Challenges of Utilizing Sensor Data Acquired by Smart Products in Product Development Activities

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Abstract: Emerging digital technologies enable capturing of a product's digital footprint through continuous monitoring of its performance, usage, and working environment while using data acquired by its embedded sensors. However, it seems that product development (PD) teams, within engineering companies, have not yet embraced the usage of sensor data acquired by smart products (SPs) when conducting PD activities. This study discusses several challenges that hinder a broader utilization of SP's sensor data, within PD. In addition to the literature review, the discussion is supported with empirical data gathered through a qualitative exploratory case study conducted in a large engineering and manufacturing company. As a result, three challenges are outlined. First, it is challenging for the company's management and PD team to gain transparency over the benefits of sensor data utilization for PD. Second, solutions providing accessibility and visualization of gathered data should be tailored to the PD activities and teams, which requires a holistic understanding. Finally, it is suggested that new skills, roles and processes should be introduced, in order to enable SP's sensor data utilization, within PD activities.

Keywords: smart product; sensor data; product development; digital twin; data-driven design

1 Introduction

Provision of the right amount of relevant information to the product development (PD) team throughout the entire PD process is one of the greatest challenges that engineering companies are facing [1]. Traditionally, the PD team would lose track of information related to the developed product once it enters the physical world and leaves the boundaries of the company [2]. Consequently, the PD team must have employed various methods (for example, surveys, interviews, observations) to solicit feedback from customers and close this information gap [3]. Incorporation of sensors and connectivity components (transmission and communication elements such as gateways) into traditional products has offered new potentials for gaining insights into how the products are used on the market. As a result, a continuous collection of product's data captured by incorporated sensors and their transmission over the internet back to the PD team has become an emerging extension to traditional feedback solicitation methods [2].

Smart products (SP) accompanied with digital technologies such as digital twin, digital thread, and digital feedback loop enable capturing of products' digital footprint by continuous monitoring of their conditions, usage, and working environment while utilizing data acquired by embedded sensors [4]. SPs consist of three essential groups of elements: physical (such as mechanical and electrical parts), smart (for example, sensors, microprocessors, data storage, and software), and connectivity components (such as protocols enabling wired or wireless connections) [5]. The data are captured by smart components and transmitted over the internet by means of connectivity components. Linking the captured sensor data and other product data with a physical SP throughout the entire lifecycle establishes SP's digital counterpart, i.e. digital twin [6]. The continuous, seamless stream of real-time or historical data captured by SP's sensors and other product data available from enterprise business systems (such as repair, history or sales data) that feeds the digital twin is often referred to as a digital thread [7], [8]. A digital thread gathers and transfers data related to a product throughout its lifecycle, thus connecting each stage of a product lifecycle management (PLM) process [6]. Integration of flows of product data and information within a company allows the closure of a digital feedback loop [9], which may lead to product reengineering or redesign and thus affect the company's entire product portfolio [10].

The growing number of SPs implementations has been noticed in various engineering industries - from automotive and aerospace to consumer goods [10], [11]. Nevertheless, it seems that PD teams within engineering companies have not yet embraced the utilization of sensor data acquired by SPs when conducting PD activities [2]. It has been argued that such a status is due to a lack of transparency on the potential benefits and applicable guidelines for systematic adoption of SP's sensor data utilization in PD activities [12]. The presented study aims to outline key challenges that a company must overcome in order to utilize SP's sensor data for the purpose of new product design or product redesign. As such, the presented study lays the groundwork for the further studies that may offer comprehensive guidelines for implementation of SP's sensor data utilization within PD activities of a specific engineering company. An initial step of the conducted study was a literature review which enabled an understanding of the state of the art in research on SP's sensor data utilization within PD activities. As a result, an overview of the related work is presented in Section 2, including the recognized research gaps. The methodology of the conducted study is described in Section 3. The empirical data were gathered through a qualitative exploratory case study conducted in the large engineering and manufacturing company. Empirical data gained through the case study are presented in Section 4. This is followed by a discussion of the challenges derived both from the literature review and the conducted case study within Section 5. Finally, conclusions and avenues for further work are drawn in Section 6.

2 Literature Review

Several factors, which are often considered in the approaches to technology adoption and implementation within companies (e.g. [5], [10], [12]–[14]), are presented within the literature review. The following factors have been identified as crucial for the utilization of SP's sensor data in PD activities: perceived benefits, infrastructural requirements, and organizational factors. Each of these factors is described in detail in the corresponding subsection (2.1 – 2.3). Related work is summarized in subsection 2.4, while research gaps are outlined in subsection 2.5.

2.1 Perceived Benefits of SP's Sensor Data Utilization

Benefits resulting from information and communication technology (ICT) adoption can be classified into four types: strategic, informational, transactional, and transformational [13]. Strategic benefits affect a company's market competence. For example, a strategic benefit may be a provision of new services by utilizing SP's sensor data as an asset, thus expanding the company's portfolio and creating a competitive advantage [10]. The informational benefits offer faster and easier extraction of information, deduction of knowledge, and enhancement of communication, which in return may result in improved decision-making in PD activities across PD stages (for example, to support a make-or-buy decision based on a component's reliability). Further, the transactional benefits refer to the support of the company's operations management. For instance, a shorter duration of PD activities such as product quality assessment (PQA) which consequently leads to faster introduction of the product to the market. The transformational benefits are those resulting from the organizational changes due to technology adoption efforts [13], [15]. For instance, improved data analysis capabilities of a PD team as a result of an introduction of new roles. According to the available literature, these benefits stem from utilizing SP's sensor data to support PD, with the key infrastructural elements as prerequisites. The key infrastructural elements are explained in subsection 2.2.

