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Optimizing smart manufacturing systems by extending the smart products paradigm to the beginning of life

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ABSTRACT

The research objective of this work is to enhance the *perception of, sensing in, and control of smart manufacturing systems (SMS)* by leveraging active sensor systems within smart products during the manufacturing phase. Smart manufacturing utilizes rich process data, usually collected by the SMS (e.g., machine tools), to enable accurate tracking and monitoring of individual products throughout the process chain. However, until now, the to-be-manufactured product itself has not contributed to the sensing and compilation of product and process data. More specifically, data measured from the product's structure during its own fabrication. In this paper, we discuss and evaluate the opportunity to actively use the capabilities of smart products within a SMS in terms of technical and economic feasibility. This opportunity emerged only recently with the advancements in smart products engineering. In this research, we developed a smart product prototype and evaluated it on a SMS testbed (CPlab) with eight distinct, fully-connected manufacturing processes. The results of the conducted experiments show the possibility to uniquely identify two distinct '*fingerprints*' of manufacturing processes solely based on data provided by sensors within the smart product itself. The sensor data was collected directly from the smart product before manufacture was completed, yet after the intended sensor functionality during the product's use phase was activated. The capability to automatically, accurately, and reliably identify process signatures and even inform the optimization of manufacturing parameters creates new opportunities for improvements in quality, scheduling, and seamless transparency across the whole value chain.

1. Introduction

Every manufactured product today is subject to a set of planned manufacturing processes defined by corresponding process parameters. When executed, each of these manufacturing processes and their outcomes inevitably deviate from the planned tasks in terms of quality (e.g., surface roughness, shape accuracy), processing time, and other processing characteristics [1]. These deviations can be within or outside of a specified acceptable tolerance. The goal of every manufacturing system is to avoid parts and processes outside of this acceptable tolerance range [2]. Process deviations stem from a diversity of culprits, such as malfunctioning machinery, operator errors or lack of training, unsuitable condition of equipment (e.g., tool wear), a variety of environmental factors, or normal statistical variances within the process operation [3]. Companies depend on reliable process outcomes that correspond with the process plan with regard to quality, yield, and time etc. to be successful on the marketplace. The Industry 4.0 paradigm highlights the objective of producing small batch sizes down to batch-size-1 with a similar efficiency and effectiveness as a highly optimized large batch production in smart manufacturing systems (SMS) [4–6].

At the same time, an increasing number of products today include some form of sensor system and connectivity to interact and communicate with their surroundings and users. These so-called smart products enable not only the provisioning of advanced services, they also collect massive amounts of data along their lifecycle. This data can include a variety of instances, from location-based data to high-fidelity sensor readings. Based on the data and its availability, new insights, for example regarding the actual, item-specific use of the product, the user preference and behavior, and additional insight can be derived through data-driven analytics.

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Most smart products with embedded intelligence on the item itself are utilized during their usage phase to provide the basis for advanced services and/or product service systems (PSS) [7,8,9]. Following the common three-phase product lifecycle model [10,11], the usage phase is considered the middle of life (MOL) of the product lifecycle, while design, manufacturing, and distribution are referred to as the beginning of life (BOL) phase. All activities around recycling, remanufacturing and disposal are part of the end of life (EOL) phase according to this depiction. Whereas smart products are common during the MOL phase, their utilization during the BOL is limited. During the BOL, SMS enable a variety of data-driven applications and services, however, the data collection and connectivity is focussed on machine tools and other sensor systems outside of the smart product itself. Therefore, today the application domain of smart manufacturing is predominately focussed on the BOL while smart products are focussed on MOL applications. These traditional focus areas of smart manufacturing and smart products along the lifecycle are depicted in Fig. 1.

When we now consider that smart products are in principle capable of sensing and communicating with their environment, the question arises why they are not deployed during the other lifecycle phases. During the EOL phase, a common argument is that the smart product is often not functional any longer as one of the primary reasons for disposal in the first place as well as the large variety and lack of standardization of EOL processes. In this paper, the EOL is not in the focus and there might very well be valuable opportunities to extend the smart products paradigm to the EOL that deserve closer attention in future work. For the BOL, smart manufacturing focusses on augmenting and supporting the data-driven optimization of the manufacturing processes. At one point during these processes, a product becomes 'smart'. This happens theoretically when the sensor systems, computing capabilities, and connectivity - the key requirements of a smart product to interact with its environment – are activated. Once the smart product is active, it theoretically can augment the SMS by providing additional data and context for, e.g., better predictions.

Fig. 2 shows the proposed expansion of the smart products paradigm from the MOL to the BOL. This expands the traditional focal area depicted Fig. 1 towards overlapping with smart manufacturing during the BOL phase of the product lifecycle. The overlap is due to the utilization of the smart products' capability to sense and communicate in the early stage of the BOL while the SMS itself provides process and product data as well. The principle idea is that leveraging the smart products' functionality during manufacturing leads to an augmentation and value-added combination of information that provides better insights and richer data overall.

Our research approach aims to address this rather conceptual idea in two ways: We will first present a theoretical perspective on the technical (restrictions, functionality) and economic feasibility (value, benefits). In the second step, we will present a prototypical use case we conducted to evaluate the technical feasibility in a lab environment. These steps relate to two research questions.

The *first research question* addresses the overall feasibility:

R1: Is the early state utilization of smart product data feasible?

R1a: Is the early state utilization of smart product data economically feasible?

R1b: Is the early state utilization of smart product data technically feasible?

The *second research question* investigates the demonstration and application of an early state smart product utilization:

R2: Can the benefit of such an application be validated by demonstration?

The key contribution of our research is to critically assess the current MOL-only focus of smart products with embedded intelligence on the item itself (other than aggregated on containers), change this perception, and expand the smart product paradigm to the earlier phases of the product life cycle (manufacturing phase / BOL), thus enabling smart products to actively enhance, augment, and improve the manufacturing CPS processes themselves. This will further push the boundaries towards self-organizing, autonomous, and decentralized control of complex manufacturing CPS and their components [12–16]

The paper is structured as follows: in section 2 we provide a brief overview of the relevant state of the art before discussing the feasibility of the smart products' paradigm towards the BOL phase on a theoretical level. Section 4 augments the theoretical contribution with a case study, thus addressing R1. In section 5 we discuss the implications with regard to manufacturing organization and processes as well as selected industries (addressing R2) before concluding the paper with a reflection and outlook on future research.

2. State of the art

The manufacturing industry is currently going through a digital transformation that is commonly referred to as the fourth industrial revolution ('Industry 4.0') or smart manufacturing paradigm. Merging the virtual, or cyber, with the physical world is at the core of this transformation [17–20,21]. In the following, we will present a concise state of the art of the underlying principles relevant for this paper through a manufacturing lens: smart manufacturing; data analytics; smart products; sensor integration; and 3D printing of mass-customized and geometrically complex structures with integrated electronics.

2.1. Smart manufacturing

Smart manufacturing [22] describes "a data intensive application of information technology at the shop floor level and above to enable intelligent, efficient and responsive operations" [23,24], while also highlighting the data and technology focus [25]. Smart manufacturing emphasizes the importance of including human ingenuity and the creation of manufacturing knowledge from data. In essence, SMS resemble complex CPS [26] that integrate operational technology (OT) and information technology (IT) to improve manufacturing operations through sensor systems and advanced data analytics. SMS can be understood as complex systems of systems, in our case, integrating a smart product CPS in the governing smart manufacturing CPS.

