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Examination of the Utilization of Use Phase Data for PSS Design

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Abstract

Product-Service Systems (PSS) generate a large amount of heterogeneous data during their use phase. This data often provides the basis for services such as predictive maintenance. The integration of use phase data into the PSS design offers the potential for optimization of designs and customizations in the development process for both the physical product and the services. This article aims to identify potential use phase data that can be integrated into PSS design and to demonstrate how this integration can be incorporated into PSS design processes. It displays how the use phase data in combination with digital models, digital shadows, and digital twins can lead to improved PSS design and more customized PSS configurations.

Keywords: Product-Service System; PSS Design; Data Analysis

1. Introduction

The gathering of data along the life cycle of Product-Service Systems (PSS) plays a central role in the performance of services [1]. Particularly in the use phase, large amounts of data can be obtained.

In a Business-to-Business (B2B) context, data collected within a PSS is used mostly to fulfill a specific operational need. For instance, a manufacturing company might gather machine performance data from a customer's equipment through a PSS. This data is then used to predict maintenance needs and thereby improve machine efficiency [2]. However, it is rarely used for other purposes, such as product development or marketing activities. In the conceptualization of a PSS and the associated planning and definition of data streams, little consideration is usually given to making the data usable for upstream life cycle phases [3].

The utilization of use phase data is also dependent on the way the data is gathered and processed. There are differences in the degree of automation, continuity of recording, preprocessing, and storage. These differences create barriers to the use of this data in the design phase. An additional obstacle is that the data that can be used for design processes is fundamentally different from the raw data from use [4].

However, improvements in PSS design can be achieved through utilizing data from the use phase by the conceptual inclusion of digital models, digital shadows, or digital twins in the PSS design process [5]. This can potentially lead to PSS that are better adapted to the customer needs, for example in the form of a leaner and more precise service offering, the discontinuation of including unused features, or an optimized configuration of subsequent PSS generations. To exploit this potential, further analysis is required to be able to incorporate the data into the design process in a targeted manner. Also, design frameworks need to be adapted to alter requirements based on the use phase data.

The remaining paper presents a literature review in Section 2, concluding with the identified research gap. In Section 3, an examination of use phase data based on a rising level of data integration into the design phase of PSS is presented. Section 4 ends the paper with a brief conclusion and future research potential.

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2. Literature Review

2.1. PSS Lifecycle

The lifecycle of PSS can be roughly divided into PSS design, PSS realization, and End-of-Life (EOL) [6]. The design of a PSS begins with the planning phase, where potential ideas are identified, selected, and specified to meet the needs of both the customer and the provider. This stage focuses on understanding customer demands and ensuring the solutions are aligned with the provider's objectives. In PSS development, these selected ideas are transformed into market-ready PSS elements, which include a combination of physical products and service offerings. These elements are designed to be flexible and customizable, allowing them to be adapted to specific customer needs. Finally, the customer makes a purchase decision, selecting a tailored PSS solution based on the available configurations that best suit their requirements [7]. The realization of a PSS begins with the production of the physical product, which is then delivered to the customer for its intended use. While the product is in use, services are provided according to the customer's needs. These two aspects, the use of the physical product and the delivery of services, occur simultaneously and in coordination. To support this delivery, the required service resources must be supplied by the value-added network. The final phase is the EOL stage, where the product is either disposed or recycled [7].

2.2. PSS Lifecycle Data

Throughout the PSS lifecycle, data is created and used for different purposes. In PSS design, foremost models are built, such as CAD models or service blueprints [8]. In addition, production plans for the physical products are created based on forecasted customer demands [9]. SONG AND SAKAO identify several supporting data needed for the PSS concept design. For PSS requirement identification and analysis, product life cycle information is needed. PSS modularization requires data on service processes and resources, such as the aforementioned service blueprints. For PSS configuration, a library of PSS module instances needs to be established [10].