Potential benefits of SP's sensor data utilization have been explored across various domains and industries [16], as presented in Table 1. For instance, Jones *et al.* [16] offer a general overview of SP's sensor data utilization potential, while highlighting the need for the contextualization of the suggested benefits and implementation challenges faced by particular industry [16]. Wanasinghe *et al.* [17] provided such an overview of SP's sensor data utilization contextualized for the oil and gas industry, and Naticchia *et al.* [18] for the construction industry. However, when considering related studies in engineering industries, it can be noticed that a very few of them offer validation of the indicated benefits (e.g. [19], [20]). Hence, only potential of SP's sensor data utilisation has been indicated in the majority of the reviewed studies.

2.2 Infrastructural Requirements

The following infrastructural elements have been outlined in the relevant literature (e.g. [5], [10], [21]) as prerequisites for employment of sensor data acquired by SPs to support PD: data sourcing, data transmission and communication, data storage, and data exploitation. Based on their sources, data can be divided into internal and external ones. External data is any data that exists outside of the company and is either publicly available or owned by a third party [21]. Internal data refers to private or proprietary data that the company owns and controls [21]. This data is further divided into enterprise data (generated while executing everyday business activities) and sensor data (acquired by SPs) [5]. Data transmission and communication elements encompass network technologies such as gateways (e.g. Wi-Fi router), protocols (e.g. Bluetooth, or MQTT), and data security approaches (e.g. firewalls, and encryption) [22]. Data storage elements refer to database systems that enable aggregation, normalization, and management of real-time and historical product data. Data exploitation elements enable data analysis and visualization [10], [22]. As presented in Table 1, the infrastructural elements are often considered in the related studies on SP's sensor data utilization. Moreover, the primary aim of the majority of the reviewed studies is a development or customization of these elements for specific use cases (e.g. [23]).

2.3 Organizational Factors

Gaining a comprehensive understanding of product data management and ways of product information exchange between individuals on the level of the entire organization is a demanding task [1] since product data and information are used in various departments and product lifecycle stages [24]. However, product data management and information exchange must be considered when developing data management and exploitation solutions [1]. Utilization of sensor data with the goal of supporting PD introduces the need for new skills of current or an introduction of new PD stakeholders (as well as the staff to provide these skills) [5], [13]. Finding and employing the qualified personnel with overarching set of needed skills is a challenging task itself [12]. Further, utilization of SP's sensor data asks for a change of organizational processes and management of new information flows [25]. Still, organizational factors are usually not considered in the studies of SP's sensor data utilization within engineering industries, as seen in Table 1.

Table 1
Studies of SP's sensor data utilization

Paper	Industry	PL stage	PD activity or use case	Technical system	IR	OF	BV
[3]	Engineering	PD	Not specified	Rotary spindle	✓	✗	✗
[26]	Engineering	PD	Decision support	Centrifugal pump	✓	✗	✗
[27]	Engineering	PD	Geometry assurance	Not specified	✓	✗	✗
[28]	Engineering	PD (design)	Geometry assurance	Assembly factory	✓	✗	✗
[25]	Construction	Maintenance	Asset management	Bridge, highway	✓	✓	✗
[29]	Engineering	PD (design)	Performance simulation	Water pump	✓	✗	✗
[30]	Engineering	Entire PL	Product validity	Not specified	✓	✗	✗
[31]	Engineering	PD	Virtual testing	JET divertor	✓	✗	✗
[32]	Engineering	PD (design, manufacturing)	Geometrical variation management	Not specified	✓	✗	✗
[24]	Engineering	Manufacturing	Product quality and production efficiency improvement	Welding production line	✓	✓	✗
[33]	Engineering	Manufacturing	Process simulation, control, and analysis	Cutting tool	✓	✗	✗
[34]	Engineering	Maintenance	Root cause analysis, product quality monitoring	Not specified	✓	✗	✗
[19]	Engineering	PD (design)	Virtual design evaluation	Factory	✓	✗	✓
[35]	Manufacturing	Manufacturing	Coordination accuracy	Aircraft	✓	✗	✗
[9]	Engineering	PD (design)	Aerodynamic performance	Aircraft	✓	✗	✗
[36]	Engineering	PD	Virtual simulation	Not specified	✓	✗	✗
[37]	Engineering	PD (design), manufacturing, service	Not specified	Bicycle, drive shaft, power transformer	✓	✗	✗
[20]	Engineering	PD	Decision making during rapid design	Manufacturing system	✓	✗	✓
[23]	Automotive	PD (design)	Not specified	Wiring harness	✓	✗	✗
[38]	Steel	Entire PL	Not specified	Not specified	✓	✗	✗
[39]	Engineering	Entire PL	Not specified	Welding production line	✓	✗	✗
[2]	Engineering	PD (design)	Task clarification, conceptualization, verification	Bicycle	✓	✗	✗
[18]	Construction	Maintenance	Facility management	Building	✓	✓	✓
[40]	Engineering	Not specified	Monitoring the machine operation	Harvester	✓	✗	✗
[41]	Engineering	PD (design), manufacturing, maintenance, EOL	Virtual verification	Espresso machine, 3D printer	✓	✗	✗