On the manufacturing shopfloor and along the value chain there are many IT-systems that collect, analyze, distribute, and manage manufacturing and product related data. Such systems include but are not limited to manufacturing execution systems (MES), quality management systems (QMS), enterprise resource planning systems (ERP) as well as many dedicated tools such as simulation and optimization software. Cloud based platforms such as are increasingly deployed to manage the increasing volume, veracity, and variety of data, provide scalability, as well as user-friendly connectivity and access to advanced tools [27].

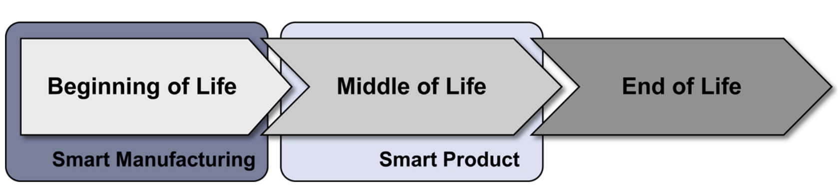

Fig. 1. Product Lifecycle Phases and traditional focus areas of Smart Manufacturing and Smart Products.

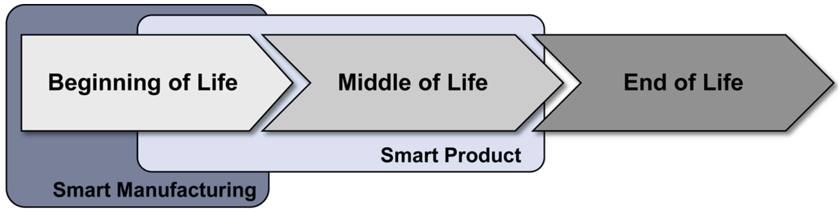

Fig. 2. Product lifecycle phases and proposed overlapping focus areas of Smart Manufacturing and Smart Products.

2.2. Data analytics

SMS provide access to large amounts of product, environmental, and manufacturing process data. As a logical consequence of the availability of this increasing amount of data, a key component of today's SMS to leverage this emerging resource is *data analytics* [25,28–30]. This expansive data poses the next challenge - how do we derive value-adding and actionable insights from these large and continuously growing amounts of data? Here machine learning, or data-driven analytics, are seen as a promising venue besides the established physics-based models [31]. Data-driven analytics in manufacturing receive significant attention from academia [22,32,33], funding agencies (e.g., NSF, NIST, DoD, & DoE in the US), and industry alike [34–36]. Data analytics was first used in manufacturing in the early 1990s [37–39].

Since those early days, several significant advances have been reported in data analytics [40,41], data mining [33,38,42,43], machine learning [3,35,44,45], and industrial applications [40] just to name a few. Data analytics in manufacturing have a significant advantage over many other domains - expert teachers are readily available in many cases that enable powerful supervised learning to be applied in order to find patterns within the wealth of data that are not perceivable by humans [37].

An application area that has seen significant advances through data-driven analytical methods is quality assurance (QA) [46]. A data-rich picture of the manufacturing operations provided by sensors in a SMS enable prediction, monitoring, and control of product and process quality in (near-)real-time [47]. The proposed paradigm shift aims to include additional data points collected by the smart product itself and thus enable a richer data picture and in consequence the ability to improve data-driven QA applications even further, improving the timeliness and preventing the release of low quality parts to customers.

2.3. Smart products

Smart products, also known as intelligent products, are argued to be a key technology of industry 4.0 [48,49]. There are several definitions of smart products available (see [7] for more an overview). A comprehensive perspective that is widely used by [50] defines a smart products as "*a physical and information based representation of an item [...] which possesses a unique identification, is capable of communicating effectively with its environment, can retain or store data about itself, deploys a language to display its features, production requirements, etc., and is capable of participating in or making decisions relevant to its own destiny*". Smart products, their characteristics, and their capabilities can vary significantly. [51] proposed a classification model for smart products, later extended by [7] (see Table 1).

Table 1
Classification model for smart products (based on [35,37]).

Location of Intelligence	Aggregation level of Intelligence	Level of Intelligence
1 Intelligence through network 2 Intelligence at object	1 Intelligent container 2 Intelligent item	1 Information handling 2 Problem notification 3 Decision making 4 (Pro-)active / social

Now when we consider the opportunity from a manufacturing-centred perspective, smart products are often understood as intelligent and connected machine tools [52] and/or intelligent containers [51] for tracking and tracing of parts and in a logistics scenario where the aggregation level of intelligence is on the container (e.g., pallet). In the latter example, common technologies that are employed in industry today include radio frequency identification (RFID) tags [53,54], barcodes and/or data matrix codes [55], as well as distinct variants combining active triangulation augmented with geolocation [56].

2.4. 3D printing of electronics

Embedding electronics in 3D printed structures is a vibrant research topic and additive manufacturing has emerged as a promising technology in this sense, as additive manufacturing (AM) provides access to intermediate layers during the layer-by-layer fabrication process (some new AM processes feature out of plane fabrication, which still aligns with the requirements put forth here). For over a decade, the integration of electronic components, batteries, antennas and actuation within these complex forms has been successfully demonstrated [57–66]. Geometries can now include conductive traces to provide electrical interconnection between embedded components by micro-dispensing and aerosol jetting of conductive inks. Early example structures are shown in Fig. 3 and an overview of the capability of distinct AM processes to manufacture integrated electronics is illustrated in the following (see Table 2). The current effort is attempting to leverage the functionality that can now be introduced early during manufacturing to collect self-reporting process data to support the qualification / certification of the part. However, 3D printing sensor systems including their power supply remains an active research topic and needs to develop further to reach the maturity required for an industrial application of smart products during the BOL as proposed in this work.

Vat photopolymerization (VPP) is a high-resolution photocurable polymer process which fabricates durable and deformable materials. The feedstock materials available from *Carbon*, *FormLabs*, and 3D Systems now allow for assembling and fusing of multiple printed subcomponents during a final thermal ultraviolet (UV) curing step. This approach enables a novel construction paradigm in which embedded components can be populated on the superficial surfaces of the components prior to mating and assembly with a mortise-and-tenon polymer welding methodology. The fusing of structures with UV curing is the linchpin of the proposed idea: multiple high-resolution polymer substrates can be (1) fabricated, (2) robotically populated with electronics, (3) connected electrically by printed conductive inks, and then finally (4) consolidated together into a single, complex, multi-layered structure with fully embedded electronics. During the latter stages of the proposed fabrication paradigm, sensors and electronics can be not only integrated, but also activated in order to improve the monitoring of manufacturing to optimize the process and potentially qualify the structure. Data collected internal to the structure during the "birth" of the product can be archived in the digital twin for the specific part to be referenced

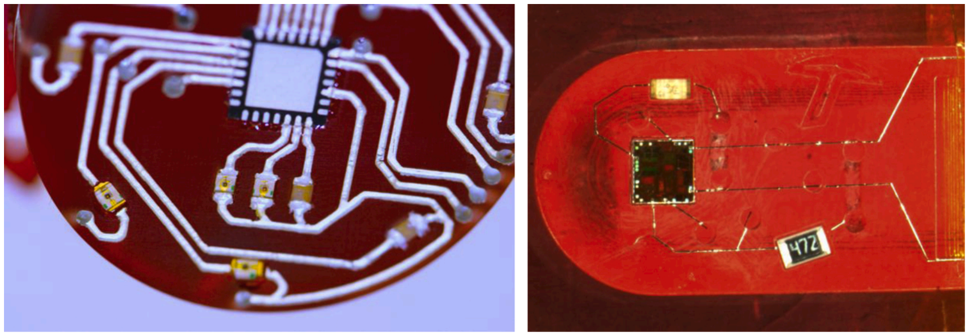

Fig. 3. Examples of 3D printed electronics: a cylindrical magnetometer (*left*) and a printed pill with an unpackaged silicon microcontroller and passive components (*right*).

