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Moving to additive manufacturing for spare parts supply

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ABSTRACT

This study seeks to investigate when and how a transition to additive manufacturing (AM) becomes profitable for the low-volume spare parts business. As a starting point, we conducted a case study at an OEM of radar systems which foresaw various opportunities that become available with the transition to AM. In particular, it is the case company that can perceive the prospects of shortened lead times and the promise of tool-less manufacturing. However, scepticism regarding whether a transition will pay off amid high AM piece prices and uncertain AM technology advancements remains. We employed stochastic dynamic programming to assess the situation encountered at the company. Therefore, we regarded particularities such as a decreasing AM piece price over the course of the service horizon and determined if (and when) AM should be prepared or tooling be discarded. It turned out that an immediate investment in AM technology is the most effective strategy and leads to more than 12% cost savings. Numerical experiments further substantiate the results of the case study and indicate that long lead times, high inventories, and severe backorder costs in the classical situation are all arguments in favor of an early investment in AM technology; this occurs despite an (initially) higher AM piece price and additional setup costs. Moreover, we observed that postponing the investment in AM is often not advisable. Instead, conventional manufacturing and AM are recommended to be used in parallel before making a complete transition to AM.

1. Introduction

Additive manufacturing (AM), also known as 3D printing, is becoming increasingly important in discrete manufacturing. Its potential is exemplified by several applications. In the aerospace industry, AM technology is used for the production of complex lightweight designs that, compared to their conventionally manufactured counterparts, enable substantial fuel savings. One of the most popular examples that showcase this application is the Airbus A320 nacelle hinge bracket, in which AM enabled a 64% weight reduction compared to the original part. Another application area is the medical sector where AM is used for the production of patient-specific solutions on a large scale. Most disruptive examples are customized insoles, hearing aids, or orthopedic implants; see, e.g. [1–3].

Another potential area of application is the low-volume, high-value spare parts business; see, e.g. [4–7]. Currently, uncertain demands, long lead times, and high downtime costs often impose large spare parts stocks – resulting in high amounts of tied up capital. Furthermore, after the regular production phase concludes, arranging spare parts supply is often challenging. Suppliers demand high incentives for maintaining production capacities or may even decide to discontinue supply entirely. A solution to both problems could be a transition to AM technology. For instance, based on short setup times and no requirement for tooling, Walter et al. [4] argue that AM technology may support spare parts provisioning on demand and thus help to reduce large spare parts stocks. Moreover, utilizing generic AM processes may relax the dependency on suppliers and thus decrease the risks and costs associated with supply disruptions. Additionally, AM processes are a candidate for decentralized production which could upsurge the supply chain responsiveness at low costs.

The transition to AM technology comes with several challenges. Typically, after the regular production phase, companies possess the capability and knowledge to source spare parts produced by conventional manufacturing (CM) that usually does not hold for the potential AM version. Another aspect is the uncertainty associated with switching to a less mature manufacturing technology. For instance, a decrease in AM production costs is likely in the near future; however, the order of magnitude and the timing is difficult to predict. A lack of in-house knowledge regarding AM technology complicates the identification of promising cases (cf.

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[8,9]) and may prompt a risk averse attitude at the management level. Consequently, companies would rather trust proven methods than embrace and explore new opportunities presented by AM technology.

In this paper, we quantify under which conditions a transition to AM technology is profitable to reduce the uncertainty associated with moving to AM for spare parts supply. Furthermore, we examine which transition strategies are most viable for various conditions.

The starting point for our analysis is a case study conducted at a world-wide operating OEM for radar systems. In particular, we focus on a protection cover that is used for shielding electronic components from moisture, heat, and accidental damage. As most of the case companies' spare parts that potentially appear producible with AM, the protection cover is a mechanical component that is designed to outlast the lifetime of the radar system. Hence, the protection cover exhibits (very) low failure rates that, in most cases, are caused by external factors such as unintended stress levels, imprudence during maintenance/shipping activities, or extreme weather conditions. With CM the replenishment lead time of the protection cover exceeds more than half a year because of low demand quantities and the fact that the company is the sole customer. For the latter reason, the OEM and *not* the supplier owns product-specific tooling which induces additional inventory costs.

Using stochastic dynamic programming and numerical experiments, we demonstrate that moving to AM technology pays off under various conditions in the low-volume spare parts business. For example, in the case of the protection cover, a higher AM piece price and additional AM preparation costs are compensated by lower holding costs. Moreover, to the surprise of the OEM, an immediate investment in AM is the best strategy to minimize total service costs.

