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# Self-sensing Smart Products in Smart Manufacturing Systems

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### Abstract

We are surrounded by a growing number of products with embedded intelligence relying on sensors and internet access. These smart products, that already transform our lives, are also physical entities that need to be manufactured. Manufacturing today similarly relies on data and data-driven insights to improve quality, efficiency, and safety on the shopfloor. This paper discusses the vision to utilize the ability of smart products to sense and communicate already during their own manufacturing to enrich the smart manufacturing system's data for better insights development and optimization. We furthermore, discuss the barriers and opportunities embedded in such a paradigm shift.

*Keywords:* smart product; smart manufacturing; integrated sensor system; product lifecycle; PLM

### Highlights:

- Paradigm shift for the expanded use of Smart Products spanning middle of life (MOL) and beginning of life (BOL).
- Discussion of the benefits & opportunities of integrating smart products' capabilities to SMS.
- Discussion of the barriers & challenges of integrating smart products' capabilities to SMS.

# 1. Introduction

The world is changing rapidly in the wake of the fourth industrial revolution. Connectivity, data, and the Internet of Things (IoT) - the key smart manufacturing technologies - are applied across the board, from our homes to factory floors. In David Dornfeld's vision, he outlined the impact of data to improve and optimize the various levels of a manufacturing system (Dornfeld 2014). Dornfeld in particular emphasized "facility level" data, "system/line level" data, and "process level" data and its individual temporal scale (Vijayaraghavan and Dornfeld 2010). By utilizing the different data streams and leveraging their insights to optimize a manufacturing

system, it transforms said system into a Smart Manufacturing System (SMS) (Tao et al. 2018; Kusiak 2019). At the same time, during the engineering and product design phase of the product lifecycle, data plays an ever more important role as well. Smart Products (Meyer, Främling, and Holmström 2009; Gutiérrez et al. 2013) possess a unique identity and generate

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of the life cycle. This leads to the question, why the increasingly available, rich SMS data and the (smart) product data are currently not leveraged jointly. Incorporating the item level data provided by smart products in combination with facility/system/process level data accessible through the established connectivity on the smart manufacturing factory floors may lead to a myriad of novel, value adding applications in SMS.

In this vision paper, we first discuss the current state and problem, before proposing our vision to integrate the two emerging paradigms smart manufacturing and smart products. Following, we take a critical look at the potential benefits and challenges of such a paradigm shits and conclude with a brief outlook and call for action.

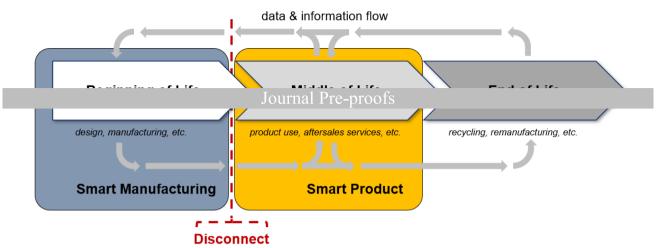
# 2. Background and Problem

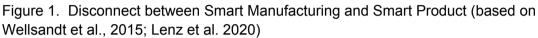
The common three-phase product lifecycle model (Jun et al. 2007) features three distinct phases: design, manufacturing, and distribution are processes associated with the beginning of life (BoL) phase; the usage phase of a product is considered part of the middle of life (MoL); while recycling, energy recovery, and disposal are situated in the end of life (EoL) phase (Wellsandt et al., 2016).

Smart products with integrated sensors are cheap and omnipresent today, found in products from shoes to watches, cell phones to modern appliances (Wuest et al. 2018). The data collected by smart products during the usage phase (part of the MoL) offers tremendous value to service providers as well as manufacturers to improve product design, customization, and personalization (Kiritsis 2011).

However, the full benefits provided by this new access to data have yet to be exploited across the different lifecycle phases. Currently, only traditional sensors that are integrated within the SMS are leveraged during the manufacturing of smart products themselves, during the beginning-of-life stage (BoL) (Lenz, Wuest, and Westkämper 2018).

While both lifecycle phases, BoL & MoL, are data-driven or at least have significant datadriven components in place, to date, smart products (MoL) and the smart manufacturing of these products (BoL) are not aligned and integrated. The sensing capabilities of smart products are activated only after the manufacturing (and assembly) processes are completed and the products are delivered to the customers – aka. the users of the smart product. Simultaneously, machine tools and sensing equipment within the SMS collect external process measurements of the to-be-manufactured smart product; however, these in-situ measurements are limited to an 'outside' perspective (e.g., surface quality, temperature of the environment, etc.).





Ultimately, the sensing and communication capabilities of the smart product itself are not leveraged during the manufacturing process to augment the existing sensing environment of today's SMS. This disconnect is depicted in Fig 1. Several challenges exist that offer possible explanations why the full features of a smart product are not yet utilized during the manufacturing of said smart product. First, the manufacturing process of every product, including smart products, begins with raw materials and comprises a series of different processes – including processes that involve (very) high temperatures and plastic deformation (e.g., forging or casting). In order for the product to be considered a smart product, the sensor system needs to be operational and able to communicate. This functionality generally requires complex processes including assembly, software installation, and the application of a battery (power supply), which may outweigh the benefits of additional data during manufacturing.