Table 2
Qualitative comparison of competing AM technologies for 3D printed electronics.

System	Material Options	Surface Finish	Build Volume	Production Speed	System Expense	Material Expense	Over Mold
Thermoplastic Extrusion	o	–	+	o	+	+	o
Selective Laser Sintering	o	o	+	o	–	o	o
Material Jetting	–	+	+	+	–	o	–
Vat Photopolymerization	+	+	o	+	o	+	+
Sheet Lamination	+	o	+	+	–	+	+
Directed Energy Deposition (Ceramics)	+	+	–	–	–	–	–

throughout the full life cycle.

Table 2 shows a comparison of processes in the context of 3D printed electronics – highlighting the selected VPP for this project versus thermoplastic extrusion (TE, often referred to as fused filament fabrication (FFF)), selective laser sintering (SLS), material jetting (MJ), sheet lamination, and direct energy deposition of ceramics. By integrating intelligence and sensing capabilities into structures, next generation products can now be fabricated with the freedom and mass customization of additive manufacturing. However, this new data acquisition paradigm can be leveraged during manufacturing to inform the subsequent manufacturing processes and to provide information in order to support qualification of a structure once completely fabricated.

2.5. Closed-loop PLM

Product lifecycle management (PLM) manages all product related information during the whole product lifecycle. A closed-loop PLM system enables all stakeholders during the lifecycle of a product to track, manage, and control product information [67]. A basic system architecture for closed-loop PLM consists of communication channels with the product during its operation and a platform [10]. Examples are one of a kind products and investment heavy assets [68,69]. Furthermore, the closed loop helps accessing the servitization potential of products [9].

Asset Llifecycle management (ALM) is a related area with the objective to optimize the value and efficiency of an asset, often capital equipment, over its lifecycle. In recent years, along the whole manufacturing industry, ALM is transforming towards a more digital and data-driven model of operation. Recent progress includes the exploration of sensor-data fueled digital twins for ALM [70], the application of ontologies in ALM [71], and total cost of ownership models for ALM [72]. Sensorized assets within the ALM perspective constitute smart products themselves. However, while their MOL phase is on the manufacturing shopfloor – this is as part of the SMS as production equipment, not during their own manufacturing / BOL [70]. Thus ALM aligns with the current perspective of both smart products being predominantly used during their MOL, and smart manufacturing focussed on the BOL.

3. Feasibility of smart products' applications in manufacturing

Feasibility is understood as the possibility that an undertaking can be achieved or is reasonable. In the context of early state utilization of smart products' data the feasibility is a measure of the technical and economic viability. This section is theoretical in nature and intends to provide a perspective on general measures and issues that need to be considered when it comes to extending the smart product paradigm to the BOL. It is not intended to provide detailed technical details on data models, connectivity, and other important aspects of the implementation.

Data collection can be improved by introducing smart products seamlessly collecting in-situ data throughout the manufacturing process and communicating this data, and thus accurate state of the product in real-time, in order to continuously update the process plan. Smart products are context- and location-aware by recognizing and processing their situation and environment independently of the process parameters and machine tools used [7,50,73]. With proactive and network capabilities, these products can collect sensor data in an unprecedented manner and communicate the data to the surrounding and controlling smart manufacturing system.

3.1. Technical feasibility

We define the technical feasibility as sufficiently achieved when the sensor functionality surpasses the process restrictions. This condition is only valid for a single product and changes with every process step of the manufacturing chain.

Fig. 4 shows the progression of technical feasibility with an increasing number of processes. The initial process is essentially the processing of the raw materials and with increasing succession of processes altering the material and state as well as adding parts to the unfinished product throughout the manufacturing process. Fig. 4 (*left*) shows two exemplary products 'Product_1′ and 'Product_2′. The products start initially with high process restrictions, which may hinder a smart product utilization during the alteration of the unfinished product. For examples and details on process restriction see section 3.1.1. An opposite development can be observed for the sensor functionality (see section 3.1.2.). Here the initial value is zero. Then step-by-step

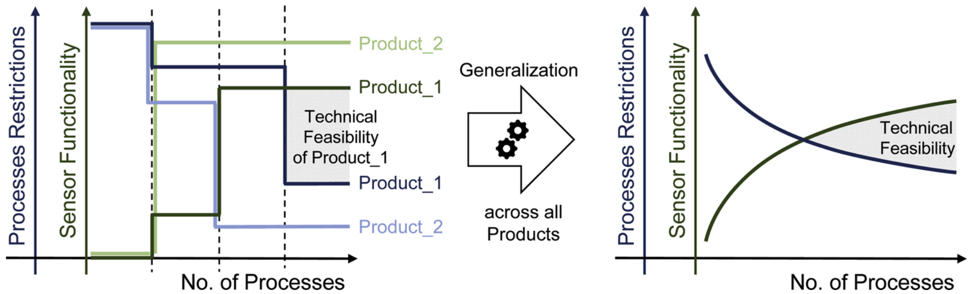

Fig. 4. Technical feasibility on item-level (*left*) and generalized (*right*).

functionalities are added and later activated. Fig. 4 (*right*) shows a generalized view of the behavioral averaging of this relationship that is valid for all products ranging from a job shop-type process chain to more complex process chains.

3.1.1. Process restrictions

One bounding dimension of the technical feasibility is the process restriction. Here a *value* can be assigned to represent the composite of all restrictions hindering the operation of a smart product during the manufacturing process for each process. These restrictions are all process features which are either fundamentally incompatible with the operation of a smart product or can damage the computing hardware and/or sensors during operation. Categories of restrictions include *thermal*, *electrical*, *chemical*, and *mechanical*. *Thermal* restrictions are excessive process heat required for heat treating or curing of material. *Electrical* restrictions are required to avoid damaging an electronic device (e.g. electrostatic discharge, ESD). *Chemical* restrictions include the use acids for etching processes.

The fourth category of process restrictions is *mechanical*. Here the applied force loads onto the product exceed operational limits of the smart products components. In order to enable feasibility as early as possible the restricted processes need to be shifted earlier in the manufacturing chain according to the logical bounds of the assembly priority chart (precedence graph). Depending on the manufacturing processes employed, there might be additional (sub-)categories that need to be included that do not fall within the four previously discussed.