The remainder of this paper is organized as follows. In Section 2, we review the literature and specify our contributions. Subsequently, in Section 3, we develop the mathematical model which we used to analyze the situation encountered at the OEM and to conduct numerical experiments in Section 4. In Section 5, we summarize our findings and suggest directions for future research.

2. Quantitative models in the AM literature

Using AM technology for spare parts provisioning is receiving increasing attention in the literature. In this section, we focus on quantitative insights but refer to Walter et al. [4] and Holmström et al. [10] for a discussion on the conceptual value of using AM technology in spare parts supply chains.

Initial efforts to quantify the value of spare parts provisioning with AM technology was undertaken by Liu et al. [11] and Khajavi et al. [6]. They examine whether a decentralized or a centralized deployment of AM capacity is more economical for spare parts supply chains in the aerospace industry. It was concluded that demand pattern, AM equipment costs, and automation are important factors that determine the AM supply chain layout. Furthermore, if compared to the regular supply chain, Liu et al. [11] show that AM supports substantial safety stock reduction. Later, Li et al. [12] demonstrate that an AM supply chain typically outperforms conventional supply chains regarding carbon emission. As we motivate in Section 3, we consider an external AM supplier in this paper. To that end, we do not regard decisions associated with the location of AM capacity.

Sirichakwal and Conner [13] evaluate the influence of AM-imposed production lead times and holding costs reductions on the stock-out probability. They observe that AM-induced holding costs reductions decrease the stock-out probability while a shorter AM replenishment lead time may influence the stock-out-probability either way. The latter ambiguity primarily appears to be caused by the integrality of stock-levels. Additionally, their results indicate that AM is the most effective for low-demand environments. Given that they do not adopt a costs perspective, the magnitude of associated cost savings remain unclear.

Westerweel et al. [14] investigate which AM part reliability and AM production costs level have to be achieved to reach a break-even point compared to sourcing with CM methods. Overall, it turns out that a low AM part reliability is more restrictive than high AM production costs. However, they find that in the absence of AM performance benefits, relying on AM methods exclusively is currently less beneficial. However, they do not address questions regarding whether moving to AM during the lifecycle may be profitable or whether a (temporary) dual sourcing approach may pay off. We see to fill this knowledge gap by considering an evolving system. Moreover, in comparison to Westerweel et al. [14], we regard anticipated AM piece price reductions (e.g. [6,15–17]) and changing demand rates over the course of the service horizon.

Song and Zhang [18] consider the parallel use of AM and CM methods. They assume that AM technology functions as a capacitated emergency channel in which spare parts are produced on demand. Knofius et al. [19] study a dual sourcing approach with AM and CM methods as well. In comparison to Song and Zhang [18], they do not consider a capacitated emergency channel but allow for regular supply with AM. Furthermore, they investigate how reliability differences between the AM and CM part versions may influence the sourcing strategy. Both papers indicate that dual sourcing often appears profitable. In particular, this holds true for the current AM development stage where AM process variability and unit costs are high relative to CM. However, it remains unclear as to how AM technology advancements may alter the value of different sourcing strategies over the course of the service horizon. Furthermore, in both studies the authors disregard AM preparation costs which may be caused by supplier selection, design adoptions, material selection, process calibration, certification, qualification, etc.

Our contribution to the literature is as follows:

1. We investigate if the preparation of AM technology is recommendable and what potential gains are to be expected under various conditions. In contrast to other studies, we take into account that after the regular production phase, knowledge and product-specific tooling is often already available for sourcing spare parts with CM while AM still has to be prepared.
2. We analyze how and when a transition to AM technology is advisable for spare parts supply during the remaining service horizon. Therefore, we consider an evolving inventory system where AM piece price and demand rates may change over the course of the service horizon.
3. Apart from deriving general guidelines for decisions on how and when to switch to AM technology, we also conduct a case study in the defense industry. Hence, we meet the request for more case-based research in the application domain of AM technology; see, e.g. Weller et al. [20] and Savastano et al. [21].

3. Model

To study the situation encountered at the OEM of radar systems, we initially develop a stochastic dynamic programming model that mimics the evolution and describes underlying trade-offs and decisions. A general outline is presented in Section 3.1. In Section 3.2, we justify and motivate the model assumptions. Section 3.3 formalizes the situation encountered at the OEM and introduces the notation. In Section 3.4, we explain the costs evaluation, and we describe the transition logic of the stochastic dynamic program in Section 3.5.