The data created in the PSS realization differs significantly from the data in PSS design. From the production of the physical product, process data (e. g. machine settings, energy consumption, or cycle times), quality data (e. g. first pass yield, scrap rates, or inspection results), supply chain data (e. g. supplier quality data or shipment data), environmental data (e. g. emissions or hazardous material data), or data from advanced sensor capturing in an Internet of Things (IoT) context [11, 12]. Data from the use phase is dependent on the respective physical product. For technical PSS, use phase data can include operation time, downtimes, availability, wear, consumptions, quality data, or occurring errors. In combination with user interaction, data on operator input and efficiency can be gathered within the boundaries of data security. Looking at life cycle data, safety data, and data about maintenance and environmental aspects can be obtained [13, 14]. Data-driven PSS are based on smart products and services. With sensors and software, data-driven PSS collect data and can deliver services based on their analysis [15].

To optimize the use of data from PSS realization for the planning and development of both products and services (design phase), as well as for the refinement of service offerings and content (use of PSS), the automation of data exchange is crucial. This enables the real-time utilization of data, enhancing the responsiveness and efficiency of the system. The technical solution for this can be seen in the concept of digital models, shadows, or twins.

2.3. Digital Models, Digital Shadows, and Digital Twins

The digital twin (DT) is a digital representation of a physical system that is connected bidirectionally and can exchange data automatically and in real-time. This real-time linkage enables continuous monitoring and control of the physical system. In addition, the stored data can be used to analyze historical data or predict future behavior of the physical system using various models within the DT. A DT is characterized by high fidelity, as it precisely replicates the physical system and is continuously updated [16]. However, the term DT was used in literature for different applications and various levels of data integration, which is why KRITZINGER ET AL. introduced three levels: digital model (DM), digital shadow (DS), and DT [17].

The DM is a static representation of the physical system without automated data exchange. The DS extends this model by enabling data from the physical system to automatically flow into the DM, though only unidirectionally. The DT represents the highest level of data integration with a bidirectional data exchange that occurs in real-time. This distinction is based on the level of integration and automation of data exchange, as shown in Figure 1. The DT offers the greatest potential for PSS by enabling continuous optimization of products and services through real-time data exchange.

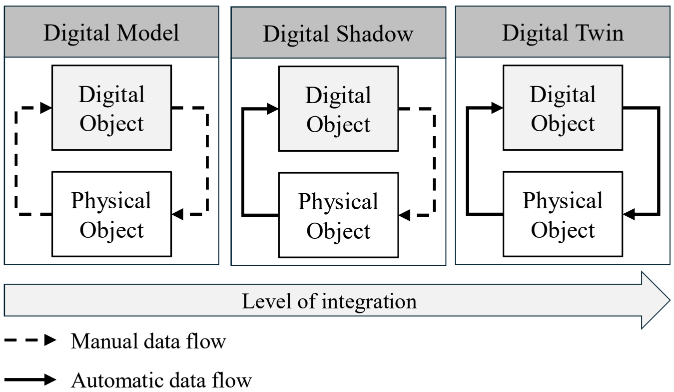

Figure 1: Differentiation of digital model, shadow, and twin [17]

Physical objects can be augmented with DMs, but without automated data exchange, these remain static. To automate data exchange and implement digital shadows or twins, various key technologies must be implemented [18] which enhances data integration and increases the potential for PSS applications.

For the physical objects, hardware like sensing and measurement technologies, as well as actuators, need to be implemented to generate the necessary data [19]. Additionally, data handling technologies are of importance, as there cannot be DT solutions without an automated data exchange. Therefore, the proper transmission method (e. g. wireless transmission using Wi-fi, Bluetooth), the data management (e. g. selection of databases), and the computing technologies (e. g. edge computing, cloud computing) must be selected [18]. For the other dimensions of the DT, like the virtual entity and the services, models need to be developed depending on the aspired added value of the DT-PSS solution [19].

2.4. Existing Approaches to include Data in PSS Design

Despite the aforementioned barriers, several approaches exist that include different kinds of data in PSS design.