3.1.2. Sensor functionality

The utility of a smart product is connected to its current functionality of interacting with its environment through sensor readings, communication, etc. This functionality is generally enabled only after the process step when the smart product can be powered on and the embedded operating system can be booted to a state at which sensor data can be read, processed, and communicated. The minimum prerequisites for this early-stage functionality includes the installed logic hardware and power supply (internal battery or external). This dimension has a step function increase upon activation of the electronic components of the smart product. After the initial inception and activation of the functionality, the value-added provided by the sensor functionality only increases slightly with successive process steps. Examples for an increase in functionality after initial activation include the ability to collect sensor measurements after activating additional sensor modules.

This 1/0 type of view on sensor functionality stands true for both 3D printing of embedded sensor systems as well as more traditional assembled sensor systems. For the latter, the functionality is activated only after the power supply is connected (at a minimum). For the former, the structure has to be printed and a power supply (either battery or induction etc.) has to be incorporated. Once this basic functionality is achieved and the smart product can sense and communicate measurements to the environments. The option of adding additional modules or printed circuits theoretically exists, but in most cases the initial activation will provide all relevant functionality the smart product requires or is capable of for the rest of the BOL phase. Here it is important to distinguish between some MOL smart products that utilize more sophisticated sensor systems in which additional functionality can be imposed via software updates. It is expected that initially BOL-type of smart products employ more basic sensor systems with limited capability with regards to software-based upgrades. Embedding sensor systems via AM hard wires the circuits and sensors in the structure itself. Examples of directly printed smart products exist and a set of AM processes were identified which are capable to manufacture smart products [74].

3.2. Economic feasibility

The economic feasibility in this context is defined with regard to the initial implementation compared to economic benefits realized by the integration over a to-be-individually-defined period of time (e.g., one year). The appropriate time frame depends on a variety of factors such as product value, industry, and lead time. The implementation cost is further depicted in chapter 3.2.1. and the integration benefits are detailed in 3.2.2.

Fig. 5 shows the economic feasibility for each specific process in the manufacturing chain for two exemplary smart products and the generalization of this behaviour. Initially, the cost of enabling the sensing and computing capabilities are high, due to process restrictions and costly redesign to facilitate the smart product capabilities at the early process stages. At the same time, the benefits tend to be lower at the early stages due to the limited functionality of a smart product at the initial manufacturing and assembly steps. After a certain process maturity level, the functionality increases to full operational (MOL) capabilities. The hypothetical 'Product_1′ depicted in the Fig. 5 reaches this state at the third process stage. At this point, the benefits outweigh the implementation costs – and the economic feasibility is given. In the case of hypothetical 'Product_2′, the point of economic feasible is never reached during the manufacturing phase due to the limited benefits of implementation in this case.

3.2.1. Implementation cost

The implementation cost is understood as the sum of all or part of the actual total costs to implement the measures that result in the smart product capabilities for one specific production process in the manufacturing chain. This cost depends on the product design and its redesign effort to enable smart product capabilities at one specific manufacturing process. Earlier implementation has higher implementation cost due to all the consideration of the succeeding manufacturing steps. Certain product designs only allow a smart product implementation at a late stage in the process chain, where the majority of the product is already assembled. The implementation of smart product capabilities in an early stage of the manufacturing process is preferred but design constraints limit the possibility for an early implementation. For instance, the frame or body shell of the product has to be present in the final form to attach sensing and processing components.

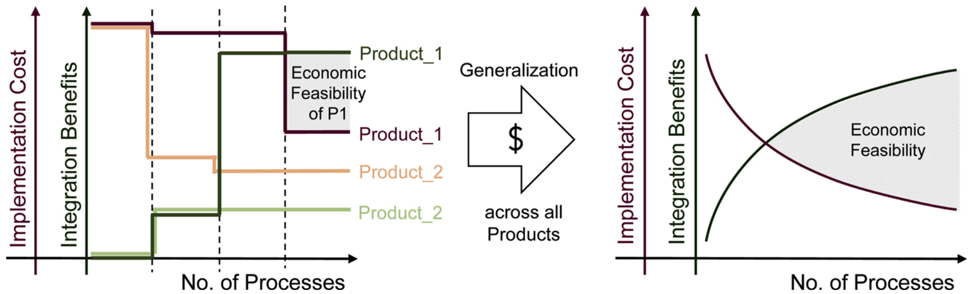

Fig. 5. Economic feasibility on item-level (*left*) and generalized (*right*).

3.2.2. Integration benefits

The benefits are derived from the value of the information gathered at this process and all succeeding processes in the manufacturing chain. As these benefits are not limited to shop floor applications but may impact the whole value chain, determining the benefits is a moving target and needs to be carefully assessed for each case and revaluated regularly with a diverse stakeholder group along the whole digital supply network. The benefits increase with each process station due to the impact of the gathered information on multiple processes. This impact is further detailed in chapter 5. Examples of this value are process improvements enabled by this information These process improvements can be energy efficiency, increased uptime due to downtime tracking, quality improvements, or scrap reduction.

3.3. Overall smart product feasibility

The overall feasibility of a smart product application in its manufacturing stage is primarily dependent on its technical and economic feasibility. The technical feasibility, as outlined in section 3.1, is present when sensor functionality is active despite present process restrictions. The economic feasibility, as shown in section 3.2, depend on the benefits outweighing the implementation cost. Both conditions must be fulfilled for the overall smart product feasibility during its manufacturing stage (BOL). This consideration is essential to find the manufacturing process in the manufacturing chain where operational capacity is desired.

4. Case study - sensor integrated smart product assembly

To demonstrate the process monitoring possibilities of a smart product during the BOL stage, a prototypical demonstration was developed and fabricated. The specific goal is to emphasize the feasibility of a smart product monitoring application in its own manufacturing stage. The case study consisted of three main stages: data collection, data pre-processing, and data analytics. In the following, first, the hardware setup is introduced, then the collected data is visualized and analyzed.

4.1. Smart product

The smart product used in this case study resembles an additively manufactured mock-up of a cell phone case with battery and integrated sensor system. We chose a cell phone mock-up because today's smart phones are essentially highly-capable smart products that include a variety of sensors, communication capabilities, and processing power. In this case, the sensor unit described below is similar to sensors that we can find in most current smart phones. Therefore, his prototypical case study resembles the 'real world' on a principle level. A current smart phone – our smart product - is manufactured and assembled, and uses its own sensors that are later utilized during its MOL to collect data already during its BOL. The additive manufacturing process used to create the prototype smart product for the case study was stereolithography (SL). Fig. 6 shows both the original, non-sensorized part (Fig.6 a)) produced on the testbed and the newly designed smart product with the integrate

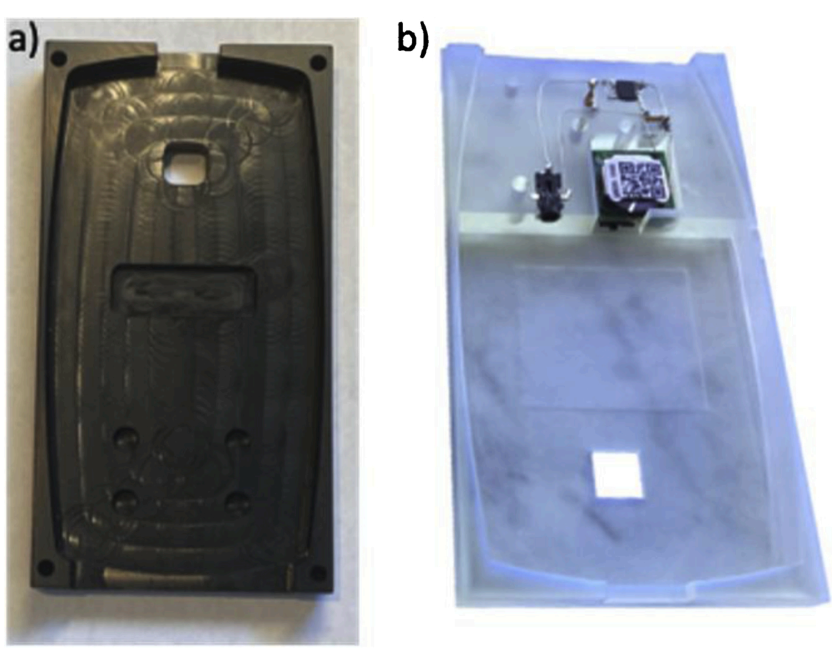

Fig. 6. Original Product (a) left), 3D printed Smart Product with Integrated Sensor System (b) right).

sensor unit (Fig. 6 b)).