3.1. Outline

We consider an OEM who is responsible for maintaining an installed base of (radar) systems. We focus on one specific component that is sourced initially with a CM method. The CM approach requires specific tooling which, because of low demand rates, is owned by the OEM. Technological advancements, however, allow the OEM to source the component with a tool-less AM method as well. In this paper, we consider an external AM supplier since the setup, operation, and maintenance of an AM production system seems not justifiable from an economic perspective for the OEM. For example, Eyers and Potter [22] elaborate that an AM production system typically demands a significant investment in resources other than the production capacity. However, the model is applicable to the case in which we consider in-house AM production as well. For such a scenario, the AM replenishment lead time has to be replaced by the net AM throughput time. Furthermore, the AM purchasing costs (cf. Section 3.4) have to be replaced with AM production costs. We refer to Fera et al. [23] and Costabile et al. [24] for more details about AM production costs estimations.

From the OEM's point of view, a tool-less AM approach associated with (significantly) shortened replenishment lead times may render a transition from CM to AM attractive. In fact, a shorter replenishment lead time may reduce the stock-level and may decrease risks associated with a stock-out. However, the OEM is uncertain whether an investment in AM technology pays off — in particular, given the possibly higher AM piece price. Moreover, if a transition to AM is deemed profitable, the OEM is uncertain when to invest in AM. For example, constantly decreasing AM piece prices and a lack of experience with AM technology are compelling reasons to postpone the investment. Additionally, it is unclear how the ability to source items with AM could influence the sourcing strategy. For instance, as described in Section 2, one can envision a dual sourcing concept where AM and CM are used in parallel. Alternatively, one may argue that using two sourcing methods in parallel causes unnecessary costs. For instance, by employing a single sourcing approach with AM, the OEM may realize a substantial reduction in holding cost as product-specific tooling required for the CM process can be discarded.

We develop a stochastic dynamic program to investigate the described trade-offs. Our decision variables reveal the preferred sourcing method and order quantity in each period, if (and when) to prepare AM and if (and when) to discard tooling necessary for CM. In particular, we study for each period which decisions minimize the service costs composed of setup, purchasing, holding, backorder, and discarding costs over the remaining service horizon.

3.2. Assumptions

Before outlining the model in detail, we describe and motivate the underlying key assumptions we used to construct the model.

1. *All lead times are deterministic and shorter than one period.* Lead times are typically a matter of contractual agreements with suppliers. In case a supplier is unable to meet these agreements, delays are typically compensated. Hence, it seems reasonable for our analysis to stick to the mutually agreed lead times. Moreover, given that we typically consider a period length of one year in our analysis, assuming lead times of less than one period appears justifiable.
2. *Holding costs are encountered at the beginning of the period.* Equivalently, we may account for the holding costs at the end of each period. Here, however, we charge holding cost at the beginning of the period as it allows an evaluation independent of the demand realization.
3. *Failures occur according to a Poisson process.* The Poisson demand assumption seems most appropriate, given that we consider a low-demand environment with mechanical parts that are dimensioned to outlast the intended maintenance interval or lifetime of the capital good (common practice for downtime critical mechanical components of capital goods). Accordingly, failures are random in nature and could, for instance, be caused by unintended stress levels, imprudence during system usage, maintenance, shipping activities, or unobservable quality issues during the production.
4. *The expected number of failures are the same for an AM and CM part.* As discussed in Section 1, we consider parts with (very) low failure rates which are motivated by typical properties of printable parts. This characteristic has several consequences. First, possible failure rate differences between the AM and CM versions are small in absolute terms. Second, during the service horizon, the installed base composition only changes marginally as most parts outlast the life cycle of the (radar) system and thus leave the overall demand nearly unaffected. Finally, by assuming identical failure rates, it is not necessary to keep track of the installed base composition which reduces the state space substantially.
5. *Failed parts are replaced in negligible time if stock is available.* The replacement time of a failed part is short in comparison to the order lead times. Furthermore, given that we assume identical failure rates (see Assumption 4), the associated replacement frequency is independent of the decisions.
6. *The OEM takes any required measures to fulfill outstanding demand.* To analyze a long service horizon, we consider a long period length. Thus, in case of a stock-out occurring in some period, it seems realistic to allow for emergency shipments during that same period. In case tooling is no longer available or AM is not prepared, a stock-out may also lead to an immediate setup of the preferred method (which, if we stick to CM produced parts, means a purchase of tooling again).
7. *Fixed order costs are incorporated in the piece price.* Given that we consider a low demand environment, economies of scale are limited. Thus, we assume that ordering costs are incorporated in the piece price of each item.
8. *Emergency orders are carried out piece by piece.* See Assumption 6.