SAKAO AND NERAMBALLI examine the potential of big data analytics for PSS design in a literature synthesis. The authors show that the main sources for big data are the use of products and the performance of services. Also, a schema for conceptual PSS design is presented, showing that PSS design can benefit from big data analytics in functional unit definition, stakeholder identification, requirement consolidation, creating of value propositions, integration of value-adding elements, balancing services and products, and evaluating combinations and configurations of a PSS. SAKAO AND NERAMBALLI discovered several research opportunities for big data enhanced PSS design, such as using data analysis to obtain insights into customer expectations and preferences, building clusters of PSS, or different PSS value propositions [20].

REN ET AL. combine operation data with deep neural networks to enhance the maintenance performance of an industrial PSS centered around a CNC machine. The research shows that use phase data can be used to improve the operation of PSS in use. The authors emphasize that the design of PSS is crucial to establish the possibility of gathering and analyzing data with the application of sensors and IT infrastructure [1].

BERTONI uses historical PSS operational data to identify alternative design configurations within a feasible design space. In this data-driven design approach, surrogate models for each potential design configuration are created using machine learning and design of experiment techniques [21].

CHEN ET AL. examine how customer reviews can be used to better understand customer requirements using different data analysis methods. They demonstrate that requirements can be found quicker and can be better understood [22].

Mourtzsis et al. integrate measures of lean manufacturing in PSS design by the utilization of key performance indicators (KPI). They use KPI from different sources to optimize the PSS design process to support designers with lean principles [23], validated with a use case from the machine tool industry [24].

ZHENG ET AL. propose a design framework for platform-based and DT-enabled PSS. It consists of the four steps of platform development, data acquisition, data analytics for service innovation, and DT-enabled service innovation [5].

Besides these approaches, other potentials of including use phase data in PSS design were identified. Data from the consumption of operating resources, such as electricity or fuel, can be used to perform life cycle assessments in the design of later PSS generations [25], leading to enhanced sustainability. The use of big data in manufacturing has applications, divided into out-of-enterprise and intra-enterprise applications [26].

2.5. Research Gap

While large amounts of data are collected during the use phase, particularly in B2B contexts, this data is primarily used for operational purposes, such as maintenance, rather than being utilized to enhance the design of future PSS generations. DMs, DSs, and DTs present a solution to bridge the gap between use phase data and PSS design. By using varying degrees of data integration and automation, these digital representations of PSS offer pathways for incorporating use phase data into the design process.

It remains unclear how the integration of use phase data through DMs, DS, and DTsaffects PSS design processes. Furthermore, it is vital to investigate how the various data types outlined in Section 2.2 can be used within this context and what variances occur due to the different capapilites of the digital representations of PSS.

3. Utilization of Use Phase Data for PSS Design

The utilization of use phase data in PSS design is dependent on the degree of automation of data flows. The differences in data flows and their high-level effects on the design are shown in Figure 2. The upper part of the figure shows the basic PSS lifecycle described in Section 2.1. Under the PSS lifecycle, the three degrees of data automation according to KRITZINGER ET AL. [15] are shown with manual and automated data flows.

The first design variant, the design with a DM, relies mainly on experience and predefined requirements, with little to no feedback from the use phase and without automated data exchange. The data flow is largely manual from the analysis of products from EOL. Data in the design phase is basically limited to the predetermined models and plans (Section 2.2).

Design with DSs uses experience and requirements, enhanced by data collected from the use phase. This adds a layer of automation. Data collected during the use phase is automatically fed back into the design process, enhancing design based on real-world usage data. However, this data exchange is still unidirectional, meaning no real-time adjustments in the realization of PSS can be made.

The design with DT uses real-time data for both design and ongoing adjustments, allowing the system to be continuously refined based on actual usage. This represents the highest level of data integration and allows adjustments to be made to design, manufacturing, product configuration, and service offerings throughout the use phase. This also requires all different data from PSS design as well as PSS realization.

