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PRODUCTION MANAGEMENT

Development of a simulative approach in order to estimate the impact of smart services on a production system

Linking the influence of smart services to economic potential in production

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Abstract

The increasing digitalisation and development of the fourth industrial revolution have created new opportunities in the B2B manufacturing industry. These opportunities come in the form of smart services, which are made possible by the interconnectedness of machines and products and the collection and analysis of data. However, there is uncertainty among potential users about the benefits of these smart services for their production systems. This paper aims to address this uncertainty by developing a simulation model that quantifies the impact of a smart service on a production system, using monetary benefit as a key performance indicator. To do so, the influence of a smart service on a production system is analysed and a generic production system model is developed. The generic model can then be used to analyse different smart service configurations and production systems to examine the effect of the smart service. This is demonstrated through the application of the simulation method to a use case studying the benefit of intelligent quality control and predictive maintenance.

Keywords Cyber-physical systems · Industry 4.0 · Simulation · Smart service · Performance measurement

1 Introduction

The industrial value creation is characterised by the implementation of the fourth stage of industrialisation, the so-called Industry 4.0. This is based on concepts and technologies that include cyber-physical systems (CPS) and the Internet of Things (IoT) [1]. One consequence of this change is the digitalisation of industrial production. The digitalisation entails a paradigm shift away from the classic business model towards the servitisation of manufacturing. The term servitisation of manufacturing refers to the transformation of manufacturers into service providers. This creates the possibility of entering a direct relationship with industrial customers via digital services.[2].

In this context, smart services are increasingly gaining strategic importance [3]. Smart services are characterised by a high degree of autonomy and data-drivenness [4]. Due to this, smart services offer manufacturing companies as well as industrial customers new opportunities, for example through remote monitoring and control as well as predictive maintenance [5]. However, due to their novelty, users and providers of smart services lack comparison possibilities and empirical values to be able to individually assess the impact of a specific smart service on the production at an early stage [6].

Therefore, the scope of our paper is to provide both suppliers and users of an industrial smart service with a tool that fulfils the following two objectives: First, it should provide a measure to quantitatively estimate at an early state the potential of a smart service when applied in a production. Second, it should be possible to experiment different parameter sets, e.g. production volume, and their consequences.

The goals should be achieved without disrupting the real production system. Here, a simulation method may be suitable. In addition to not disrupting production, a simulation offers the following advantages [7]:

- a simulation can typically be understood even by non-professionals increasing the acceptance rate

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- a simulation is modular and can be easily expanded or adapted if more complex or different questions arise
- a simulation can reveal underlying distributions and, thus, can reveal the uncertainty of results

The comprehensibility of simulation results and the modularity of the model are particularly strong arguments. These advantages justify the potentially higher effort required to develop the simulation model in this work, compared to an analytical model, for example. Therefore, the simulation method is focused in this work. As it shall be used for a first assessment of a smart service, its output shall be the pecuniary benefit of the smart service use.

The remainder of the paper is structured as follows: Next, the basics of smart services are presented. Furthermore, selected works are introduced that deal with the benefit-oriented investigation of services in production. In Sect. 3 , the simulation model is developed by first defining assumptions that outline the conditions under which the simulation is valid. Using these assumptions, a model of a production system is created. The approach is then validated using a case study from the high-precision products industry, in which data is collected from an industrial partner and used to parameterise the simulation. The results are discussed, followed by a conclusion and outlook.

2 State of the art

In this work, the term smart services is used in the sense of intelligent services that complement or even substitute a physical product. Although there is no standardised definition of smart services, different topics are linked to smart services [4]. Smart services use data generated by sensors to adapt their own behaviour through data analysis, resulting in new individual benefits for customers [8]. Often, artificial intelligence or machine learning is used to achieve such behaviour [4]. The basis of every service, and therefore for every smart service, is the underlying business model [9]. The business model describes a collection of objects, concepts and their relationships, with the aim of defining the enterprise logic of the company [10]. This broad definition shows that there are many different possible business models for smart services. The same is true for smart services. As a result, a simple overview of all possible smart services is impossible to create. Instead, different structuring frameworks can be used to get a better understanding of what smart services cover. Sticking to the business model, a set of 55 business model types can be distinguished [11]. These 55 business model types are holistic as stated by the authors. At the same time, they are still vague and not manufacturing specific. Bullinger et al. identified different smart services in the manufacturing industry based on a survey, including services for spare parts management, maintenance, and repair [9].