IR – Infrastructural requirements; OF – Organizational factors; BV – Benefits validation

2.4 Studies of SP's Sensor Data Utilization in PD Activities

The majority of the related studies report on utilizing SP's sensor data in the later stages of the product lifecycle (e.g. usage and maintenance [24]). As a consequence, knowledge gaps remain for several product lifecycle stages – PD being one of them. From the information-processing perspective, PD represents an interlinked sequence of information processing activities which translate information about market needs and technological opportunities into information assets for production [42]. Still, only a few efforts have been devoted to the support of initial stages of

PD (planning, concept development, and design) by utilizing SP’s sensor data (e.g. [2]).

Studies situated in PD stages of product lifecycle often use the digital twin concept as a high-fidelity virtual model for virtual simulation (e.g. [36]), verification (e.g. [43]), product quality monitoring (e.g. [34]), and enhancement of manufacturing processes (e.g. [35]). The primary purpose of a digital twin, beside the highly realistic representation, is usually the automation of various processes (i.e. transactional benefits). In addition, related work on using SP's sensor data in PD activities is usually tailored for a specific use case (e.g. virtual verification of an espresso machine and a 3D printer [43]). As a result, the findings and suggestions identified across the related literature are not directly applicable in a different context.

The second set of research studies focuses on the management of sensor data acquired by SPs through a concept of the digital thread. These studies propose frameworks and approaches for supporting engineering activities by extending PLM systems with elements for sensor data incorporation and utilization (e.g. [44]). Nevertheless, data utilization is often enabled through individual applications (e.g. for geometry assurances [28]) while only few efforts have been devoted to their implementation within enterprise business systems. The existing studies have been set in the construction industry context (e.g. [12]), whereas the recognized issues remain unaddressed for PD within engineering companies.

2.5 Research Gaps

It is here argued that the requirements for achieving the benefits (informational, transactional, and transformational) of SP's sensor data utilization in each PD stage and for different types of PD activities are not yet fully understood. The available literature does not offer guidance on which data exploitation elements (e.g. data analysis and visualization applications) are suitable for the specific activities within the PD stages. The majority of literature aims at the development of digital twins as high-fidelity virtual models. However, it is not clear whether such a solution would be appropriate or needed for data utilization across the entire PD. The alternative solution might be tailoring of data analysis and visualization elements for various types of activities within PD stages. Further, a vast number of studies are conducted in controlled environments such as factories, while only a few studies attempted to examine consumer products outside of the company, as part of the usage lifecycle stage. The conducted literature review suggests that scholars mostly tend to study potentials of emerging digital technologies rather than providing transparency on how these technologies may already support PD activities and which levels of fidelity are suitable for achieving benefits in each of them. Consequently, utilization of SP's sensor data which does not necessarily require high-fidelity models has been poorly studied in the literature.

3 Research Methodology

The empirical part of the research draws on a qualitative exploratory case study conducted in a large engineering and manufacturing company – a global provider of products, systems, and services for the construction industry. The case study was of the opportunistic nature, with three primary goals:

(1) Provide a transparency on the status of infrastructural elements and organizational factors within the company

(2) Based on the status and current PD practice, suggest several PD activities for which SP’s sensor data utilization may be beneficial

(3) Explore and describe the challenges standing in the way of SP's sensor data utilization to support PD

The case study results (presented in Section 4) and extracted challenges (listed and discussed in Section 5) are based on the empirical data gathered using several methods – interviews, analysis of documentation, and a pilot study. These data gathering methods are further described in subsection 3.1. The case study design has followed the methodology proposed by Yin (2003).

3.1 Data Gathering Methods

In the related studies (e.g. [46]), information behavior of PD teams was researched utilizing both direct (e.g. interviews, questionnaires, work sampling) and indirect (e.g. observations) research methods to specify information needs and requirements regarding the specific tasks and activities which the teams conduct. Following the suggestions on multi-method approach and multiple data sources in case study research [45], a combination of data collection methods was utilized. The employed methodology consisted of semi-structured and unstructured interviews, an analysis of personal, workgroup, and organization documentation, and a pilot study. Empirical data collected using the methods within the large engineering company as the unit of analysis [45] yielded the insights listed in Table 2. These insights were intended to provide empirical data on the preliminary propositions for research [45] which were derived from the literature review (as presented in section 2). It is suggested that several infrastructural requirements and organizational factors must be addressed to allow for an employment of sensor data acquired by SPs in a way that will benefit PD within a large engineering company. Hence, gathered data was intended to provide insights on the status of the infrastuctural elements (subsection 3.3.), organizational factors (subsection 3.1), and current PD practice (subsection 3.2) within the company. Based on these insights, the pilot study was defined, as explained in subsection 3.4.