3.3. Notation and mathematical model

The remaining service horizon of the radar systems is composed of discrete time periods of equal length, denoted by $n = 1, \ldots, N+1$ (say, years). Depending on contractual agreements, the installed base size IB_n may change over the course of the service horizon. The component considered in our analysis occurs k times in each system and, if stock is available, is supplied from a single stock point in negligible time. Otherwise, demand is backordered and the OEM incurs unit backorder cost b per period. To reduce the backlog time, an emergency order may be initiated during the period. For each stored part, holding costs are encountered at the beginning of period n. Holding costs are expressed in terms of a holding costs fraction κ of the associated current piece price. Demand is modelled by the random variable D_n in period n and determined by the current installed base size IB_n and failure behavior of the installed components.

Originally, the OEM orders CM items from a supplier with a mean order lead time l_C and piece price c_C. The production of CM items requires product-specific tooling which, due to low demand rates, is owned by the OEM. If tooling is available, the OEM may decide to discard it at a cost fraction δ_T of the tooling piece price c_T. In the event the OEM wants to (re)purchase tooling (because the demand

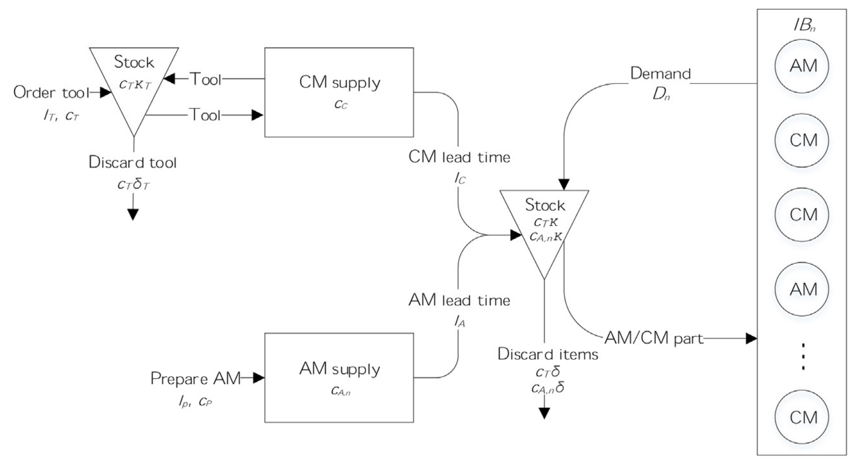

Fig. 1. Supply chain layout.

realization is higher than anticipated or tooling was not available in the first place), it is possible to order tooling for the tooling piece price c_T associated with a mean order lead time of l_T. Tooling holding costs are expressed as a fraction κ_T of the tooling piece price c_T and are charged at the beginning of the period if tooling is available and will not be discarded. At the end of the service horizon (i.e. $n = N + 1$), tooling and any item stock are discarded. The costs for discarding a part are supposed to be a fraction δ of the associated current piece price.

The setup of the AM process takes l_P, costs c_P, and is required only once. The setup contains activities such as supplier and material selection, design modifications, qualification, and the determination of printing process parameters. The replenishment order lead time of an AM item is equal to l_A which is usually much shorter than l_C (cf. Section 1). The AM piece price is equal to $c_{A,n}$ in period n. We model the AM piece price as a function of n in order to describe anticipated piece price changes of the AM process. Typically, $c_{A,n}$ will be a decreasing function of n as AM production costs are expected to decrease rapidly (cf. Section 2). Later, we model the AM piece price by means of an experience curve defined as $c_{A,n} = c_{A,1}n^r$ with $r = \log(1 - cf)/\log(2)$ and $0 \le cf < 1$. For a more detailed discussion on the AM piece price development, refer to Appendix A.1. The resulting supply chain layout and the associated parameters are shown in Fig. 1.

For each period n, we describe the model state with a four dimensional vector $\mathbf{i_n} = (i_{1,n}, i_{2,n}, i_{3,n}, i_{4,n}) \in \mathbf{I}_n$ where $i_{1,n} \in N_0$ refers to the current number of CM items in stock, and $i_{2,n} \in N_0$ to the current number of AM items in stock. Furthermore, $i_{3,n} = 0$ if no CM tooling is available and $i_{3,n} = 1$ otherwise, while $i_{4,n} = 0$ if the AM process has not been prepared yet and $i_{4,n} = 1$ otherwise. Note that in case AM has not been prepared yet ($i_{4,n} = 0$), we know that $i_{2,n} = 0$ (no AM parts in stock). Hence, it would be sufficient to use a three dimensional state space. For clarity of presentation, however, we stick to a four dimensional representation.