By broadening the perspective, smart services can also be seen as part of a product-service systems (PSS) [8]. Besides the identification of further frameworks, the link between smart services and PSS is especially interesting because valuation approaches found in literature are mostly designed for PSS in general and not specifically for smart services. While some approaches in the context of PSS mention a financial analysis to determine the financial impact of smart services, concrete approaches on how to determine quantitative benefits are missing [12–14]. This is especially true for an early stage estimation. A literature review on the financial assessment of smart services shows that relevant approaches are dispersed and come from many different fields. The following non-exhaustive sample of existing work illustrates this point.

Schmidtke et al. [15] use value stream mapping to map the actual process of a complex production system and design the target state. The target state is then implemented in a discrete-event simulation and verified before the actual implementation with a focus on feasibility and economic efficiency. The impact of smart services is out of scope. Kim et al. [16] present a method for evaluating PSS models and thus enable the comparison of different models. Their approach considers five dimensions in the evaluation: Sustainability, customer value, profitability, quality and costs. The approach is qualitative. Both approaches are not based on quantitative methods but consider different important aspects. Overall, they provide a useful work which may not be suitable for a quick financial analysis.

Anke [17] develops a web-based tool to continuously assess the profitability of a smart service at an early stage of service design. As a basis for the tool, a meta-model is provided that links the main elements of the smart service with its financial impact and with which the evaluation results can be calculated immediately. Although financial aspects are considered, the tool is focused on the design of a smart service and not on the assessment.

The following approaches which are only a small subset of literature show that the simulation method is valuable in the manufacturing context but has not been considered for smart services: Wadhwa et al. [18] implement a discrete-event simulation of a multi-stage supply chain. With the simulation, they investigate the effect of the disturbances demand fluctuation and process delay on the key figures delivery time, delivery delay and stock level.

Lavy et al. [19] construct a simulation approach to show, among other things, the correlations and relationships between and among KPIs and input variables within a system plant and for the whole plant. Another objective of this study was to show that due to variability and future uncertainty, simulation is a valuable tool to generate possible future scenarios and make decisions based on forecasts and logic.

Greinacher et al. [20] present an approach for the assessment of lean management methods in the production context. They use a simulation-based approach for monetary evaluation. Energy and material consumption were focused. Thus, detailed analysis of duration, costs as well as energy and material efficiency per product type can be collected.

Regarding the method used for financial assessment, different possibilities exist. As shown by previous work, simulation can be a valuable tool for the financial assessment in the context of production. Here, the discrete-event simulation is most frequently used [7]. Therefore, a discrete-event simulation is a possible tool for investigating the impact of smart services in production systems [19]. For the development of a discrete-event simulation the standard model of VDI 3633 can be consulted [21]. The standard model suggests the following steps:

- goal and task description
- system analysis and model formalisation
- implementation and experiments

While the goal and task description are already given in Sect. 1, the system analysis and model formalisation are elaborated in Sect. 3 . Finally, the executable model and the application are linked to Sect. 4.

3 Methodology

In this chapter, a formalised simulation model for the implementation of the objectives is derived. In the context of the derivation process, various assumptions are made under which the simulation model is valid.

3.1 The generic three process components and the smart service

The production system and its elements are analysed using a top-down approach and then formalised into a general model.