## 3. Proposed Vision

We propose to radically extend the smart product concept to the earlier phases of the product life cycle. This extension will enable us to better utilize the smart products' sensors during the manufacturing process. In this scenario, the smart product is powered as early as technically possible to activate its internal sensing and communication capabilities. Once powered on, its sensor capabilities are used to provide data for manufacturing optimization purposes. This early state enablement allows leveraging the value-adding in-situ sensing capabilities of the smart product to measure preliminary manufacturing data during the BoL. The potential value of expanding the manufacturing data perspective with real-time, in-situ data collection by the manufactured product itself is transformational.

The potential future impact of this vision is the improvement of manufacturing processes with regard to energy usage, quality outcome, (product and process) state detection, and real-time scheduling/routing. Traditionally, smart manufacturing utilizes built-in sensors into the manufacturing system. In cases where such sensor systems are not available or cannot provide the required data, the sensors from the smart product can fill the gap. Additionally, in cases SMS sensor data is available, the smart products' data can augment the data picture and allow better analysis and insight development.

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 to acquire in-situ or without destructive methods. Also, filling the life cycle record of an individual product as early as possible has

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The use case is sound, however, the technology to create such capable smart products seems far-fetched. Yet, Additive Manufacturing or 3D printing offers the possibility to implement this vision early and with reduced technical barriers. 3D printing can fill this void as a foundational process for building multi-functional, sensing enabled structures for smart products. With 3D printing leveraged to directly manufacture structures with integrated sensing, unprecedented data can now be measured already during the manufacturing of next generation smart products itself. This opens up new insights and opportunities to create knowledge of and improvements for the smart manufacturing system. 3D printing in particular offers advancements such as implementation of sensors before assembly, reduction of process restrictions, increased design freedom and here the benefits of early smart product capabilities outweigh the cost of product adaptation for early smart product capabilities .

# 4. Discussion - Barriers and Opportunities

The technical feasibility of this breakthrough innovation depends on the smart product itself as well as its manufacturing process(es). 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. The barriers and challenges to achieve the technical and economic feasibility, as well as the opportunities, are depicted in Table 1.

	Technical	Economic
Barrier & Challenges	Process restrictions	Implementation cost
	<ul> <li>Restrictions prevent operation of Smart Product in BoL</li> <li>Categories of process restrictions: thermal, electrical, chemical, mechanical, etc.</li> </ul>	<ul> <li>Total cost of enabled Smart Product 'sensing'</li> <li>(Re)design effort significant factor</li> </ul>
Opportunities	Sensor functionality	Integration benefits
3	<ul> <li>Interacting through sensor readings &amp; communication</li> <li>Booted state: sensor data can be read &amp; processed</li> </ul>	<ul> <li>Value-add of new data, information, &amp; insights</li> <li>Impact across value chain, not limited to shop floor</li> </ul>

Table 1: Barriers and Opportunities (based on Lenz et al. 2020)

The biggest obstacles are hard process restrictions, prohibiting the smart product from reaching the 'booted state' (aka. actively sensing and communicating with its environment), either for thermal, electrical, chemical, or mechanical reasons. Typically at the mid-assembly operation, powering the electronics can be achieved through redesign. The opportunities

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opportunities outweigh the barriers an early adaptation of smart product in SMS is considered feasible.

### **5.**Conclusions and Outlook

We envision a radically extension of the Smart Product paradigm, traditionally exploited during its active usage phase (MoL), to the earlier phase of the product Lifecyle (BoL) (see Fig. 2). By extending its capabilities to provide additional, previously not available data will expand the achievable analysis and data-driven insight development during manufacturing and assembly operations – driving the progress in SMS. Smart Manufacturing and manufacturing data analytics are depending on accurate, high quality and high quantity data – today this data is captured 'externally' of the product, and thus omits crucial aspects of the transformation process.

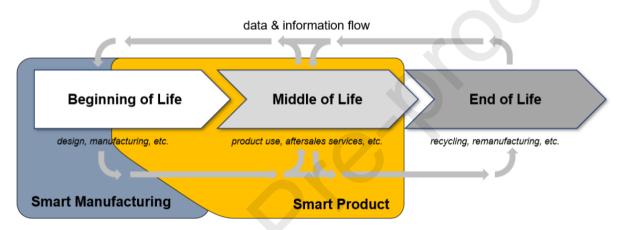


Figure 2 Integration of Smart Manufacturing and Smart Product Paradigms across the Product Lifecycle

Overall, the proposed vision expands on the initial vision of integrating "facility level", "system/line level", and "process level" data by adding "product state" data for radically improved analytics opportunities in Smart Manufacturing Systems.

While the vision is promising we have only started to scratch the surface and substantial work remains. Interdisciplinary research is required to tackle this problem and make this unconventional vision a reality. Research areas that need to work together to overcome the remaining barriers of this vision are depicted in Fig 3.



Figure 3. Relevant research domains to progress towards the vision of smart products in SMS

Concluding, if we are successful in overcoming the technical and economic barriers and successfully integrate smart products' capabilities in SMS, it will not only positively impact operations (e.g., lead time, bottleneck detection, energy efficiency, traceability, product properties & quality, etc.), but also (manufacturing) strategy (e.g., quantify impact, mixed-model lines, etc.).

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### **Declaration of interests**

 $\boxtimes$  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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□The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: