entity employing data and models enabled by information and communication technologies [1–4]. Digital Twins can be applied to support product real-time remote monitoring, simulation, and predictive maintenance, among other functions [5–11]. These applications typically represent advanced value-added services that, combined with physical products, constitute Product-Service Systems, or shortly PSS [12–15]. A PSS is defined as "an integrated product and service offering that delivers value in use" [15]. Thus, Digital Twins can be considered relevant enablers of PSS [16, 17].

The relationship between Digital Twin and PSS is an emerging topic in the literature. Recent literature reviews show

that the publications focusing on Digital Twin have rapidly grown, especially after 2015 [18–20], reflecting an increasing interest from industry and academia. Works to date have extensively explored the Digital Twin conceptual and technological aspects [3, 17, 18, 21]. Moreover, there has been a strong focus on reporting single Digital Twin case applications [18]. The relationship between Digital Twin and PSS started to receive more attention only recently [16, 22–25].

Although the literature on the intersection between Digital Twin and Product-Service Systems has been expanding, there is still a gap related to the required data and systems integration. Current works typically do not address the role of traditional manufacturing information systems (Product Lifecycle Management – PLM, Enterprise Resouce Planning – ERP, and Manufacturing Execution System – MES) in providing

information to Digital Twin to support PSS. Hence, this research aims to propose a comprehensive Digital Twin data architecture to support PSS operation. Therefore, a Design Science Research (DSR) approach is applied. The proposed architecture has been implemented in a Learning Factory.

The remainder of this paper is structured as follows. Section 2 presents the literature background. Section 3 discusses the research methods. Section 4 details the proposed Digital Twin data architecture to support PSS. Section 5 presents the case application and assessment. Section 6 discusses the theoretical and practical implications. Finally, Section 7 summarizes the main conclusions, discusses the research limitations, and provides recommendations for further research.

## 2. Literature background

The research stream relating Digital Twin to PSS has gained more attention recently. Table 1 presents an overview of relevant research with this focus.

Table 1. Selected literature combining Digital Twin and PSS.

	8 8
Reference	Main focus and contribution
Brissaud et al. (2022) [16]	Review the literature and advancements in PSS in the last 10 years, focusing on Industrial Product-Service Systems (IPS2).
	Position Digital Twin – among other technologies – as an enabler for IPS2.
Bertoni and Bertoni (2022) [22]	Present a literature review focusing on Digital Twin application for PSS (DT PSS).
	Propose a mapping definition for the DT PSS.
	Identify gaps in the literature, such as the lack of models and tools.
Leng et al. (2021) [25]	Propose a novel Digital Twin optimization approach for a large-scale automated PSS warehouse.
	The proposed solution was tested in a prototype.
Mourtzis et al. (2022) [23]	Propose a framework to include customers in the PSS design process leveraging Digital Twin and Virtual Reality technologies.
	The proposed framework was implemented in a software platform and assessed in a case application.
Mourtzis et al. (2022) [24]	Propose a Digital Twin framework and application for smart grid (energy) PSS applications.
	The proposed solution was implemented in a software platform and tested on the university campus.

The first two works listed in Table 1 [16, 22] are literature reviews. [16] present a review of the Industrial Product-Service System (IPS2) developments in the last ten years compared to the beforehand expectations. The topic is explored extensively, and Digital Twin emerges as a critical technology for the next IPS2 developments. [22] specifically focus on the intersection between Digital Twin and PSS. The results indicate the need for more research providing models and tools.

The remaining three works listed in Table 1 [23–25] present specific Digital Twin applications in PSS for warehousing systems, design processes, and smart grids. The proposed frameworks are prototyped and assessed in testing environments. Despite the important advancements, none of the works listed in Table 1 explore the Digital Twin data

architecture to support PSS. Additionally, the extant literature does not relate the Digital Twin to software packages (e.g. PLM, ERP, and MES) that are usually required to operate PSS.

Beyond the works specifically relating Digital Twin to PSS, a consolidated research stream focuses on information models for Digital Twins. Existing research covers various perspectives, including ontologies [26], information architecture [27, 28], big data [29], and communication protocols [30]. However, these works do not address the required information integration to allow Digital Twins to support PSS. The complexities of digital twins to support services may require a hierarchical system of aggregated digital twins coupled with a services network [31].

The PSS literature presents relevant requirements for information integration. A data architecture for PSS should facilitate the service offering [16]. As services must be provided during the product usage phase, data for PSS must be acquired from the field operation – this is typically enabled by Internet of Things (IoT) solutions providing data acquisition and transmission through sensors, processing, and communication functionalities [32]. Moreover, PSS offerings need access to design and manufacturing data – e.g., as-designed, and as-built Bill of Materials (BOMs) – to offer predictive maintenance and spare parts services. This information is frequently available in software packages, including PLM, ERP, and MES [33]. Finally, a data architecture for a Digital Twin for PSS should also fulfill the general requirements for Digital Twins, mainly real-time data, data integration, and data fidelity [34].