The first assumption is that a smart service does not directly influence all steps of a production process, but rather has an effect on a specific area or even only on a single process (A1). To estimate the potential of a smart service, it is therefore not necessary to consider the entire production process in detail, but only a relevant section. Detailed mapping of the processes would also contradict the goal of an early rough estimation. As a consequence, a simplification is made so that the simulation is not too complex in setup. The simplification involves dividing the production system into three process components: The pre-process, main process and post-process. By definition, the smart service only affects the steps within the main process. This effect is represented by a change of the abstract production targets time, quantity and quality. The main process is also influenced by the pre-process, which includes all steps before the main process, and in turn, the main process influences the post-process, which includes all steps after the main process.

The model of a smart service is not a specific smart service, but a general smart service in the context of production. The relevant data required for the model parameterisation are determined in the following sections. These are mapped in the simulation by means of statistical distributions. Likewise, the required system elements are determined in the following.

Three additional assumptions are summarised here for the derived model structure: Changes in the system can be represented as events that lead to state changes in the model (discretisation assumption) (A2). Only few system elements are significant (A3). So, only these affected elements are included in the model. The production to be modelled corresponds to a flow production (A4). The concept is depicted in the middle of Fig. 1.

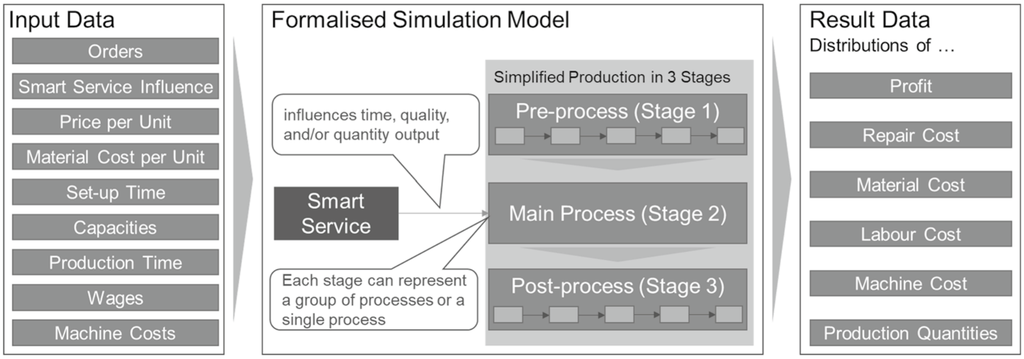

Fig. 1 Overview of the three process concept, input and result data of the simulation model

3.2 Modelling of the production system

A crucial part of this approach is simulating the production system to measure the impact of a smart service. The production system consists of subsystems and their elements [7]. As the goal of this approach is a quick estimate of the benefit of a smart service, the necessary simulation model of the production system should be as simple as possible. Therefore, the model has already been reduced to the three process concept described in the previous chapter. Now, the focus is on the details considered within the three processes.

The orders and the products represent an important part of the production. An order is composed of different product types, each with a priority, price per unit, and material costs per unit. The quantity, the price, and the material costs may vary for each product type, but do not have to. These are also determined externally and are necessary for the later calculation of the imputed income.

At the beginning of the production of a product type, the processing stations must be set up, and the set-up time depends on the product type. The average set-up time and standard deviation for each type are given as input values and are mapped in the simulation using a logarithmic normal distribution to prevent negative values [7]. This way, negative values can be prevented. Furthermore, the products are tested for quality after each production step. In the process, the product can generally take one of three states. First, the product may meet the quality requirements and can thus proceed to the next production step. Secondly, the product may not meet the quality requirements, but can be reworked so that it then meets the quality requirements. Thirdly, the product is defective and must be sorted out. In this case, a new part must be produced.

As a means of simplification, it is assumed that once a product has been reworked, it subsequently always meets the quality requirements and can therefore continue to be produced (A5). The model does not allow for orders to be combined. Therefore, another assumption is that only one order can be produced at a time (A6).