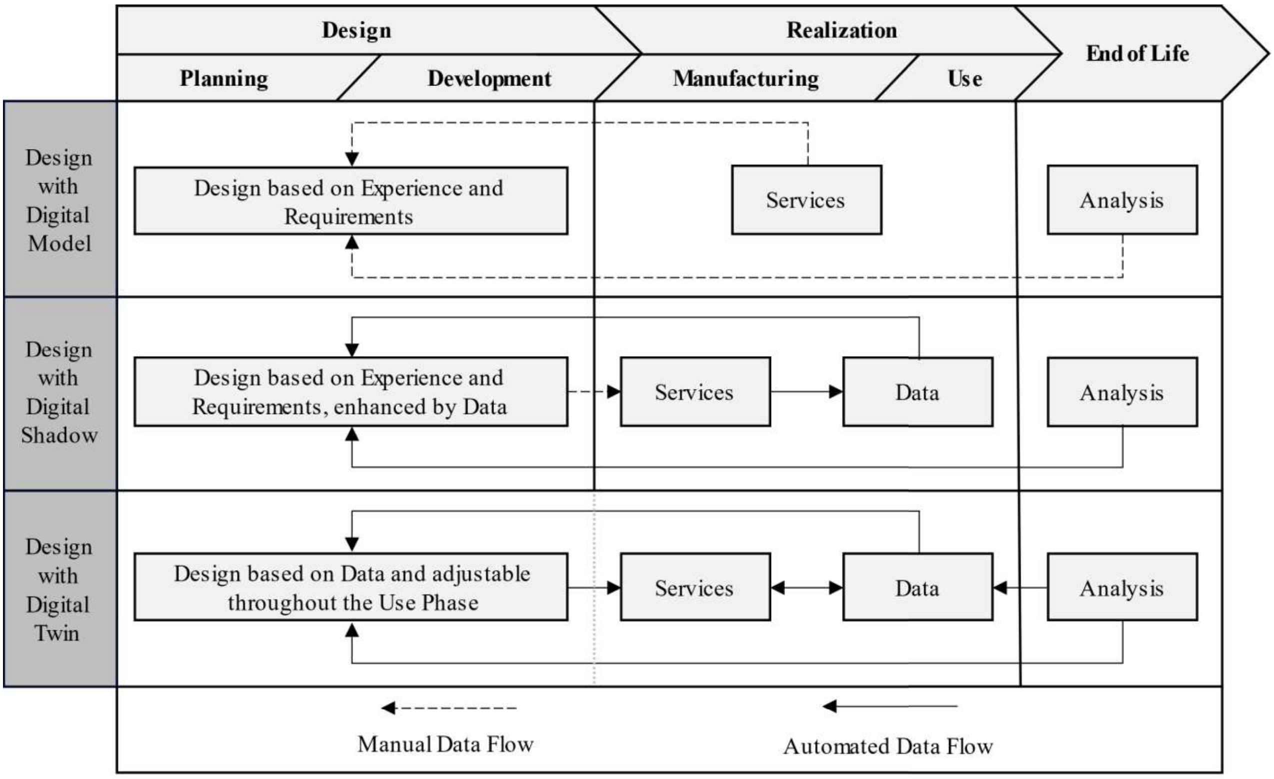

Figure 2: PSS Design variants based on digital models, digital shadows and digital twins

3.1. Design with Digital Models

Designing a PSS with DMs reflects traditional approaches where the design process is based primarily on experience, expert knowledge, and predefined customer requirements. DMs provide a static representation of the physical and service elements of the PSS without automated or real-time data exchange from the actual use phase. Assumptions are made about how the product will perform during its lifecycle based on experience, rather than use phase data.

DMs are used to create representations of the physical product and the accompanying service offerings, such as CAD models for the product or service blueprints for the services. These models represent the PSS at a certain point in time but do not update automatically based on how the system is used.

Any feedback from the product's use phase or customer interaction is manually collected and incorporated into future design cycles. Performance data might be gathered through periodic inspections or user feedback, but this process is not automated. Data collected may include customer complaints, maintenance records, or service efficiency assessments, which are later analyzed to inform future design adjustments.