At the beginning of each period n, the OEM may face a number of decisions. Actions taken are recorded in the four dimensional vector $\mathbf{a_n} = (a_{1,n}, a_{2,n}, a_{3,n}, a_{4,n}) \in \mathbf{A}_n$ where $a_{1,n} \in N_0$ describes the number of items to order and $a_{2,n}$ indicates the sourcing approach. Here, we use $a_{2,n} = 0$ to describe a pure CM sourcing approach and $a_{2,n} = 1$ to denote a pure AM sourcing approach. In case $a_{2,n} = 2$, we use CM for regular supply and AM for emergency supply. Further, $a_{3,n} = 1$ if tooling is discarded at the beginning of period n and $a_{3,n} = 0$ otherwise. Similarly, $a_{4,n} = 1$ if the AM process is prepared at the beginning of period n and $a_{4,n} = 0$ otherwise.

Certain actions may be ruled out in advance and thus can be eliminated from the action space. As discussed in Section 3.2, CM items are always used first when both AM and CM items are available in stock. Furthermore, in case we do not carry out a regular order, i.e. $a_{1,n} = 0$, we may limit $a_{2,n} \in \{0, 1\}$. Furthermore, if we discard tooling $a_{3,n} = 1$, either we do not make a regular order, i.e. $a_{1,n} = 0$, or we use the AM supplier, i.e. $a_{2,n} = 1$. Finally, if tooling is unavailable or AM has already been prepared we know that $a_{3,n} = 0$ and $a_{4,n} = 0$ respectively. Possible actions and cost assignments at the beginning of period n occur in the following order: (1) discard tooling, (2) incur holding costs, (3) begin preparation of AM, (4) order tooling, (5) order items, and (6) incur purchasing costs. The stochastic dynamic programming recursion for the total costs from period n till the end of the horizon reads as follows:

$$V_n(\mathbf{i_n}) = \min_{\mathbf{a_n} \in \mathrm{A_n}} \{C_n(\mathbf{i_n}, \mathbf{a_n}) + \sum_{\mathrm{i_{n+1}} \in \mathrm{I_{n+1}}} p(\mathrm{i_{n+1}}|\mathbf{i_n}, \mathbf{a_n}) V_{n+1}(\mathrm{i_{n+1}})\} \tag{1}$$

$$V_{N+1}(\mathbf{i_n}) = (i_{1,n}c_C + i_{2,n}c_{A,n})\delta + i_{3,n}c_T\delta_T \tag{2}$$

where $C_n(\mathbf{i_n}, \mathbf{a_n})$ denotes the expected service cost in period n if we are in state $\mathbf{i_n} \in \mathbf{I}_n$ and take action $\mathbf{a_n} \in \mathbf{A}_n$ (details are discussed in the next section). The probability to jump to state $\mathbf{i}_{n+1} \in \mathbf{I}_{n+1}$ given that we are in state $\mathbf{i_n} \in \mathbf{I}_n$ and take action $\mathbf{a_n} \in \mathbf{A}_n$ is denoted by $p(\mathbf{i}_{n+1}|\mathbf{i_n}, \mathbf{a_n})$. Eq. (2) describes the costs encountered at the end of the service horizon, i.e. costs for discarding the remaining stock and tooling. In Table 1, we summarize the notation.

3.4. Cost computations

The expected service costs $C_n(\mathbf{i_n}, \mathbf{a_n})$ in period n are composed of holding costs $H_n(\mathbf{i_n}, \mathbf{a_n})$, discarding costs for parts and tools $R_n(\mathbf{i_n}, \mathbf{a_n})$, expected purchasing costs $P_n(\mathbf{i_n}, \mathbf{a_n})$, setup costs $T_n(\mathbf{i_n}, \mathbf{a_n})$, and expected backorder costs $B_n(\mathbf{i_n}, \mathbf{a_n})$. Next, we show how we evaluate the cost factors for a given state vector $\mathbf{i_n}$ and action vector $\mathbf{a_n}$.