The machines, on the other hand, are mainly decisive for the change of state of the orders or products in the production system. The machines are characterised by their capacity, their failure behaviour, their set-up time and their production time. In addition, it is assumed for simplification that all required materials and equipment are ready at the start of production, so the machine can be used immediately (A7). Furthermore, production is carried out continuously over the entire simulation time, defined as pure working time minus break times, Sundays, and holidays. It is also assumed that the production system can smoothly continue working after any break times (A8).

Data is needed for modelling the machines, including the machining time, downtime, probability of failure, set-up time, and capacity of the machine. At the start of production of a new product type, the machine must be set up accordingly, and the processing time of the product depends on the respective processing step. The processing time is described in the simulation model using a logarithmic normal distribution, a commonly applied approach [7]. Each machine has a buffer that can hold any number of products, which are removed according to the first-in-first-out principle.

Downtime due to malfunction is an exceptional event, so it is represented by a negative exponential distribution in the simulation [22]. The probability of a machine break down is represented by the mean time between failure (MTBF). This is also determined externally and transferred to the model. As soon as the MTBF determined by the exponential function has expired, a machine failure occurs. The machine must now be repaired. The product that was produced during the failure is damaged due to the failure and must be produced again. The mean time to repair (MTTR) is expressed by a logarithmic normal distribution.

3.3 Smart service

This chapter elaborates in more detail on how the smart service is modelled. The chapter is divided into the possible influence of the smart service and the modelling of the smart service to simulate this influence.

3.3.1 The influence of smart service

The influence of the smart service is abstracted to three factors: time, quality and quantity. In the manufacturing context, this influence manifests in the availability and efficiency of the machine or the quality of the products, for example.

For the former, predictive maintenance is a specific example of a smart service. In maintenance, the early detection of machine failures can be achieved through the use of smart services. This reduces the costs of a service technician, as smaller and faster repairs can be carried out, and the downtime of the machine is shorter than when a major breakdown occurs. As a result, the time in which the machine can produce (TBF) increases, and the downtime (TTR) in which the machine has failed is reduced, leading to increased machine availability and optimised output. [23].

An example of a smart service that affects product quality is intelligent process monitoring. With intelligent process monitoring, the amount of scrap and rework is reduced, which in turn affects the TBF and TTR of a machine.

In a similar way, the influence of different smart services can be considered.

3.3.2 The modelling of the smart service

The influence of the smart service can be represented by a range of 0 % to 100 %. If the smart service has a negative effect on a parameter, the input value should be preceded by a minus sign. The cost of the smart service can easily be calculated if the business model is based on time-based remuneration, as no additional simulation data is needed. However, if the remuneration is based on usage, further data on usage must be collected in the simulation to calculate the expected cost of the smart service.

3.4 Calculating the pecuniary advantage

The calculation of the monetary benefit ΔP of a smart service on a production system is based on a comparison of the profit achieved with the use of the smart service ($P_{Smart\,Service}$) and the profit achieved without the use of the smart service ($P_{without\,Smart\,Service}$). This results in the definition of the pecuniary advantage,

$$\begin{aligned}\Delta P =& P_{Smart\,Service} - P_{Smart\,Service}\\ &= (R_{Smart\,Service} - C_{Smart\,Service})\\ &\quad - (R_{without\,Smart\,Service} - C_{without\,Smart\,Service})\end{aligned} \tag{1}$$

where profit can be described as the difference between revenue (R) and costs (C). A fixed time period is considered. All orders completed within this time period are considered for the calculation of the profit. Orders that have not yet been completed are not considered.

The revenue is calculated as the product of the sales price and the quantity sold, added up over all completed orders within the period under consideration. Let QJ be the quantity of jobs j and QP the quantity of product types p. The revenue is thus calculated as

$$P = \sum_{j \in QJ} \sum_{p \in QP} (price_{j,p} \cdot quantity_{j,p}) \tag{2}$$

In general, costs can be divided into variable and fixed costs. Since a fixed period of time is considered for the calculation of the differential profit ΔP, the fixed cost components in this equation cancel each other out, so only variable costs need to be considered. These include labor, material, manufacturing, and repair costs, as well as costs for using the smart service. The individual cost components and their calculation are discussed in more detail below.