Because there is no data feedback, most of the design decisions must be made at the planning and development stages. This includes determining the features, functionalities, and service requirements based on assumptions of customer needs and product performance. Changes after product launch are harder to implement and require manual input.

The PSS designed with DMs might be more rigid and less responsive to real-time issues that arise during its lifecycle. Adjustments to product features or services are usually made after significant delays or upon manual review of collected data. This approach is more suited for environments with infrequent changes or for systems that don’t need continuous optimization during the use phase.

PSS based on a design with DMs can have some limitations. Without automated data collection, the system's design cannot dynamically adjust based on actual usage. Changes to the PSS are based on manual data flow, meaning innovations and improvements happen only after sufficient data has been gathered and analyzed, slowing down innovations. The system design may not fully reflect real conditions, as it relies on assumptions made in planning.

3.2. Design with Digital Shadows

Designing a PSS with DSs involves enhancing the traditional design process by incorporating automatically collected, real-time data from the use phase of the system. A DS represents a more advanced level of data integration than a DM, as it allows unidirectional data flow from the physical product or service to the DM, meaning the PSS sends data to the initial design model but cannot receive updates or adjustments in real time from the model.

In addition to relying on experience and initial requirements, design decisions are enhanced by the actual data collected from the product or service during its use phase. For example, sensor data such as operating hours, maintenance logs, energy consumption, and performance metrics can be automatically collected and analyzed. This data helps identify issues like inefficiencies, wear and tear, or frequent user errors. The data collected by the DS can be visualized and analyzed to uncover patterns and trends. This analysis provides valuable insights into how the PSS is performing in the field. These insights can be used to adjust not only product features but also services, such as offering more personalized maintenance or optimizing resource use based on actual consumption data.

Unlike manual data flow in the DM approach, DSs rely on technologies such as sensors, IoT devices, and data transmission methods (e. g. Wi-Fi, Bluetooth, 5G) to automatically feed data from the physical product or service into the digital representation. This automated data collection significantly improves the accuracy and relevance of the data used for decision-making compared to manually gathered data. The data can inform areas such as maintenance planning, energy efficiency improvements, or adjustments to service offerings based on specific customer behavior. Nevertheless, changes based on the collected data can only be applied in the next iteration of the product or service, as there is no real-time feedback loop. For example, if the data shows that a machine frequently breaks down after a certain number of operating hours, this insight can be used to improve the design of future machines or enhance the associated maintenance service, but the current machine cannot be adjusted dynamically.

For PSS design processes, some adjustments need to be made compared to the design with DMs. Initial designs are created based on requirements and experience, but with a focus on integrating sensors and data-collection capabilities into the physical product and service offerings. The design process also considers how the data will be transmitted, stored, and analyzed (e. g., edge computing, cloud-based analytics). Together with data collected from used products, data collected from the DS is analyzed to identify inefficiencies, opportunities for improvement, or issues that were not anticipated during the design phase. Designers can make better-informed decisions based on how the system is used in real-world conditions. This data-driven insight is used to refine the next generation of the product or service, allowing for improvements over time based on use phase data. In addition, development cycles can be shortened and started earlier because use phase data can be collected directly after distribution. There is a threshold of minimum data needed, but time to market can be shortened in contrast to the manual data acquisition and analysis with DMs.

Due to the unidirectional communication, there is no ability to adjust the PSS dynamically, leading to time lags in implementing changes. The data collected will improve future PSS designs, but any adjustments or optimizations can only be implemented after analyzing the data and forwarding the results manually, making the system less responsive to immediate needs.

3.3. Design with Digital Twins

Designing a PSS with DTs represents the highest level of data integration, where real-time, bidirectional communication between the physical system and its digital counterpart allows for continuous monitoring, analysis, and adjustment. The DT not only collects data from the physical product or service but also can influence it dynamically during the use phase. This capability provides significant advantages in terms of flexibility, responsiveness, and optimization, so PSS designers can develop systems that are adaptable throughout their entire lifecycle. Bidirectional communication weakens the separation of PSS design and realization and merges them, as shown by the gray and interrupted line in the lower part of Figure 2.