The *holding costs* of parts and tools $H_n(\mathbf{i_n}, \mathbf{a_n})$ are accounted for at the beginning of period n but after the possible discarding of the CM tool. Here, we value AM parts according to the present period cost price. Accordingly, we have:

$$H_n(\mathbf{i_n}, \mathbf{a_n}) = (i_{1,n}c_C + i_{2,n}c_{A,n})\kappa + i_{3,n}(1 - a_{3,n})c_T\kappa_T \tag{3}$$

In each period $n \le N$, we encounter *discarding costs* $R_n(\mathbf{i_n}, \mathbf{a_n})$ in case tooling is disposed. In the last period, we also discard unused parts. Thus, the discarding costs are equal to:

$$R_n(\mathbf{i_n}, \mathbf{a_n}) = \begin{cases} a_{3,n}i_{3,n}c_T\delta_T, & \text{if } \; n \le N \\ (i_{1,n}c_C + i_{2,n}c_{A,n})\delta + i_{3,n}c_T\delta_T, & \text{if } \; n = N + 1 \end{cases} \tag{4}$$

Table 1
Notation overview.

Notation	Explanation
IB_n	Installed base size in period n
$n \in \{1, 2, \ldots, N+1\}$	Period index
b	Backorder cost per time unit
κ	Holding cost fraction for items
D_n	Total demand in period n
$D_n(t)$	Demand during time interval t with $0 \le t \le 1$
k	Part multiplicity in each system
l_C	CM replenishment lead time where $0 \le l_C \le 1$
c_T	Tooling order cost
l_T	Tooling replenishment lead time where $0 \le l_T \le 1$
κ_T	Holding cost fraction for the tool
δ_T	Tooling discarding cost fraction
l_P	Lead time for AM preparation where $0 \le l_P \le 1$
c_P	AM preparation costs
$c_{A,n}$	AM piece price in period n
c_C	CM piece price
l_A	AM replenishment lead time where $0 \le l_A \le 1$
δ	Item discarding cost fraction
$\mathbf{i_n} \in \mathbf{I}_n$	Four-dimensional state vector in period n, $\mathbf{i_n} = (i_{1,n}, i_{2,n}, i_{3,n}, i_{4,n})$
$i_{1,n}$	Number of CM items in stock at the start of period n
$i_{2,n}$	Number of AM items in stock at the start of period n
$i_{3,n}$	1 if tooling is available at the start of period n; 0 otherwise
$i_{4,n}$	1 if AM has already been prepared at the start of period n; 0 otherwise
$\mathbf{a_n} \in \mathbf{A}_n$	Four-dimensional action vector in period n, $\mathbf{a_n} = (a_{1,n}, a_{2,n}, a_{3,n}, a_{4,n})$
$a_{1,n}$	Order quantity in period n
$a_{2,n}$	Sourcing approach in period n; 0 = CM; 1 = AM; 2 = dual sourcing
$a_{3,n}$	1 if tooling is discarded at the start of period n; 0 otherwise
$a_{4,n}$	1 if the AM process is prepared at the start of period n; 0 otherwise
$C_n(\mathbf{i_n}, \mathbf{a_n})$	Expected cost in period n
$p(\mathbf{i_{n+1}} \mid \mathbf{i_n}, \mathbf{a_n})$	Transition probability

The expected *purchasing costs* $P_n(\mathbf{i_n}, \mathbf{a_n})$ depend on the order quantity ($a_{1,n}$) and chosen supplier ($a_{2,n}$). Moreover, we have to consider situation in which stock-outs require emergency orders that lead to additional purchasing costs. The expected number of emergency orders in period n, $UP_n(i_{1,n}, i_{2,n}, a_{1,n})$, equals

$$UP_n(i_{1,n}, i_{2,n}, a_{1,n}) = E[(D_n - i_{1,n} - i_{2,n} - a_{1,n})^+] \tag{5}$$

Thus, the expected purchasing costs are represented by:

$$P_n(\mathbf{i_n}, \mathbf{a_n}) = \begin{cases} (a_{1,n} + UP_n(i_{1,n}, i_{2,n}, a_{1,n}))c_C, & \text{if} \quad a_{2,n} = 0 \\ (a_{1,n} + UP_n(i_{1,n}, i_{2,n}, a_{1,n}))c_{A,n}, & \text{if} \quad a_{2,n} = 1 \\ a_{1,n}c_C + UP_n(i_{1,n}, i_{2,n}, a_{1,n})c_{A,n}, & \text{if} \quad a_{2,n} = 2 \end{cases} \tag{6}$$