The sensor system consists of an inertial measurement unit (IMU) with a three-axis gyroscope accelerometer, a geomagnetic sensor and an environment sensor unit. Specifically, the sensor bundle used the sensor components BMI160 (inertial sensor-gyroscope), BMM150 (geomagnetic sensor), and BME280 (environmental sensor). This low power module is combined with an ARM processor and a Bluetooth wireless radio in a DA14583 IoT sensor by Dialog Semiconductor printed circuit board (18 mm x 18 mm x 8 mm). These sensors are common in smart product industry applications and offer the multifunctionality necessary for sensing scenarios in the BOL stage - not just the assumed MOL during the smart product operation.

4.2. Manufacturing system test bed

The manufacturing system test bed used is a state of the art Festo-Didactics cyber-physical lab (CPlab) with eight modular manufacturing processes, fully connected manufacturing via an automated conveying belt system. The stations include for instance a drilling process, heat treatment process, and muscle press process. Fig. 7 a) shows the heat treatment process of the Festo SMS. This process is equipped with a heating element with different parameter settings. The parameter settings define the processing time, wattage, and temperature setpoint to heat treat products.

Fig. 7 b) illustrates a flipping process which takes a part from the carrier, elevates the product with a gripper, rotates it by 180 degrees and finally places it back on the carrier tray. Fig. 7 c) shows the conveyor belt connecting the process stations in a right-angle turn.

4.3. Data collection and pre-processing

The in-situ data was retrieved from the smart product to the planning system via Bluetooth and the sensor readings were written as entries in a continuous log. The data set for this study overall was 21 Megabyte of raw data retrieved during an operation time of 50 min adding up to a total of 265,500 sensor reading entries.

Table 3 shows the raw data with one sample for each entry for each type of recorded physical dimension. Data pre-processing consisted of splitting the data set into the various sensor type data subsets and visualizing the raw data.

4.4. Data analytics and results

Data analytics focusses on the gyroscope, the accelerometer and the temperature sensor data. The analytics goal was to reliably identify characteristics per process with patterns found and mathematically described by sensor readings (Table 4).

4.4.1. Gyroscope

The BMI160 is a microelectromechanical systems (MEMS) with a built-in gyroscope. The output sample collecting interval was 100 ms. This time series data describes the rate change in orientation in degrees per second. This motion called angular velocity ω is the rate of change of the net angular displacement called the turn angle φ. The obtained value by the sensor is the current angular velocity, which is defined as the turn angle over time, see Equation 1:

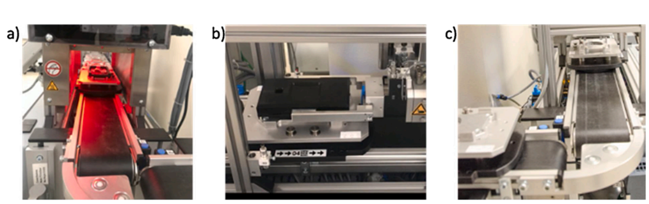

Fig. 7. a) Heat Treatment Process; b) Flipping Process; c) Right Angle Turn.

Table 3
Sample Entries in the Data Set.

Timestamp	Type	Value
2019/02/14 10:31:36.130	PRS	97751.00 Pa
2019/02/14 10:31:36.132	HMD	19.97 %
2019/02/14 10:31:36.133	TMP	25.55 C
2019/02/14 10:31:36.243	MAG	416.11 u T -79.03 u T -168.47uT
2019/02/14 10:31:36.345	ACC	−0.17 g 0.05 g -0.98g
2019/02/14 10:31:36.351	GYR	−0.06deg 0.02deg -0.08deg

Table 4
Turning Events.

Event	Color Scheme	Duration in sec	Sensor Readings	Peak ω	Avg. ω	Turn Angle φ
No. 1	Blue	3.97	41	−8,55°/s	−2.2°/s	−90.25°
No. 2	Green	4.1	44	−8.38°/s	−2.11°/s	−90,09°
No. 3	Black	3.85	39	−8.42°/s	−2.33°/s	−90.15°
No. 4	Red	3.89	40	−7.79°/s	−2.28°/s	−87.32°
No. 5	Cyan	3.71	37	−9.06°/s	−2,45°/s	−89.68°

$$\omega = \Delta\varphi / \Delta t$$

The exemplary analytical case of the smart product laying on the carrier tray propelled by the conveyor belt can be seen as a 2-dimensional problem. Here the angular velocity increases and subsequently decreases during the directional change of the overall turn angle φ . This orientational change covering the timespan from the initial state at t_0 to the resulting state at t_1 can be broken down into incremental changes between two timestamps with the angular velocity ω_{xi} of the current timestamp t_i, see Equation 2:

$$\varphi = \int_{t_0}^{t_1} \omega\ (t)\ dt = \sum_{t_i = t_0}^{t_1} \omega_{xi} \Delta t$$

In this study five turning events have been analyzed. Fig. 8 shows the trendlines of the angular velocity during the right angular turn (depicted in Fig. 7 c)) for these five events.

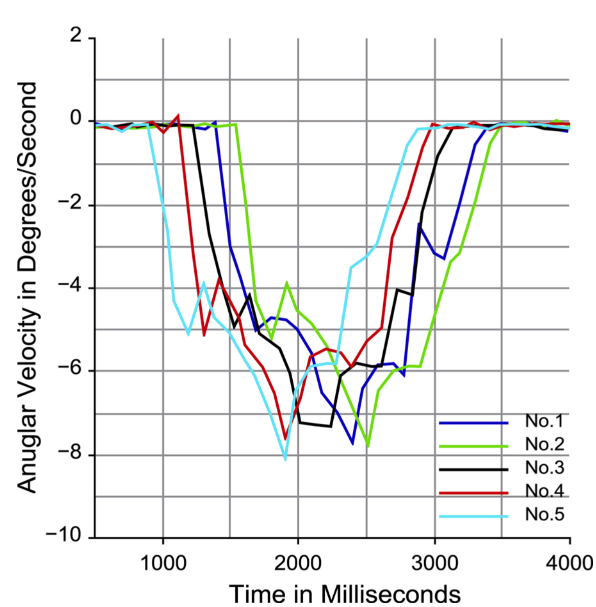

Fig. 8. Recorded Gyroscope Time Series of 90 Degrees Turn.