The design is data-driven from the start, and the system is built to be adjustable and adaptable during operation. This creates a more flexible and responsive PSS, where changes can be implemented dynamically to improve efficiency, performance, and customer satisfaction. DTs rely on technologies such as sensors, actuators, IoT connectivity, and edge or cloud computing to collect, analyze, and act upon data in real-time. The DT uses this data to simulate, predict, and optimize the behavior of the physical system. For example, predictive maintenance can be triggered based on sensor data, or operational parameters can be adjusted during operation to reduce energy consumption or increase productivity.

With DTs, PSS design is not a static process but a continuous one. The continuous data flow enables immediate feedback from the use phase into the design phase. Designers can see how the PSS is performing in real-time and make adjustments or refinements to improve the current system or inform future versions. This creates a more iterative and responsive design process, where PSS solutions are constantly being improved based on real-world data. Additionally, the integration of multiple data sources (PSS at different customers) allows for better decision-making and more precise adjustments to the PSS.

The PSS design process begins by defining the key metrics and data points to be monitored and controlled by the DT. These can include performance data, environmental factors, customer interactions, or maintenance needs. The system is then planned with the necessary sensors, actuators, and data transmission capabilities to support real-time bidirectional communication. The DT is developed to be an accurate and dynamic model of the physical system, capable of running simulations. Once the physical system is manufactured and deployed, the DT is continuously synchronized, receiving real-time data and adjusting the system as needed. During the use phase, the DT monitors performance, predicts issues, and dynamically adjusts settings or triggers maintenance to optimize the system. The real-time data flow allows the PSS to be continuously optimized based on current conditions. Designers can make adjustments to improve performance without needing to wait for the next product iteration. The system becomes highly adaptive to changing customer needs or operational environments, making them more efficient, and better aligned with actual customer usage. Over time, the data collected by the DT provides valuable feedback for the design of future PSS generations. This feedback loop enhances the design process, ensuring that future versions are more finely tuned to customer needs and system requirements. Data from the current use phase can also improve the EOL decisions, such as when and how to dispose of or recycle components in a way that maximizes sustainability and minimizes waste.

4. Conclusions and Outlook

This paper has examined the integration of use phase data into PSS design processes through varying degrees of data automation, from DMs to DSs and DTs. It highlighted a research gap in how current PSS design frameworks underutilize valuable use phase data, often focusing primarily on operational improvements rather than feeding real-world data back into upstream design processes for future PSS generations. The transition from manual data collection and static DMs to automated, real-time data integration using DSs, and DTs offers promising pathways to close this gap. However, as seen in the analysis, each of these approaches comes with its own benefits and disadvantages, depending on the level of data automation and integration.

DMs represent the least automated form of data feedback, relying on manual processes and assumptions about product performance. In contrast, DSs offer a more advanced system where real-time data is collected automatically but in a unidirectional manner, delaying system optimizations. DTs introduce bidirectional, real-time data flow, allowing for immediate adjustments to both product and service elements during the use phase. This continuous feedback loop enhances flexibility, efficiency, and overall system performance, making it the most responsive design methodology.

While this study has demonstrated the potential of digital technologies to integrate use phase data for PSS design, several areas require further exploration. Future research will focus on enhancing automation levels in data collection, processing, and feedback. Developing methods for seamlessly integrating heterogeneous data sources, particularly for systems involving multiple customers, will improve the scalability and efficiency of DTs in PSS design. Although DTs offer real-time data feedback, the complexity of handling large volumes of data efficiently, ensuring data security, and integrating predictive analytics for dynamic system adjustments still requires research. Further studies will address how to harmonize these aspects to streamline the design process and promote wider adoption of DT-based PSS. Future research will also examine how data from DTs can better inform sustainable design practices, particularly for PSS EOL decisions. Another field of research is the utilization of data to optimize recycling, remanufacturing, or reuse, contributing to a circular economy.

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