The *setup costs* $T_n(\mathbf{i_n}, \mathbf{a_n})$ consist of AM preparation $T_{1,n}(\mathbf{i_n}, \mathbf{a_n})$ and tooling procurement costs $T_{2,n}(\mathbf{i_n}, \mathbf{a_n})$. Hence we have $T_n(\mathbf{i_n}, \mathbf{a_n}) = T_{1,n}(\mathbf{i_n}, \mathbf{a_n}) + T_{2,n}(\mathbf{i_n}, \mathbf{a_n})$. AM preparation costs arise if the OEM decides to prepare the AM process at the beginning of period n, i.e. $a_{4,n} = 1$. Furthermore, in case we use AM for emergency supply, i.e. $a_{2,n} \in \{1, 2\}$, and AM has not been prepared ($i_{4,n} = 0$), preparation costs may arise to order items for backorder clearing. Accordingly, we have:

$$\begin{aligned} &T_{1,n}(\mathbf{i_n}, \mathbf{a_n}) \\ &\quad = (a_{4,n} + \min\{1, a_{2,n}\}(1 - a_{4,n})(1 - i_{4,n})PUP_n(i_{1,n}, i_{2,n}, a_{1,n}))c_P \end{aligned} \tag{7}$$

where $PUP_n(i_{1,n}, i_{2,n}, a_{1,n})$ represents the probability of an emergency shipment in period n, i.e. demand exceeds inventory ($i_{1,n} + i_{2,n}$) plus regular order ($a_{1,n}$):

$$PUP_n(i_{1,n}, i_{2,n}, a_{1,n}) = 1 - Pr\{D_n \le i_{1,n} + i_{2,n} + a_{1,n}\} \tag{8}$$

The OEM encounters tooling procurement costs if we use CM supply, i.e. $a_{2,n} \in \{0, 2\}$ and $a_{1,n} > 0$, while tooling is not available ($i_{3,n} = 0$). Note that, as explained in Section 3.3, it is not possible to discard tooling ($a_{3,n} = 1$) and then order items from the CM supplier in the same period n. Furthermore, we may encounter tooling procurement costs for backorder clearing. This event may arise if no order is carried out ($a_{1,n} = 0$) and we use CM for emergency supply, i.e. $a_{2,n} = 0$ while tooling is not available, i.e. $i_{3,n} = 0$ or $a_{3,n} = 1$. Accordingly, we have:

$$T_{2,n}(\mathbf{i_n}, \mathbf{a_n}) = \begin{cases} I_{\{0,2\}}(a_{2,n})(1 - i_{3,n})c_T, & \text{if} \quad a_{1,n} > 0 \\ I_{\{0\}}(a_{2,n})(1 + a_{3,n} - i_{3,n})PUP_n(i_{1,n}, i_{2,n}, a_{1,n})c_T, & \text{if} \quad a_{1,n} = 0 \end{cases} \tag{9}$$

with $I_{\{.\}}(.)$ representing an indicator function that is equal to one if the condition is fulfilled and zero otherwise.

When we determine the *backorder costs*, we account for stock-outs in the period in which they arise. Thus, if a stock-out occurs towards the end of period n, the entire duration of a stock-out is charged in period n. We distinguish between four scenarios leading to downtime denoted by $\Omega_{1,n}(\mathbf{i_n}, \mathbf{a_n})$, $\Omega_{2,n}(\mathbf{i_n}, \mathbf{a_n})$, $\Omega_{3,n}(\mathbf{i_n}, \mathbf{a_n})$ and $\Omega_{4,n}(\mathbf{i_n}, \mathbf{a_n})$ respectively. Accordingly, we have

$$\begin{aligned} B_n(\mathbf{i_n}, \mathbf{a_n}) &= b(\Omega_{1,n}(\mathbf{i_n}, \mathbf{a_n}) + \Omega_{2,n}(\mathbf{i_n}, \mathbf{a_n}) + \Omega_{3,n}(\mathbf{i_n}, \mathbf{a_n}) \\ &\quad + \Omega_{4,n}(\mathbf{i_n}, \mathbf{a_n})) \end{aligned} \tag{10}$$

The downtime calculations depend on the sourcing approach $a_{2,n}$. Here, we focus on the case $a_{2,n} = 1$ and refer to Appendix A.2 for the other cases. $\Omega_{1,n}(\mathbf{i_n}, \mathbf{a_n})$ accounts for backorders that arise if demand cannot be filled from the initial inventory ($i_{1,n} + i_{2,n}$), but instead with the regular order ($a_{1,n}$). In this case, we incur downtime until order arrival. $\Omega_{2,n}(\mathbf{i_n}, \mathbf{a_n})$ describes the scenario where the initial inventory and the regular order (if any) cannot cover demand. Subsequently, an emergency order becomes necessary which leads to downtime of at least the AM order lead time l_A. However, as we cover in $\Omega_{3,n}(\mathbf{i_n}, \mathbf{a_n})$, it is also possible that AM has not been prepared yet. In this case, we have additional downtime l_P for the first emergency order while we may incur a part of l_P for any additional demand arriving during AM preparation. Finally, as described by $\Omega_{4,n}(\mathbf{i_n}, \mathbf{a_n})$, we may have started AM preparation at the beginning of the period which possibly has not finished before an emergency order becomes necessary. In this case, we encounter part of the AM preparation lead time l_P as well.