The trend lines show similarities in the events. These similarities are evaluated for the duration of the event, the number of sensor readings during the event, the peak angular velocity, the average angular velocity and the turn angle calculated according to Equation 2. The color scheme mentioned in the Table 4 refers to the color in Fig. 8.

4.4.2. Acceleration

The 3-axis acceleration readings were acquired via the same IMU, the BMI160, as the gyroscope readings with an interval of 100 ms. The proper acceleration measured by the accelerometers gives the acceleration relative to a free-fall. This can be helpful to differentiate between a fixed position within the process station, the movements on the conveyor belt and the overall orientation of the smart product.

The graph in Fig. 9 plots the recorded acceleration forces acting on the part as a time lapse during the flipping operation as depicted in Fig. 7 b). The initial reading shows the g-force exerted on the part before the process commences. Once the process is initiated, we can see the forces 'switching' orientation, representing the 180 degrees rotation of the smart products during this operation reflected in the accelerometer reading.

4.4.3. Temperature

The temperature acquired via the environmental sensor module BME280 was captured with an interval of 0.5 sensor readings per seconds. The temperature profiles recorded during the case study are depicted in Fig. 10 and were recorded during the heating chamber process shown in Fig. 7 a).

The reading shows a near linear temperature increase during the heat treatment process. The process characteristic of the constant input of energy results in a constant heating rate m_k. This is defined as the rate during the initial state at t_0 to the resulting state at t_1 of the event, as illustrated in Equation 3:

$$m_1 < f^{'}(t) < m_2 \text{ for } t_0 < t < t_1$$

The events had a duration of 160 s which translated to 340 data points captured. The first event showed a slope of 0.0153 degrees per second with a root mean square error (RMSE) of 0.0259, the second event a slope of 0.01573 degrees per second with a RMSE of 0.05. After the temperature peak is reached the carrier remains in the heating chamber with the heating unit switched off. This can be seen in the graph with a linear reduction in temperature. Once the carrier starts moving again and passes onto the next manufacturing process, a

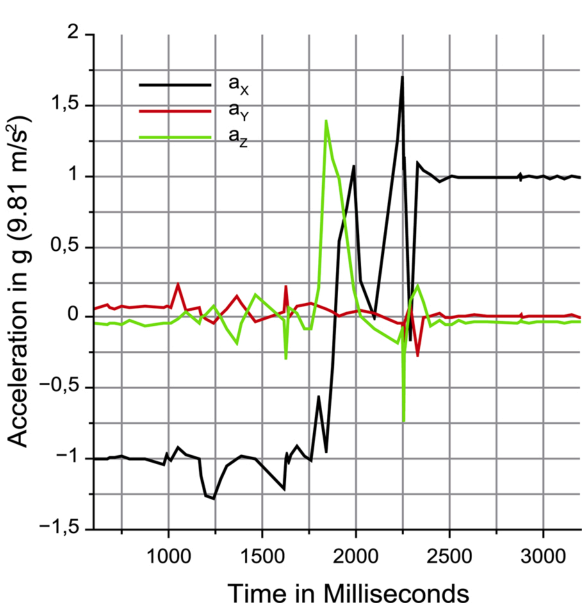

Fig. 9. Recorded Acceleration Time Series showing the Flipping Process.

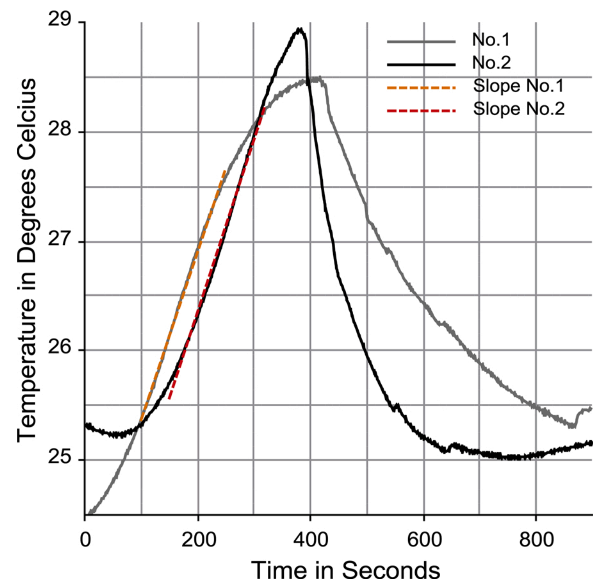

Fig. 10. Recorded Temperature Time Series.

negative exponential behaviour can be observed. This observed data picture matches the expectation based on established heat transfer models. The pattern in this case is very distinct and clearly visible based on one defining feature (temperature over time).

4.5. Use case discussion & limitations

The prototypical use case tests the very basic potential to utilize a smart product to capture data that can be used for value-adding insights in a manufacturing process. In this scenario a smart product with a sensor system that is capable of collecting a variety of sensor data and communicating it wirelessly, phased the smart product in the testbed's eight stage manufacturing process, and analyzed the data collected for the potential to identify clearly distinct manufacturing processes within the process chain.

For this study the gyroscope, accelerometer and environment sensors were used to showcase this idea. Applying sophisticated analytics methods for IMU data utilizing the geomagnetic sensor and sensor fusion methods more accurate results can be achieved.

We were able to clearly distinguish two manufacturing processes and the orientation on the conveyor belt solely based on the data collected by the smart product. The data shows clear events that exemplify unique process fingerprints. These process fingerprint models provide a variety of opportunities for optimizing manufacturing processes, including a more accurate, real-time updating scheduling and in-situ tracking and quality control. The prototypical case study had the objective to provide a proof of concept as a basic justification of the argument for an extension of the smart product paradigm towards the BOL. The prototypical implementation is at the same time also a clear limitation of the presented work

In order to provide real value to manufacturing, these 'process fingerprints' need to be confirmed in various scenarios and modelled across multiple products/parts based on unique features. In this case, we used several instances of the same process chain for one smart product. Ideally the event detection can then be run on the edge to increase the reactivity of the system. However, this involves substantial development, data collection, and modelling efforts. Nevertheless, the prototypical case study provides a basis and justification to engage in this type of future research. It is essential to initially carefully assess and select parts/products that profit the most from a richer data picture during the BOL. In the following, we present a discussion on the potential impact of the paradigm shift within selected industries and applications scenarios.

5. Discussion and impact of smart product paradigm shift

This paper describes the vision of using smart product in SMS supported by a prototypical implementation illustrating the general feasibility. However, the proposed paradigm shift has yet to happen. In the following, we will generalize the discussion and present selected scenarios where the vision can be most impactful and value-adding.

5.1. Impact on manufacturing operations

Manufacturing operations management aims at optimizing operational efficiency of the SMS. The majority of improvement and optimization tools and efforts are data-driven and depend on high quality, high fidelity, and (near) real-time data. One area exemplifying the operational tasks is scheduling. Scheduling is key to juggle machine tool utilization, throughput, and several other parameters of a manufacturing system. Many scheduling tools are based on simulations that utilize either standardized time blocks (e.g., drill hole = 5 s) or accumulated historic data [75]. Either way, this often only allows us to achieve a certain accuracy due to the inherent complexity of small batch production and individual specifications and unique performance (e.g., acceleration) of machine tools (even of the same type and model).

Incorporating a smart product in the process that is capable of providing real time data regarding its state, progress, and current whereabouts in the value chain through accurate 'process fingerprint' models of each individual manufacturing process and the connectivity and data provided by the sensor system. This enables automated tracking of the smart products' state and the creation of a seamless, item-level manufacturing history (batch-size-1). In turn this increases the granularity of data and information available. In order to fully leverage all of the benefits, the sensor-read data can be augmented with information about the process plan (schedule) from the MES. This enables virtual quality gates and feedback on the elapsed processing, idle, and transportation time between two or more manufacturing processes enabling more precise and accurate scheduling and predictions. The SMS consequently can conduct a real time calculation of the actual utilization of each process station in-situ, and ultimately an online detection of the current real time value stream mapping. Here the detection, quantification, and visualization of bottlenecks of the SMS can be used to improve the routing and scheduling of smart products which are about to be manufactured - and in the end the overall manufacturing system's outcome (e.g., throughput, machine utilization) can be improved.

5.2. Impact on manufacturing processes

On the manufacturing process side, the integrated sensor system of the smart product enables in situ data collection while it is being manipulated by a machine tool and/or process. This allows us to analyze the incoming smart product data with regard to the quality outcomes of each manufacturing process in virtually quality gates. Physical quality gates in manufacturing range from fully automated [76] to requiring manual intervention [77]. Their accuracy varies depending on a variety of factors, and many do not provide a 100 % quality inspection [78]. Quality checks are necessary due to the deviations of executed (as-is values) from the planned process parameters (set values) [12]. They deviate due to the condition and state of the manufacturing systems and distributions in dimensions and properties of various interacting components. The quality prediction model based on the data provided in situ by the smart product is expected to predict outcomes with regard to the actual achieved requirements (quality features). Machine learning clustering algorithms can be employed to distinguish between good and bad (scrap) parts at critical points of the process [47]. The richer the data picture, the better the prediction [3]. Thus when we merge the continuously collected and analyzed data from the smart product fused with the CPS provided MES objectives. This resembles an automated advanced in-situ process monitoring.

Building on the data collected and analyzed by the smart product, these insights from the process alterations (n) can be used to trigger alterations of the manufacturing process parameter settings of the next processes ($n+1$, $n+2$, …) by which the product will be manipulated. The so-called self-x capabilities [79] are autonomous measures with regard to decisions whether or not certain actions require intervention to realize a better outcome than the current scenario. Examples are electrical, pneumatic, and time related settings. For instance, the heat treatment process can be extended and set to a higher temperature if required to achieve the manufacturing objectives. Such self-correcting control fed by insights from product and process data offers enhanced capabilities over process data-based insights alone, with large variations depending on the different manufacturing processes themselves [80].

5.3. Impact on selected industries

In this section we discuss selected scenarios where the proposed extension of the smart product paradigm delivers added value. The selection emphasizes diversity of scenarios across industries (e.g., aerospace, medical equipment) and applications (e.g., cybersecurity, tracking). Table 5 provides an overview of the use cases and the potential impact of using smart products during the BOL in these scenarios. Afterwards, each use case is presented in more detail throughout the remainder of this section.

5.3.1. Aircraft manufacturing

Aircraft manufacturing represents a high complexity product (or system) and manufacturing process. Additionally, the aerospace industry is one of the most regulated today with safety regulations and mandatory tracking and tracing, certifications, and quality monitoring in place. At the same time, aircraft are highly sensorized systems once assembled and in service. Jet engines are a prime example for smart products that are often used as a prime example case for digital twins [81].

The tight tolerances and complex manufacturing processes to manufacturing aircraft components including jet engines and the regulations and certifications required (e.g., FAA [82]) provide several areas where an integrated sensor system could provide value during the BOL, namely during the assembly process. Two specific applications are the seamless tracking of certified parts along the supply network to avoid accidental mix ups and counterfeits. The second application is a more precise monitoring of the production process itself using the included

Table 5
Overview of possible use cases.

Industry/product	Potential application	Key objective	Limitations
Aircraft Manufacturing (Sec. 5.3.1)	Tracing of critical parts	Provide visibility of supply chain, and protection against counterfeit parts	Compliance with regulations and certifications of aircraft parts
Composites Manufacturing (Sec. 5.3.2)	Monitoring of layup process quality	Provide data on key quality parameters	Integrated sensor system may impact structural integrity of manufactured parts
Safety equipment (Sec. 5.3.3)	Sensorized motorcycle helmet	Track possible quality issues, e.g., drops, during BOL	Timing of sensor system activation and connectivity during transportation
Sports equipment (Sec. 5.3.4)	Sensorized golf club	Track process parameters to optimize overall performance of club (e.g., material composition)	How to power sensors system to collect relevant process data, e.g., heat treatment

sensors. For example, the blades of the jet engine are an advanced product that is manufactured using several layers of materials sandwiched together using a delicate heating profile and high pressure. An internal sensor monitoring the temperature curve could provide additional insights and reduce quality issues and scarp. Similarly, the assembly process of the fuselage is very heavy on riveting. This can be used as triggers to initiate assembly prework, something that is very common on the assembly floor in aircraft industries.

The potential value in this case is promising, however, the barriers for implementation in live production are substantial. The detailed certification process, while a reason for integrated sensors, is also a hurdle that prevents inclusion of sensors in the components. Another is the high temperatures and pressure endured by parts during the process that are problematic.

5.3.2. Composites manufacturing

In the context of composites manufacturing, specifically automated fiber placement (AFP), the implementation of digital transformation is a necessity. AFP is used for the manufacturing of primary structural parts on the Airbus 350 and Boeing 787 aircrafts where over 50 % by weight is now made of these composite parts in lieu of the traditional aluminum parts. The manufacturing process requires the implementation of four principle process parameters: heating, compaction, speed, and tension. Most of these process conditions are implemented in an open loop manufacturing setup where the output is not verified whether it is delivered as intended. Therefore, integrated sensors could provide useful data and add value to the manufacturing system, potentially reducing quality issues and scarp. Extending the smart product paradigm towards the BOL of composite structures is promising and aligns the with plethora of work on including integrated sensor systems for structural health monitoring in composites during their MOL across industries [83–85].

Utilizing the sensors during BOL could enable an augmentation of the process data collected by the machine tool (AFP equipment) such as elongation and/or integrity of fibers during the layup. Ideally it could be integrated in the closed loop control currently employed. The closed loop heating mechanism controls the output temperature on the substrate and ensures the layup window is happening at the material optimal temperature [86]. Furthermore, the data from the integrated sensor system could enable advanced analysis of the quality of the manufacturing layup and assessment of its effect enabling the operator to plan and conduct eventual repair [87,88].

The AFP process in particular is creating the structure by adding material layer by layer, the sensor system must be included during this process. Today, there is little research available whether the temperatures and pressures allow for an integration of directly functional sensors. In a more traditional and established composites manufacturing process where the layers of fiber are placed before applying the resin, the integration of sensor systems faces less barriers.