In summary, the development of a Digital Twin data architecture for PSS needs to: 1) facilitate and support the service offering; 2) acquire and transmit field operation and customer data; 3) integrate design and manufacturing data; 4) guarantee real-time monitoring, data integration, and data fidelity.

### 3. Methods

A Design Science Research (DSR) methodology is applied to propose and assess a Digital Twin data architecture to support Product-Service Systems operation. A DSR research is appropriate when the research aims to generate new artifacts (e.g., constructs, models, methods, and instantiations) to address a given problem [35].

The DSR methodology adopted in this research has six steps: 1) problem identification, 2) objectives definition, 3) design and development, 4) demonstration, 5) evaluation, and 6) communication [35]. The problem identification and the existing research gap are discussed in the introduction (Section 1) and further detailed by the literature review (Section 2). In the emergent literature on the intersection of Digital Twin and PSS, there is a need to develop further models and tools [22]. Based on the current gaps, this research aims to propose a comprehensive Digital Twin data architecture to support Product-Service Systems operation. The requirements for the solution are derived from the literature review (Section 2). The design and development of the proposed solution – the next DSR methodology step – is summarized in Section 4.

The proposed solution architecture was implemented in a Learning Factory providing the Information Technology (IT)

and manufacturing environment. Learning Factories can be defined as close to real manufacturing environments applied for educational, technology assessment, and demonstration purposes [36, 37]. The Learning Factory in this research has a comprehensive, fully operational IT environment equipped with commercial off-the-shelf PLM, ERP, and MES software packages running on the University cloud infrastructure. The employed Learning Learning Factory uses a skateboard for product and process demonstration. As a durable consumer product for mobility, sport, and entertainment, a skateboard needs services along the lifecycle, such as in-field product monitoring and maintenance. Therefore, it can be considered to compose a Product-Service System. The demonstration and evaluation of the implemented architecture are presented in Section 5.

#### 4. Solution architecture

The proposed Digital Twin data architecture for Product-Service Systems was designed considering the solution requirements derived from the literature review (Section 2). The proposal is presented in Figure 1.

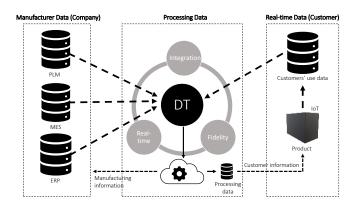


Fig. 1. Proposed Digital Twin data architecture for Product-Service Systems

First, the proposed solution was conceived to facilitate and support value-added services based on information processing. The Digital Twin provides a digital representation of the physical product. The digital representation is constructed based on the information gathered from various sources, as detailed next. Thus, the Digital Twin manages information that can be further processed by predefined algorithms and applications to predict the future status of the product and provide services. The processing within the Digital Twin element generates a response that can be stored in the Digital Twin itself (represented in the central and lower part of Figure 1) or directed to other elements of the architecture.

Second, a Digital Twin for PSS needs to acquire customer data from field operations. Therefore, the architecture considers the application of IoT devices to equip the product allowing data acquisition and communication. This data is stored in a specific database and integrated to form the Digital Twin representation (Figure 1, on the right side). The customer data management system provides the service element interface for this type of user.

Third, a Digital Twin for PSS must also integrate design and manufacturing data such as quality records (e.g., actual measurement data) and the as-built BOM. Usually managed by the manufacturer's PLM, ERP, and MES systems, this information is also integrated to form the Digital Twin for PSS (Figure 1, on the left side).

Fourth, the Digital Twin for PSS should guarantee real-time monitoring, data integration, and data fidelity. Real-time data collection is allowed by a well-established communication process based on IoT technology. The Digital Twin should explore different synchronization options with the event points of the product, especially in the case of connectivity instability on the customer side. The solution based on the architecture can be adapted according to the application, leveraging the existing infrastructure. For instance, the deployment of 5G technology can provide new alternatives to real-time data integration. Moreover, it should be able to import background data, component information, and configuration information from the physical components. Data integration is established by merging various data formats. The Digital Twin accesses two distinct data environments. The first is company internal manufacturer data (e.g., PLM, ERP, and MES). In this environment, design and production data are typically stored in structured databases that can be accessed when traditional communication protocols require. The second environment is real-time customers' information captured through IoT technologies. The connectivity reliability to the database and the variety of data is essential for generating relevant insights. Finally, data fidelity is achieved by assuring that every piece of information processed by the Digital Twin is valid and consistent over its lifecycle.

## 5. Application and assessment

The application and assessment were performed at a Learning Factory providing a technology demonstration environment.

#### 5.1. Case context

The studied Learning Factory has a comprehensive IT manufacturing environment comprising commercially available PLM, ERP, and MES software. The PLM system was implemented on a high-performance (8vCPU, 16GB RAM) Virtual Machine (VM) running an SQL Server and structured on a relational database. The ERP system was implemented on a high-performance extra memory machine (8vGPU, 32GB RAM) on a VM running SQL Server. A java-based product configurator interface was developed to receive individualized customers' orders to the ERP. The ERP backend runs a relational database on a Progress environment. Finally, the MES system was implemented on a regular (2vCPU, 8GB RAM) VM running SQL Server and having a relational database on a SQL Server environment. Besides, the MES software has an integration script with the ERP that automatically captures an XML file from the ERP and converts the data into its database format. The Virtual Machines were hosted in the university cloud infrastructure. The software vendors supported the software installation, configuration, and

management. Table 2 summarizes the IT infrastructure characteristics.

Table 2. IT infrastructure characteristics at the Learning Factory

Software	Hardware	Database	Application
PLM	8vCPU, 16GB RAM	SQL Server	Product design specifications
ERP	8vCPU, 32GB RAM	Progress	Customers' order data
MES	2vCPU, 08GB RAM	SQL Server	As- manufactured information (e.g. quality events, as-built BOM)
Product monitoring	8-bit ATmega328P microcontroller (Arduino Uno)	No-SQL	Customers' individual use data from the field

As part of this research effort, an IoT hardware and software (backend and frontend) were developed and installed in the Learning Factory physical product (skateboard) to collect users' data from the field. The IoT device was developed on an Arduino Uno firmware with a Wi-Fi module and different sensors to capture real-time data from the product use. The application of an Arduino Uno aimed to facilitate prototyping and testing. The collected data is sent to a No-SQL cloud storage and can be accessed through a REST API when authorized by the customer and requested by other applications.

Furthermore, two software applications were developed to manage the customers' activity on product use. The first application is responsible for showing the product's usage aggregate information from the product activation until the present moment. This application collects the No-SQL data through a JavaScript request and presents the information on an HTML page (interface). It also works the other way around, sending low-level commands from the HTML page that are manifested in the physical product — e.g., turning on the skateboard led-lightning. The second application collects accelerometers' data on the skateboard to reconstruct the movements of the product. With this PHP application, it is possible to represent and visualize the kinematic digital 3D model of the physical product (Figure 2). Details of the IoT implementation are reported in a previous publication [38].





Fig. 2. Dashboard interface and kinematic 3D representation of the product equipped with IoT hardware [38]

The available IT environment (Table 2) and IoT connected product (Figure 2) were applied to demonstrate and assess the proposed Digital Twin data architecture to support PSS.

## 5.2. Case application

The proposed Digital Twin data architecture for PSS was applied and tested in the Learning Factory environment. The case application followed four main steps: 1) systems integration; 2) development of the Digital Twin software; 3) development of service algorithms; 4) assessment. Each one of these steps is detailed and discussed next.

Data integration required understanding each system's export file formats and how to access information continuously. For the manufacturer data environment, the connection was to a SQL database through server connections. For the customer data environment, the connection was made through a REST API on a No-SQL database.

The PLM, ERP, and MES software were installed on the Learning Factory cloud server. A remote connection to the databases was established through a TCP-IP protocol on port 1443 connection. The ERP and MES systems were already connected through XML on an integration developed by the systems' providers, so access to both systems' data was established through a TCP-IP protocol at the MES. The integration between the ERP and MES is based on a Java application on the MES that captures information from an XML file available at a specific address on the ERP. The MES acquires from the ERP the BOM, the work order information, the manufacturing lead times, the project code, and the customer information. On the other hand, the MES provides to the ERP the work order status, production status, and resources status.

An application was developed on the customers' side to collect customers' usage data and store it on a private partition of users' cloud space to be accessed through an API. The user has control of its information, being capable of canceling the API access at any given time. The data is captured using sensors connected to a dedicated board that transfers the information through internet protocols to the customers' private database. The data captured are the x, y, and z position of the product, the timestamp of the event, and the status of the products' ledlightning. The non-structured database, to improve connection time and decrease storage space, can be accessed from a client-service perspective and serve as a multiple-viewer platform.

The Digital Twin connects information from both the manufacturer and customer environments, processes this information, and provides cross-validated insights to lifecycle phases and stakeholders. The Digital Twin was implemented on a Python/SQL platform that accesses the system's database by an ODBC and API connection. It was deployed on a 1vCPU, 1.7GB RAM virtual machine. Figure 3 details the implementation of the proposed data architecture.

After establishing the integration environment, algorithms were developed to simulate value-added services based on individual customer and product data. These algorithms were developed in Python and SQL to provide new inputs for the system, connecting the different lifecycle phases. The Digital

Twin captures relevant data and runs analyses to predict incoming events for the manufacturer and customer – i.e., predictive maintenance, demand for spare parts to be replaced, and potential product failures. The analysis results are stored in an application log and communicated to the impacted product stakeholders.