Table 2
Overview of data collection methods and insights

Insights	Data collection methods
Organizational structure (stakeholders related to PD and SPs topic)	Unstructured interviews Analysis of documentation
Enterprise business systems (productive systems and digital twin/thread solutions)	Unstructured interviews Analysis of documentation
PD process and team organization (stages and activities of the PD process, involved stakeholders)	Semi-structured interviews Unstructured interviews Analysis of documentation
Data and information flow (data and information PD stakeholders seek, use, and pass on)	Semi-structured interviews Analysis of documentation
Data and information management (IT solutions PD stakeholders utilize)	Unstructured interviews Analysis of documentation

In this study, semi-structured interviews were conducted with five PD team members (project lead, product manager, technical project lead, development engineer, quality engineer) from one of the company's business units. The team members were selected so that they are associated to a range of activities in different stages of PD. These interviews typically lasted around one hour and were based on open-ended questions, structured in a way to provide insights related to current PD practice and additional product data/information requirements. Namely, to gain insights into the organization of the PD process, stages in which it is divided, typical activities it incorporates, and stakeholders that execute them. Besides, PD stakeholders were asked to describe usual activities they perform, their responsibilities, types of data and information they seek, use or pass to their counterparts in PD projects. The examples of the questions are "Which data do you use while executing PD activities and how do you gather them?" and "Which activities do you think sensor data acquired by SPs would be beneficial for?". After the first, semi-structured series of interviews, the PD team members were visited several times to further clarify gathered information via unstructured interviews, which usually lasted between 30 and 90 minutes. Furthermore, the case study encompassed interviews with subject-matter experts (for example, test engineers), which typically lasted between 30 and 60 minutes. All the interviews were documented in writing. Selection of subject-matter experts was guided by the instructions and suggestions of the company personnel, depending on the subject in the focus of the discussion. In total, 29 company personnel related to PD and/or SPs from a variety of functional areas (e.g. business units, IT, research and technology), hierarchical levels (e.g. head of data science and architecture, head of IT architecture, head of development, global process manager), and with different roles (e.g. data scientist, group manager, PD methods coach) participated in the study.

In addition to the interviews, the interviewed PD stakeholders provided the researchers with the project documentation (such as requirement master document, quality reports and test descriptions). Additional information needed for understanding the broader context of the case were extracted from the company's internal dedicated wiki pages (e.g., the information about the status of the infrastructural elements and related ongoing projects).

As a part of the case study, the pilot study was defined and conducted to further explore the possibilities of SP’s sensor data utilization in the company’s PD activities. The primary aim was to outline and describe the PD activities for which the utilization of the SP’s sensor data may be beneficial. Besides, the pilot study was a valuable first-hand experience that provided the researchers additional insights on challenges of SP’s sensor data adoption and implementation within the company.

3.1 Company Description

On a high level, the organization of the company is divided into nine business units and the global support functional business areas (such as IT, corporate development, and human resources). Seven business units are focused primarily on developing and managing hardware products – primarily tools and consumables for construction industry. Additional two business units are responsible for the development and management of the company’s service portfolio (e.g. asset management). Within each of the core business areas, several departments carry out support business functions such as technology development or quality and process management. The strategic focus of the observed company has recently been translated from being the global leader in providing hardware products solely to providing comprehensive solutions accompanying hardware, software, and services for the construction industry. Various initiatives in different business areas have been introduced - for instance, smart factories in plants, building information modelling in the area responsible for services, and SPs in engineering. The ongoing projects at the company, concerning the SPs and accompanying data they can collect through sensors, are aiming for the continuous wireless data collection. The ongoing projects concerning the SPs are focused on the development of new services for customers and end-users of the products (e.g. asset management). However, none of the ongoing projects is focused on the internal users of sensor data acquired by the SPs, such as the PD team. Consequently, understanding of the benefits that integration of newly available sensor data might bring in PD is still unclear.

3.2 Product Data Management

The management of product-related data has been enabled as a collection of individual software solutions. Majority of the solutions is under the responsibility of a dedicated group within the company's IT department. Division into the groups is based on the product lifecycle stage they support (e.g. product development or usage and maintenance). For example, IBM Jazz® is used (mostly by the project lead and technical project lead) at the beginning of the PD process for the purpose of requirements input. In the concept development, system-level design, and detail design stages, Siemens NX® is used by development engineers as a CAD solution. Furthermore, SAP Engineering Control Center® serves as the product data management and integration platform between engineering design data (e.g. CAD models and drawings, material maser data, and bills of material data) and other product-related enterprise data (such as repair or sales data). It supports development engineers starting from the system-level design stage and enables communication of design data with stakeholders from production, manufacturing, and sourcing.

3.3 Key Infrastructural Elements

Figure 1 presents the key infrastructural elements often prescribed by the literature (e.g. [5]) and adopted specifically for the observed company. Hence, Figure 1 provides transparency on infrastructural elements which are implemented within the company and these which are yet to be defined to allow the full utilization of SP's sensor data. Grey boxes in Figure 1 present solutions that are already available within the observed company. Orange boxes present elements for which solutions are not yet defined in the context of the observed company. The presented elements are further elaborated in the remainder of the section.