5.3.3. Safety equipment manufacturing (Example: motorcycle helmet)

Safety equipment has little tolerance for quality problems as the consequences of product failure can be catastrophic. An example of safety equipment are motorcycle helmets. Today, we find a large variation of motorcycle helmets on the market, influenced on the one hand side by laws, policies, and customer preference, and on the other by advancing technology, materials, and new safety insights. One of the more recent innovations are integrated sensors in motorcycle helmets, e.g. IMU sensors similar to the use case presented in section 3 of this paper [89,90]. The data collected by this sensor system during the MOL enables annotation of video data but also safety aspects such as drops that might impact the structural integrity of the helmet. Other future aspects of a ‘smart helmet’ are the ability to only start the motorcycle when the helmet is correctly donned.

Sophisticated motorcycle helmets and similarly helmets used in football, aviation, military / special forces, bikes, etc. are carefully crafted to perform their task of protecting the user during the usage. Modern helmets are designed to absorb impact, alleviate forces, and reduce trauma just to name a few. The use of additive manufacturing of elastomers is allowing for density-varying lattices that can tailor the mechanical response of the system. Furthermore, novel sensors can be interwoven between the lattice unit cells to provide precise deformation sensing, a sensor that may have utility in the context of this smart product paradigm [91]. To perform at the edge of what is possible, the structure is often sensitive to drops and previous use - including the handling during shipping, manufacturing, and other BOL phases. Therefore, utilizing the helmet as a smart product during the BOL would allow the user to judge the current state of the helmet based on data, not only based on trust and the assumption that it was handled with care and not, e.g., dropped accidentally when stocking the shelf or moving the combat backpack.

In the case of the helmet, the IMU sensors will provide value after the helmet is assembled during the logistics and final inspection. However, currently the helmets need to connect via Bluetooth to a mobile phone to ensure connectivity. To truly provide seamless tracking and monitoring, independent wireless connectivity would have to be built in. The use case for such an expensive solution (today) is only valid for high profile helmet systems such as NFL players, Navy SEAL operators, or professional race drivers. In the future this case might be valid broadly as it delivers a clear value add and can potentially save lives.

5.3.4. Sports equipment manufacturing (Example: golf club)

Golf is a $84 billion a year industry [92]. Professional and casual players are investing significantly in golf equipment such as high-quality golf clubs. Modern golf clubs are high tech products that utilize state of the art design, research, and materials such as titanium. In the players’ quest to improve their game, they are often obsessed with data and analysis to understand their shortcomings and potential to improve. No wonder that integrated sensor systems have found their way into the sport, and more particularly in the golf clubs themselves to collect a myriad of data during the MOL that can be used to analyze and hopefully improve the players handicap [93].

Smart golf clubs can include a variety of different sensor systems, from IMUs to strain gages [93,94]. As mentioned before, golf clubs utilize advanced materials and manufacturing processes and can cost several thousand dollars. Customers tend to be very involved and particular about the expected quality and utilizing the integrated sensor system intended for the MOL during the manufacturing phase (BOL) can provide additional data to ensure consistent high quality of the delivered products and also to reduce the scrap rate impacting the bottom line.

5.4. Implications and limitations

Overall, these diverse scenarios show the potential exists with a clear value add for expanding the smart products paradigm from the MOL to the BOL. This proposed paradigm shift has several implications for academic research and also mangers interested in the opportunities it presents. With regard to academic implications, there are a myriad of areas that need further investigation. On the technical side, research in sensor integration, sensor technology, and sensor power systems is crucial to enable small-scale and rugged sensor systems that can be powered during the BOL. Connectivity is another field where research needs to be conducted to overcome the barrier of communicating the smart products’ data during processing in SMS. On the economic side, more research into models and frameworks around the feasibility of selected use cases and their business models is required. Both academics and managers need to rethink their business models that might need to be adopted. For managers interested in this paradigm shift, it is crucial to carefully assess whether there is a value proposition of gaining additional insights during the BOL for their specific smart product. Especially during the beginning, there are probably one very few selected use cases that make economic sense. Over time, when the technical barriers have been addressed and the business models are developed, more use cases may profit from the development.

There a several limitations that need to be considered when considering the presented research and the paradigm shift overall. Regarding the research, the case study did not focus on the early part of the manufacturing process. The early processes are generally more physically demanding in terms of thermal, mechanical, and chemical exposure and thus not as inclined to work with sensors as proposed. Furthermore, the case study is set in a lab testbed and not in an industrial environment, e.g., the assembly of a real smart phone. Therefore, the complexity was reduced with the intention to focus on the general feasibility. This needs to be studied further both in terms of the technical and economic feasibility. A critical barrier of adoption is the required connectivity of a smart product. Traditionally, connectivity is established once the smart product is activated by the user after purchase. This barrier is consistent with most consumer-facing products and can potentially be overcome by connecting the smart products to factory shop floor Bluetooth gateways to overcome the connectivity issue.

6. Conclusion & outlook

Our world is changing rapidly in the wake of the fourth industrial revolution. Connectivity, data, and the Internet of Things are everywhere, from our homes to our factory floors. Smart-connected products with integrated sensors are cheap and omnipresent from shoes to watches, from cell phones to modern appliances. The data collected by smart-connected products during the usage phase (MOL) offers tremendous value to service providers as well as manufacturers to improve product design and customization and/or data-driven personalization. However, these benefits have yet to be fully leveraged.

Currently, only traditional sensors that are integrated within the smart manufacturing system (SMS) such as in machine tools, quality monitoring systems, or quality gates are leveraged in the manufacturing of smart products during the beginning of life stage (BOL).

In this paper, we proposed to radically extend the smart product concept towards an earlier point in the product life cycle, thus leveraging the value-adding in-situ sensing capabilities of the smart product to measure preliminary manufacturing data during the BOL. We argue that 3D printing can now serve as the foundational process for building multi-functional structures as smart products and enable functional integrated sensor systems early in the manufacturing process chain. The potential value of expanding the manufacturing data perspective with real-time, in-situ data collection by the manufactured product itself is transformational. Particularly, manufacturing processes that depend on high-fidelity process data to achieve the desired outcome will tremendously profit from not only additional data points but data from within the structure itself - previously impossible without destructive evaluation methods. Leveraging 3D printing to directly manufacture structures with integrated sensing, unprecedented data can now be measured during manufacturing of next generation smart products.

The technical feasibility of this breakthrough innovation depends on the product itself and the manufacturing process. However, mapping the viability of this approach over a number of processes for several different products highlights profound opportunities in the later phases of the SMS. Combined with a judgement of the economic benefits, the value proposition for a specific smart product and SMS can be determined.

We presented a prototypical feasibility study based in our smart manufacturing test bed that illustrates that integrated sensor systems can principally provide value adding data directly from the manufacturing process. While this study is only a first step towards this vision of BOL enabled smart products, we ground our findings in current industrial reality by discussing selected scenarios of promising applications (e.g., helmets, jet engines, golf clubs) to better reflect the opportunities as well as barriers. Substantial work remains and interdisciplinary research is required to tackle this problem and make this unconventional transformative vision a reality.

The presented work has several limitations that need to be considered moving forward. The prototypical application was done in a lab testbed and not an industrial manufacturing setting. The challenges with respect to noise, connectivity, access, and transparency present additional barriers. Another aspect is data security and, most of all, ROI of such a system that will define its applicability. The 3D printed sensor systems are technically available, however, the effect of those on structural integrity especially on one-of-a-kind products need to be considered as well. Another key aspect that requires more analysis when smart products become nodes within the SMS is cybersecurity and other sensitive areas impacted by this paradigm shift [95].

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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