$$\begin{aligned}C =& C_{Labour\,Cost} + C_{Material\,Costs}\\ &+ C_{Production\,Costs} + C_{Repair\,Costs}\end{aligned} \tag{3}$$

In the case of the labour costs ($C_{Labour\,Cost}$), the assumption was made that the smart service only influences the labour costs for rework and that rework is thus done manually. This means that the number of other employees as well as their work performed with and without the use of the smart service is assumed to be constant. In addition, it is assumed that the employees are paid for the rework according to the work they actually do (A9). This results in the labour costs to be considered as

$$\begin{aligned}C_{LabourCost} =& \sum_{j \in QJ} (employee\ hours_{j,rework}\\ &\cdot hourlywage_{j,rework})\end{aligned} \tag{4}$$

The material costs ($C_{materialcosts}$) consist of the produced quantity and the material costs per unit. The sum of all completed orders and all product types is calculated.

$$\begin{aligned}&C_{Material\,Costs}\\ &= \sum_{j \in QJ} \sum_{p \in QP} (C_{materialcosts,j,p} \cdot quantity_{j,p})\end{aligned} \tag{5}$$

Production costs ($C_{ProductionCosts}$) are the costs for operating the machines. These consist of the costs during operation (MC, machine costs) and the costs when the machines are at a standstill (MSC, machine standing costs). The distribution between operation and standstill of the machines can be calculated by means of the machine availability (A). This indicates the proportion of time during which a machine is in operation. The machine costs and machine downtime costs are defined as time-related variables. Let QM also be the quantity of machines and T the operating time. This gives the production costs as

$$\begin{aligned}&C_{ProductionCosts}\\ &= \sum_{m \in QM} (A_m \cdot T \cdot MC_m + (1 - A_m) \cdot T \cdot MSC_m)\end{aligned} \tag{6}$$

The breakdown of a machine is often accompanied by subsequent repairs. The cost of repairing a machine is also included in the total cost. These consist of the product of the machine repair time and the service technician's hourly wage (ST). The materials needed for the repair are already included in the hourly wage of the service technician (A10). To calculate the total repair costs, the sum is calculated over all machines.

$$\begin{aligned}&C_{RepairCosts}\\ &= \sum_{m \in QM} (repairtime_m \cdot hourlywage_{ST})\end{aligned} \tag{7}$$

Based on the previous explanations of Sect. 3 the input and result data of the simulation model can be determined. They are summarised in Fig. 1 on the left and right side respectively.

4 Application of the smart service simulation

Next, the presented approach is applied to a real use case. The production system within the use case is based on a real production system of an industrial partner. All values were collected via interviews and empirical observations from the production. The industry partner currently considers the application of smart services from a supplier and wants to assess possible benefits. The smart services to be analysed are abstracted from currently available smart services. Therefore, the impact of the smart services had to be estimated. The smart service modeled in this work affects five parameters of the main process. These are the percentage of rejects, the percentage of rework, the MTBF, the expected value of the mean time to failure, and the standard deviation of the MTTR. A total of 1,000 runs are performed for a simulation period of five years for each scenario in order to create a sufficiently large data basis for the evaluation. The expected values and standard deviations of the respective processes are estimated on the basis of 18 orders provided.

Two scenarios are analysed as part of the use case. The scenarios differ in terms of the smart services used. The first scenario, “Quality,” reflects a smart service that influences the quality of the products and affects the amount of scrap and rework. For the scrap and rework rate, an exemplary reduction by 15% is assumed through the use of the smart service. The second scenario, “Predictive Maintenance,” represents a smart service in predictive maintenance. The chosen values are based on already existing smart services [24]. In the second scenario, a reduction in MTTR of 30% is assumed. In addition, the MTBF is assumed to increase by 30%. The smart service also influences the standard deviation of the MTTR. It is reduced by 7.5 percent compared to the simulation without a smart service. In addition to these two scenarios, the influence of the simulation runtime is also investigated. For this scenario, a simulation runtime of one, two and three years is also examined. This demonstrates how scenarios can be varied.