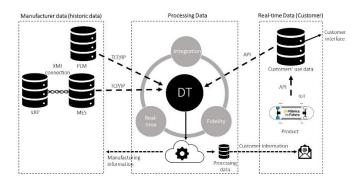


Fig. 3. Implementation of the proposed Digital Twin data architecture to support PSS.

An algorithm to recommend wheel replacement was implemented to demonstrate the use of Digital Twin information to provide a service for the customer in a PSS setting. This algorithm captures, from the customers' database, the product initiation date, the total traveled distance, and the average speed. Then, this information is analyzed considering the actual wheels' maintenance parameters. The wheels' characteristics are obtained from the product structures of the PLM and ERP systems. The exact manufacturing batch parameters are captured from the MES system. The algorithm combines user and manufacturing parameters and forecasts when each user will achieve the recommended traveled distance to replace the skateboard wheels. The algorithm then indicates whether the maintenance schedule is approaching or overdue and provides feedback to the customer and the manufacturer about the need to order new wheels and schedule maintenance.

#### 5.3. Case assessment

The case assessment was performed considering the solution requirements established from the literature: 1) facilitate and support the service offering; 2) acquire and transmit field operation and customer data; 3) integrate design and manufacturing data; 4) guarantee real-time monitoring, data integration, and data fidelity.

As demonstrated, the implemented data architecture was able to support a value-added service (predicting the need for wheels maintenance). The implemented solution also acquires data from both the manufacturing and customer usage environments. The proposed architecture provides data integration and fidelity logic. The integration between environments is possible because the proposed Digital Twin model is conceived for heterogeneous operation and preserves the original data structure. The database is structured considering an individual monitor for each product ID, supporting scalability. A hash code is created associating the product's ID and its correspondent usage information. Hence,

the application connects data from different stages of the product lifecycle, processes data, and generates new information, providing conditions for creating a PSS. The proposed architecture structure based on distinct data environments is necessary to prevent data redundancy. The use of the existing systems to store the data ensures data fidelity and data governance. Finally, the fast connection time (0.0075s to the ERP, 0.0089s to the MES, 0.051s to the PLM) and the IoT device on the customer side allows for real-time data connection.

## 6. Discussion and implications for the theory and practice

The proposed Digital Twin data architecture for Product-Service Systems contributes to the theory and practice. Regarding the theory, the proposal adds to the emerging research stream on the intersection of Digital Twin and PSS. This proposal also responds to Bertoni and Bertoni (2022) call for developing models and tools for the Digital Twin PSS. Moreover, the present proposal presents another reference case to the evolving body of knowledge in the field, complementing previous initial works [23–25]. From the Digital Twin research stream perspective, current results add a novel data architecture integrating PLM, ERP, and MES systems to the Digital Twin. From the PSS research perspective, the results address the need for technological enablers to support wider PSS adoption [16].

The contributions to the practice are twofold. First, the presented results illustrate how a Digital Twin can be implemented in practice to support PSS. The case application in the Learning Factory featuring a close-to-real IT environment (including operational ERP) grants a valuable experience account for the industry. Second, the wheel replacement service offering exemplifies how Digital Twin and PSS can interoperate to provide value-added services. Based on this example, other business applications can be considered. For instance, collecting information from the customers' use can provide information for the designers to analyze the actual product use in the field. Data from use can be combined with manufacturing information to simulate product behavior, predict product events, and thus provide valuable insights to customers. The proposed solution may be useful for multiple stakeholders along the value chain and product lifecycle, such as designers, manufacturing operators, customer relations professionals, suppliers, and customers. In the current implementation, this will require the stakeholders to access the Digital Twin system interface. For instance, the Digital Twin data repository may provide insightful information for designers by defining the next product generations.

#### 7. Conclusions

This work presents a novel Digital Twin data architecture to support Product-Service Systems operation. The proposed architecture was conceptualized and implemented in a Learning Factory providing a case application. The case assessment indicates that the proposed architecture fulfills the established requirements from the literature. The results contribute to the emerging research stream combining Digital Twin and PSS and may further support PSS dissemination in practice.

The research conducted also has some limitations that need to be observed. The application was limited to a single case in a close to real environment. Although the Learning Factory demonstration was constructed based on commercially available software packages, a Learning Factory does not have the same level of complexity present in actual manufacturing operations.

This work opens interesting opportunities for future research efforts. The proposed data architecture may be expanded and detailed into corresponding data and process models. Novel algorithms can be explored to generate customer and product insights in the interface between Digital Twin and PSS. The scalability of the solution still needs to be resolved. Additionally, there is an opportunity to expand the solution application and assessment to other cases and contexts, such as different types of Product Service Systems.

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