3.3.1 Data Sourcing

Data sources described in this subsection are these providing internal data since the interviewed PD team highlighted this type of data as commonly used when executing PD activities. Most of the internal data is enterprise data, generated while executing everyday business activities. They are available through various enterprise business systems (e.g. product data management or customer relationship management). Repair data, sales data, and complaints have been identified (during the case study) as the common data types used in the execution of PD activities. Availability of sensor data acquired by SPs directly depends on the amount and type of sensors incorporated into the products. At the company level, sensor data are divided into operational (for example, torques, displacements, machine condition, usage of features) and environmental data (for instance, location, ambient temperature, moisture level). Sensor data available for the SP in the focus of the pilot study is described in Section 4.

3.3.2 Data Transmission and Communication

The nature of communication between SPs and the company is bi-directional. Sensors incorporated into SPs are read out and the data is transmitted via Bluetooth or NFC to a gateway (such as mobile phone or a router), which sends them through the Internet of Things (IoT) stack to the cloud if an internet connection is available. The IoT stack is seen as a black box intended to connect the SPs with the cloud using the set of communication protocols and providers (such as HTTPs or MQTT).

The other direction of the communication considers software updates and additional options such as locking the device or setting the name of the user on the product screen.

3.3.3 Data Storage

Two separated databases are used to store the company's data. The center of the company's enterprise business systems is SAP S/4 HANA®, where enterprise data are stored. On top of that, SAP Business Warehouse is used as a permanent repository for reporting, analyzing, and interpreting business data stored in SAP S/4 HANA®. SAP HANA Cloud Platform® is used as a cloud solution. A storage solution for the integration of data coming from different sources in multiple formats (i.e. common data environment) was missing at the time of conducting the case study. As a result, only the manual joint exploitation of data stored across different databases was possible.

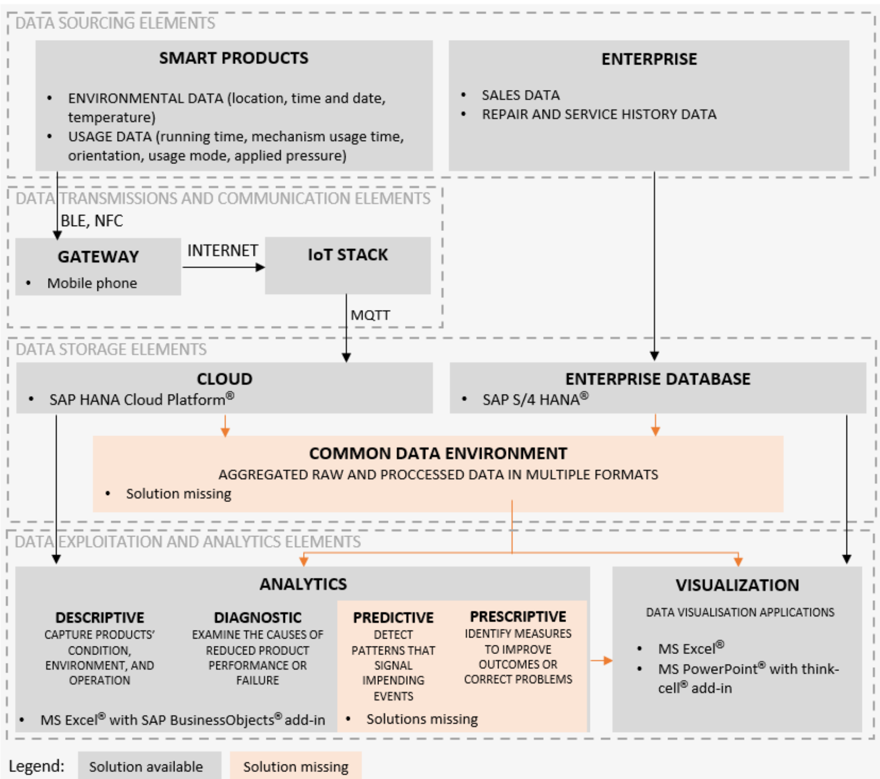

Figure 1
The key infrastructural elements for SP's sensor and enterprise data utilization, based on [5]

3.3.4 Data Exploitation

During the PD projects, the stakeholders receive and transmit product data and information from and to project counterparts in different forms; mostly documents, spreadsheets, and presentation slides using MS Office® tools with add-ins such as SAP BusinessObjects® and think-cell®. The project documentation is stored digitally on SharePoint®. Reporting is mostly done through a Microsoft Excel® add-in which enables processing of data stored in the company's main database using predefined queries. The report specifications and queries are defined by dedicated experts from the business area, while their IT counterparts define the data model. Any additional analysis is done manually by an individual PD stakeholder (usually employing Microsoft Excel® and think-cell®) or with support of experts within a business or IT area. Sensor data acquired by SPs is available via a web application as the user interface. It enables data filtering by customer, product type, specific product, or selected period. Provided data is available in the format of the Microsoft Excel® spreadsheet. The interviewed PD stakeholders outlined that they are missing an IT solution which would allow the joint management, analysis, and visualization of product-related data.