4.1 Scenario 1: quality

First, we look at the number of jobs processed. Table 1 shows the number of jobs processed for the two scenarios examined. As can be seen from Table 1, on average 2.9 more jobs are processed than without using the smart service. Thus, it can be expected that the use of the smart service produces a positive pecuniary advantage.

Figure 2 shows the distribution of profits as a histogram for all two scenarios analysed. The profits with the use of the smart service are shown in light gray, whereas the profits without the use of the smart service are shown in dark gray. It should be noted that the costs of a smart service are not taken into account in this case (cf. Sect. 3). A vertical line shows the mean value of the respective distribution. Additionally, the profits are described in Table 2. If the smart service is used, the mean profit is about €43.88 million, whereas the profit without using the smart service is only €43.67 million.

Similar to the profit, the pecuniary advantage is shown as a histogram in Fig. 3. The descriptive values can be found in Table 3. Note that the profits, and thus the monetary benefits, are calculated without smart service costs. The monetary benefit under this scenario averages €0.21 million. If it is assumed that the smart service costs are less than €0.21 million over five years, it is worthwhile to use it. Looking at the lower quantile, it can already be seen that the monetary benefit is above €0.12 million in 75 percent of cases.

Table 1 Number of completed jobs of the two scenarios with and without smart service as well as their difference

		$\bar{x}$	σ	Min	$x_{0.25}$	$x_{0.5}$	$x_{0.75}$	Max
Scenario 1	With smart service	624.117	9.046389	590	618	624	630	651
	Without smart service	621.190	9.063446	586	615	621	627	650
	Difference	2.927	1.843657	− 4	2	3	4	9
Scenario 2	With smart service	621.808	9.169799	588	616	622	628	652
	Without smart service	621.281	9.103896	588	615	621	627	650
	Difference	0.527	1.678717	− 6	0	1	2	6

Table 2 Profits of the two scenarios with and without smart service in millions of euros

		$\bar{x}$	σ	Min	$x_{0.25}$	$x_{0.5}$	$x_{0.75}$	Max
Scenario 1	With smart service	43.8839	0.1854	43.0892	43.7621	43.8816	44.0113	44.4256
	Without smart service	43.6674	0.1830	43.0879	43.5366	43.6666	43.7999	44.2174
Scenario 2	With smart service	43.7201	0.1724	43.1927	43.6007	43.7296	43.8407	44.2281
	Without smart service	43.6737	0.1810	43.1211	43.5498	43.6682	43.7976	44.2001

Table 3 Pecuniary benefits of the two scenarios in millions of euros

	$\bar{x}$	σ	Min	$x_{0.25}$	$x_{0.5}$	$x_{0.75}$	Max
Scenario 1	0.2166	0.1331	– 0.3305	0.1289	0.2173	0.3016	0.7057
Scenario 2	0.0464	0.1226	– 0.3575	– 0.0006	0.0308	0.1243	0.4445

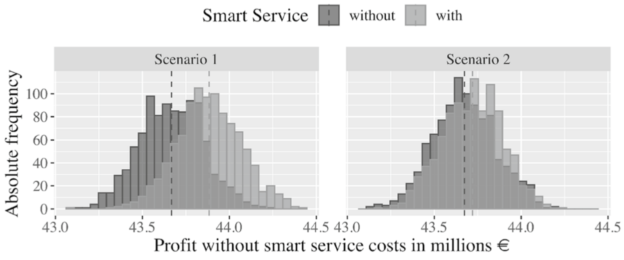

Fig. 2 Profits of the two scenarios with and without smart service

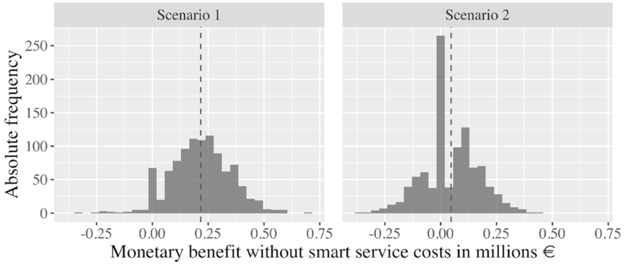

Fig. 3 Pecuniary advantages of the two scenarios

The expectation that the use of smart services would have a positive impact on profits was confirmed. The use of the smart service leads to a reduction in the proportion of rejects in the main process. This explanation is consistent with the observed increase in completed jobs (cf. Table 1). In addition, it follows that more high-quality products can be produced.

4.2 Scenario 2: predictive maintenance

The smart service modeled here influences the MTTF as well as the MTBF. When looking at the histograms of the profits for this scenario presented in Fig. 2, it can be seen that the profits change only slightly due to the use of the smart service. Over an observation period of five years, the use of the smart service results in an average increase of only 0.5 jobs (cf. Table 1).

These findings are also reflected in the consideration of the pecuniary advantage. The distribution of imputed income is represented in Fig. 3. It can be found that approximately 20 percent of the values lie in an interval of € – 10,000 to € 10,000. The mean imputed income in this case is approximately €46,400 (see Table 3). In this scenario, it should also be noted that the calculation of the imputed income does not yet take into account any costs for the use of the smart service. Since these lower the pecuniary advantage again, the use of the smart service under investigation does not seem worthwhile in this scenario. To understand why the smart service only generates a lower imputed income, the modeled production system must be considered once again. The smart service affects the MTTR as well as the MTBF. 18 days was assumed as the MTBF. At the same time, the MTTR is just 1.5 h. This time is low compared to the total production time of 4032 h per year. It can therefore be stated that machine failures only have a minor impact on the production system. At the same time, this also means that the smart service used only generates minor monetary effects for this reason.

4.3 Variation of the simulation runtime

In the scenarios considered so far, a fixed time horizon of five years was simulated in each case. Finally, this section examines the influence of the simulation period. For this purpose, the smart service of the first scenario is used and an investigation period of one, two and three years is simulated. To ensure comparability despite the different study periods, the respective average annual values are given instead of the total amounts. In addition, the values of profits and pecuniary advantages are described in Tables 4 and 5. We find that the standard deviation falls as the runtime increases. This can be explained by the fact that fluctuations in the production process are compensated for with longer runtimes. It is noticeable that the average annual profit of €8.7 million for a runtime of one year and without using the smart service is slightly lower than the average annual profits of longer runtimes.

In addition, the influence of the simulation term on the imputed income is considered. With a runtime of one year, it is noticeable that about one third of the simulation runs show a pecuniary advantage close to zero. This effect can also be seen for a runtime of two years to some extent. At a runtime of three years, this circumstance does not seem to have any influence. Similarly, the different distribution of the pecuniary advantage seems to have little influence on the calculated median pecuniary advantage. The median of the distribution also seems to be unaffected. The pronounced peak of the histogram for values close to zero could have two causes. First, the production system is started "cold" at the beginning of the simulation. This means that there is no transient phase of the system. This effect could be more pronounced with a

Table 4 Average annual profits at different simulation runtimes with and without smart service in millions of euros

		$\bar{x}$	σ	Min	$x_{0.25}$	$x_{0.5}$	$x_{0.75}$	Max
Year 1	With smart service	8.7408	0.0873	8.3904	8.6859	8.7422	8.8032	9.0238
	Without smart service	8.7014	0.0890	8.3598	8.6465	8.7044	8.7620	8.9691
Year 2	With smart service	8.7626	0.0588	8.5724	8.7219	8.7646	8.8041	8.9458
	Without smart service	8.7192	0.0591	8.4484	8.6807	8.7200	8.7583	8.8955
Year 3	With smart service	8.7707	0.0489	8.5599	8.7391	8.7711	8.8041	8.9132
	Without smart service	8.7284	0.0473	8.5578	8.6971	8.7298	8.7620	8.8784