3.4 Pilot Study Description

The pilot study was set in the context of an incremental PD project – development of a new generation of an SP existing on the market. The product in the focus of the pilot study was a professional drilling tool for hand-held and rig-based coring. It was selected among other products because a new (third) generation, which incorporates smart and connectivity components, was in the launch preparation stage at the beginning of the case study.

Available architecture of the system for using the drilling tool's sensor data is presented in Figure 2. The drilling tool sends the captured data via Bluetooth to the user's mobile phone (with an installed application) which acts as a gateway. The mobile phone transmits real-time data to the cloud when the internet connection is available. The MQTT is used as a communication protocol that allows identification and communication from the drilling tool to the cloud. Sensor data stored to the cloud are available to the PD team through the company-specific web application. If the internet connection is not available, the data are captured and stored locally. In such case, the sensor data are transmitted to the cloud once the internet connection is established and they are available to the PD team as historical data through the same company-specific web application.

Figure 2
Available architecture of the system for using the drilling tool's sensor data

The sensors embedded in the drilling tool provide environmental data (such as a temperature, current real-world time and date) and usage data (such as motor running time, drilling mechanism usage time, applied pressure, gear usage, slip clutch usage, pre-drill mode usage, orientation). As a part of the pilot study, a mock-up solution of an application for data exploitation and analysis was suggested. An interface showing information that may be extracted from the abovementioned data is presented in Figure 3.

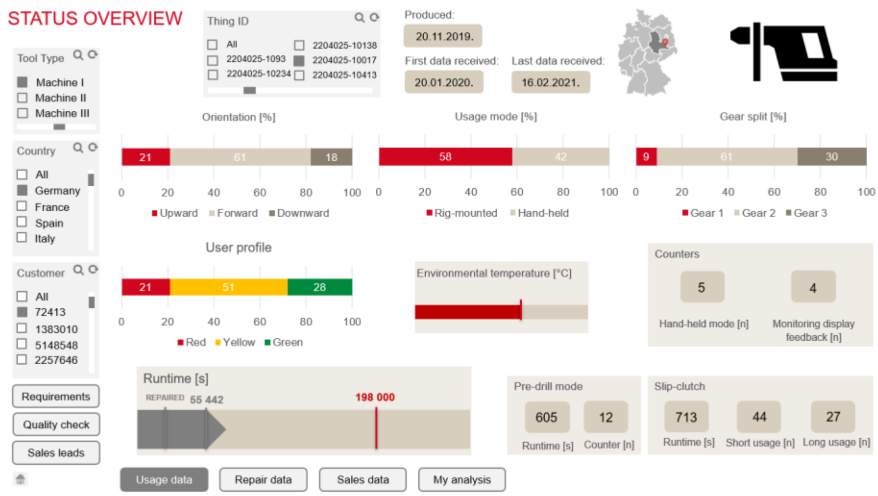

Figure 3

Drilling tool status overview

The following section describes the utilization of these available drilling tool's sensor data in specific PD activities of the observed company.

4 Results

The suggested PD activities, which may particularly benefit from the utilization of sensor data acquired by the observed SP, are related to the PQA, requirements validation and testing. In the current PD practice, the interviewed PD team utilizes historical sensor data acquired by the previous product generations when conducting these activities. Hence, the PD team has an articulated need for product data acquired by sensors when assessing product quality as well as validating and testing product requirements. However, as the project manager highlighted, the sensor data available from the previous product generations have been extracted manually from the small percentage of traditional products that came into the repair center (approximately 10%). As a result, the team has not been able to conduct statistically rigorous data analysis, which would provide them insights regarding the behavior and usage of the entire product generation. Besides, these data are unstructured (without a standardized meaning, unit of a measure, and integrity rules), aggregated (without a timestamp), and there is no common data model that would allow for data analytics or mapping with other data types. Consequently, only several attributes (primarily product runtime or a lifetime of particular components) have been used in the PD activities - mostly for the analysis of the repair data and the quality issues. Considering the additional capabilities of the new product generation (as described in subsection 3.4), the PD team wanted to know how sensor data acquired by the SP can benefit the execution of PD activities. As the design engineer suggested, it was assumed that sensor data from the majority of the SPs on the market will be available to the PD team as historical data.

4.1 Sensor Data Utilization for the PQA

A typical PQA includes the identification of the predecessor products' strengths and weaknesses as part of the planning stage of PD as well as the analysis of the product under development before it is finally introduced to the market (production ramp-up stage). Implications for supporting the execution of PQA by utilizing SP's sensor data were discussed with the PD team's quality manager and the expert responsible for defining the quality report specifications. They highlighted that the availability of SP's sensor data would provide quality managers with the additional reports on the product's usage and, thus, enable a more thorough assessment of the product quality. Based on these data, quality managers may determine when and under which conditions a specific quality issue appeared (considering, for example, a gear split, a drilling orientation distribution, a temperature, and a runtime). As the quality manager accentuated, diagnostic analysis may enable investigation of the relationship between the defect type recognized by the repair technicians and the usage history. For instance, water entry problems are often related to an upward drilling orientation. Also, long activations of a slip clutch may indicate the user's inexperience, thus defining a misuse as the cause of the defect (instead of a development or a manufacturing problem). Furthermore, if several attributes are taken into account, a pattern recognition could be yielded through predictive analytics. As a result, the quality manager may define quality improvement measures to avoid an unwanted behavior of the product (e.g. by suggesting requirements revision or addition) and a way it is operated by a user (for example, by providing the additional usage instructions). Besides, the quality of the product could be checked after a timespan defined as product lifetime in a design specification. Consequently, design specification may be changed for the next product generation.

4.2 Sensor Data Utilization for the Requirements Validating and Testing

When defining product requirements, the PD team considers the customer requirements and market needs, analyses the technical feasibility and validity of requirements, and investigates the dependencies among the requirements. The interviewed product manager believes that the greater availability of information on product usage might lower the effort needed to investigate and question customers and end-users about the usage and behavior of the product. The development engineer added that special caution is needed regarding the erroneous reuse of obsolete requirements drawn from the predecessors' PD projects or similar products on the market.

The requirements and available SP's sensor data were mapped during the two dedicated meetings with the development engineer. The results showed that data captured by sensors embedded in the new generation of the product might provide insights for 54 out of the 267 (20%) defined requirements. The majority of requirements which might be addressed are in the form of explicit technical specifications. For example, sensor data provide information on the number of activations of the hole starting button, the display feedback button, and the switch. Thus, the number of expected activations of these buttons and the switch (in the requirements list) can be compared to the actual number of their activations. Newly gained insights might change specification value and thus affect product design and test conductance. For instance, it can be revealed that users do not use the buttons or the switch (and the functionalities activated by pressing on them) to the degree that would justify their production costs. The development engineer thinks that the newly gained information might redirect the attention of the PD team to these product features and guide the redesign of the product. Furthermore, the test engineer said that utilization of SP's sensor data might support them in the execution of PD activities related to product testing. Namely, the change in the specification value directly affects test conditions since they are linked to the technical requirements. For example, the number of activations defined by the requirement affects both the time needed for the test engineer to conduct the dedicated in-house test of a component (such as prototype test in the design stage of a PD process) as well as that component's cost. If the design specification states that the buttons and the switch must endure fewer user activations than it was previously thought, the testing of these parts in the design stage of the fourth product generation will be adjusted accordingly.

5 Discussion

Three challenges facing productive utilization of SP's sensor data in PD activities have been extracted and outlined based on the empirical data gathered during the case study. These challenges are: the perception of benefits, suitability of data exploitation elements and any organizational changes. They are further discussed in the remainder of this section.

5.1 Perceiving the Benefits

The utilization of sensor data (captured during the usage stage of a product's lifecycle) in PD activities is not a novelty itself neither in the academic literature nor the industrial practice [47]. SPs add to the value of sensor data through smart and connectivity components which enable real-time or postponed feedback from each product on the market when it is connected to the internet. Hence, the capabilities of smart and connectivity components incorporated in SPs dictate the types and the amount of data available for further analyses and visualizations. However, the primary intention of integrating the smart and connectivity components in products is usually not to support and enhance PD activities. Rather, these components are typically incorporated for different purposes and tailored for individual use cases that are not related to PD. For example, the observed company's ongoing projects concerning the SPs and their sensor data are focused on the development of new services for customers and end-users of the products (such as asset management) rather than for the internal users of data such as the PD teams. Besides these components, the infrastructural elements must be defined and developed to enable digital twins, digital threads, and digital feedback loops within a company (for example, a common data environment and additional data analysis applications). The perceived value of technology adoption must be tangible to the company's management in order to assure their support in the definition and provision of key infrastructural elements. However, such persuasion is currently hindered due to the lack of empirical studies that investigate and validate the return of investment in the utilization of continuous stream of SP's sensor data within PD activities. For example, in the case of the observed company, the PD team's decision to incorporate sensors was driven mainly by an availability of technology and competition's efforts to develop SPs. Consequently, the benefits of sensor data utilization presented across the literature are often not tangible or relatable. Besides, the available literature does not provide the implementation guidelines applicable and tailored for the PD activities within the specific company. The utilization of sensor data acquired by SPs may support PD activities primarily through informational (providing better-informed decision-making) and transactional benefits (such as performing virtual instead of physical activities). An overview of the suggested informational and transactional benefits of sensor and enterprise data utilization in PD activities across PD stages (as suggested by [42]) is provided in Figure 4. These benefits are derived from the use cases described in the related literature and the conducted case study. Two suggested use cases described in subsection 4.2.1 depict the mapping of available sensor data to the requirements and quality reports. Such a mapping of sensor data should also be conducted to the other PD activities. As a result, possibilities to reap the benefits throughout PD may be clarified, together with their costs.