Table 5 Average annual pecuniary benefits for different simulation periods in millions of euros

	$\bar{x}$	σ	Min	$x_{0.25}$	$x_{0.5}$	$x_{0.75}$	Max
Year 1	0.0394	0.0667	– 0.2234	0.0000	0.0038	0.0867	0.2302
Year 2	0.0434	0.0427	– 0.1015	0.0018	0.0431	0.0724	0.1984
Year 3	0.0423	0.0356	– 0.0711	0.0195	0.0421	0.0654	0.1760

shorter runtime. A second cause could lie in the profit calculation itself. Thus, only completed orders are considered for the calculation of the profit. If a large order is started at the end of the first year but has not yet been completed, this could have a significant effect on profit. This effect on profit also decreases with longer duration. Overall, it can be stated that the pecuniary advantage due to the calculation of the profit may be distorted for shorter simulation durations.

5 Discussion

To evaluate the results of this work, the implemented simulation is compared to the original objective.

By comparing the estimated average monetary benefit with the expected costs of the smart service, a decision can be made on whether to use the smart service. However, this is based on the assumption that the expected smart service costs can be estimated. Since the monetary benefit is a random variable, the simulation is run several times to examine the distribution of the monetary benefit and the mean monetary benefit caused by the use of the smart service.

The results show that there is potential for smart service in the given use case, although scenario 2 (“Predictive Maintenance”) suggests that a smart service would need to be more effective than the one assumed in the use case.

It should also be noted that the simulation carried out for validation did not include a transient phase. This can lead to distortions, especially with shorter simulation runtimes. In addition, the profit included in the calculation of the imputed income is calculated on the basis of all orders completed by the end of the simulation.

Although the approach is designed for use with any smart service, it has only been validated for two types of smart services, so more testing is needed to prove that it is also suitable for other types of smart services.

In conclusion, the developed simulation model is a suitable approach for roughly estimating the benefit of a smart service used in production. However, there is a tradeoff between the simplicity of the simulation and the accuracy of the results. A more detailed simulation may provide more insights but also require more setup effort. It should be noted that the model can easily be expanded, either to reassess results with more effort after initial approval, or to cover different aspects of production management, such as measures of lean management and their interrelation with smart services. Overall, the simulation model is an easy-to-use tool for the financial evaluation of a smart service, meeting the objectives of providing a simple model that supports decision-makers in justifying or rejecting the use of a smart service on first glance.

6 Conclusion and future work

The aim of this work was to develop a tool that approximates the financial effects of smart services in production and provides initial decision support.

The underlying production system was designed using the top-down method and is oriented towards flow production for the system section under consideration. The system section is divided into three processes: a pre-process, main process, and post-process. The modelled smart service only affects the main process by definition. Both the smart service and the production system under investigation can be customized, allowing different scenarios to be simulated and compared. The entire software is open source and can be freely used [25].

In addition, the developed simulation model was validated using a real production system as an example. Two scenarios were examined, representing different smart services. The effect on the arithmetic mean and median of the imputed income is only slight. To address this issue, a transient phase could be added to the simulation and the calculation of the monetary benefit could be implemented on a product basis instead of an order basis.

In the context of this work, several areas for further investigation have been identified. The simulation model presented can be extended to depict production systems in more detail, such as by including the modelling of means of transport and buffers. While this would increase the precision of the results, it would also increase complexity and effort for the user. On the other hand, the relationship between the smart service parameters and the monetary advantage could be generally investigated on the basis of the developed simulation model. If these correlations are known, the buyer of a smart service is enabled to determine the optimal configuration of the smart service for his own production system. Similarly, the provider of the smart service can use this information to improve both its negotiation strategy with potential customers and the smart service itself. A third direction for investigation could be the analysis of complex relations between customers and providers in order to set an acceptable price for both parties. There is already a broad base of research in this area using game theory that could serve as a foundation for this work [26–28].

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