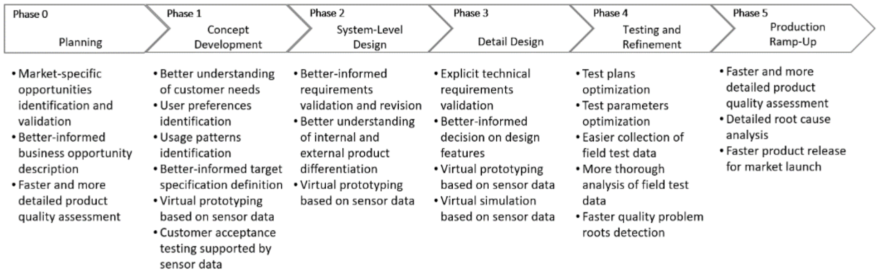

Figure 4

Overview of the benefits of sensor and enterprise data utilization in PD activities

5.2 Tailoring Data Exploitation Elements to the PD Activities and a PD Team

Once sensor data acquired by SPs are transmitted to the company's cloud, they are analyzed and visualized. Management and exploitation of data acquired by SPs have often been recognized as the most common challenges when implementing digital technologies in companies [5]. The reason is the bilateral nature of the exploitation elements which enable data analysis and visualization. The exploitation elements should be flexible to make data accessible to different company's functional users and stakeholders (e.g. development, marketing and sales, after-sales service). The flexibility may be achieved by enabling a digital thread [9]. At the same time, the exploitation elements should provide data analysis and visualization tailored to users' and stakeholders' needs and preferences to assure the specific benefit realization. The interviewed PD team emphasized the need for such a solution, which would allow management, utilization, and analysis of continuously acquired sensor data from SPs and product-related data stored in the central repository. Customization may be achieved through a modular approach – by using digital models with varying amount of the presented attributes [30]. The digital models should be adjusted for each product lifecycle stage, PD activity, and the use case with a specific benefit as a goal. For instance, requirements validation may be accomplished using low-fidelity models with only several specific attributes that concern the particular requirement (such as runtime or the number of switch activations). On the other hand, virtual simulation for the quality issues analysis asks for more attributes and a model of a higher fidelity in order to be perceivable. Regardless of the digital twin fidelity level, it is here suggested to enable data exploitation through engineering support tools which the PD team members already use for the execution of respective tasks and activities [3]. An example would be the incorporation of newly available sensor data into the support tool for requirement management that the interviewed PD team uses. In this way, available data would be contextualized into useful information that can be directly queried by the PD team within their usual tasks and activities [48]. Besides, the confidence in decision making is positively affected when data are provided through a familiar visual representation [49]. Further, two out of three steps in making sense of received data and information [1] may be supported when they are presented through familiar visual representations incorporated within the already enabled engineering support tools. Namely, (1) integration of the represented data into one's understanding of the situation by elaborating it and evaluating its quality with contextual knowledge, and (2) inferring its implications for one's tasks and responsibilities on how to apply it [1]. Hence, the process of making sense of received data and information may be easier, faster, and more systematic (less dependent on individual data interpretation skills).

5.3 Managing the Required Organizational Changes

Productive utilization of sensor data acquired by SPs within a company requires the organizational changes concerning new skills, roles, and processes. For example, a revised PD project workflow for SPs in the observed company now has an additional step which should nudge consideration and exploration of (1) embedding additional sensors in products and (2) enabling enhanced capabilities of other smart and connectivity components (e.g. faster and continuous data transmission) that may benefit stakeholders throughout the PD process. However, the problem recognized in the current company practice is the absence of a project focused entirely on the recognition of the benefits and requirements for SP's sensor data utilization in PD activities. A thorough understanding of the PD process, the team, and the available data is needed to enable recognition and evaluation of the benefits. It is a necessity to analyze the processes so that one may understand the need for data exploitation solutions, and to design processes and solutions together in order to assure effective support [50].

Since making sense of available data and extraction of relevant information out of them depend on data interpretation skills [1], it is also necessary to support PD team members by introducing new roles responsible for exploiting and formalizing data, and deducing knowledge from them. Similarly, [3] the role of a knowledge engineer should be introduced to act as a bridge between product data (sensor data and other enterprise data) and incorporation of deducted information and knowledge into PD activities, for example, by using knowledge-based methods within a PLM system. In the case of the observed company, it has been suggested to establish a new role (a project manager) in the area of information management, responsible for the management of sensor data utilization across business units by relating it to the PD projects, processes, activities, and tasks. Hence, this new role should encourage and maintain a continuous collaboration between several company's areas and functions, namely, information management, data science, IT, business units, and dedicated business area departments (such as technology development or quality and process management).

Conclusions and Further Work

Several infrastructural and organizational challenges must be addressed to allow for the utilization of sensor data acquired by SPs, in a way that will support and benefit PD, within a large engineering company. First, it is challenging for the company's management and PD team to gain transparency over benefits of sensor data utilization for PD. Both theoretical and empirical research on use cases from the majority of product lifecycle stages, PD stages and activities, as well as, the different product types, are still missing. The lack of detailed studies across all PD stages, and product lifecycle in general, implies that many potential benefits are still unrevealed. Secondly, solutions providing accessibility and visualization of gathered data should be tailored to the PD activities and teams, which asks for a holistic understanding of the PD process, team, and available data. Data acquisition should be automated, whereas the extraction of information and deduction of knowledge should be systematic and formalized to reduce uncertainties in data utilization. Finally, it has been suggested that the new skills, roles, and processes should be introduced to provide transparency over benefits of sensor data utilization for PD and enable its implementation within PD activities. Future work on this topic would include experimental studies within several companies, including the consideration of different products and the various types of PD projects. Based on the empirical findings of further studies, guidelines on utilization of sensor data acquired by SPs and a more exhaustive presentation of its benefits may be offered.

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