For $\Omega_{1,n}(\mathbf{i_n}, \mathbf{a_n})$ we have

$$\begin{aligned} &\Omega_{1,n}(\mathbf{i_n}, \mathbf{a_n}) \\ &\quad = \sum_{d=r+1}^{r+a_{1,n}} Pr\{D_n(t) = d\} \frac{0.5(d-r)(d-r+1)}{d+1} t, \quad \text{if} \quad a_{2,n} = 1 \end{aligned} \tag{11}$$

with $r = i_{1,n} + i_{2,n}$ and $t = (l_A + l_P(1 - i_{4,n}))$ representing the relevant fraction of period n before order arrival. For the derivation of the formula we used that Poisson demand arrivals are uniform distributed over the relevant time interval, conditional on the number of arrivals in the interval. Accordingly, in case of d demand arrivals in t, the downtime is equal to $t\sum_{a=1}^{d}(d+1-a)/(d+1) = t\sum_{a=1}^{d} a/(d+1) = t(0.5d(d+1))/(d+1)$.

$\Omega_{2,n}(\mathbf{i_n}, \mathbf{a_n})$ is defined by

$$\Omega_{2,n}(\mathbf{i_n}, \mathbf{a_n}) = UP_n\{i_{1,n}, i_{2,n}a_{1,n}\}l_A, \quad \text{if} \quad a_{2,n} = 1 \tag{12}$$

using that we assume piece by piece ordering form the emergency source (cf. Section 3.2). $\Omega_{3,n}(\mathbf{i_n}, \mathbf{a_n})$ is only relevant if AM has not been prepared yet nor the AM preparation has started yet,

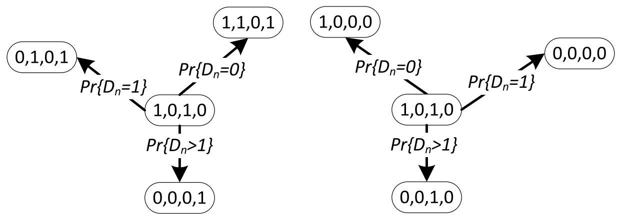

Fig. 2. Transition with action $\mathbf{a_n} = (1, 1, 1, 1)$ (left) and action $\mathbf{a_n} = (0, 0, 1, 0)$ (right).

i.e. $i_{4,n}$, $a_{4,n}$, $a_{1,n} = 0$. In this case, we have additional downtime l_P for the first emergency order while we may incur a part of l_P for any additional demand arrival during AM preparation. Given the Poisson assumption, the latter time fraction can be expressed by $\sum_{d=1}^{\infty} Pr\{D_n(l_P)\}d/2 = (\lambda_n l_P)/2$ where λ_n denotes the mean demand rate in period n. Intuitively, this relation follows because each demand arrival during the preparation lead time l_P, encounters $0.5 l_P$ downtime on average. Accordingly, we have

$$\Omega_{3,n}(\mathbf{i_n}, \mathbf{a_n}) = Pr\{D_n \geq i_{1,n} + i_{2,n} + 1\} l_P \left(1 + \frac{\lambda_n l_P}{2}\right),$$
$$\text{if} \quad i_{4,n}, a_{4,n}, a_{1,n} = 0 \wedge a_{2,n} = 1 \tag{13}$$

Finally, $\Omega_{4,n}(\mathbf{i_n}, \mathbf{a_n})$ accounts for the possibility of starting AM preparation at the beginning of the period (either because we ordered with the AM supplier or prepare AM proactively, i.e. $i_{4,n} = 0 \wedge (a_{1,n} > 0 \vee a_{4,n} = 1)$) which possibly has not finished before an emergency order becomes necessary. In this case, we encounter part of the AM preparation lead time l_P as well and thus have

$$\Omega_{4,n}(\mathbf{i_n}, \mathbf{a_n}) = \sum_{d=r+1}^{\infty} Pr\{D_n(l_P) = d\} \frac{0.5(d-r)(d-r+1)}{d+1} l_p,$$
$$\text{if} \quad i_{4,n} = 0 \wedge (a_{1,n} > 0 \vee a_{4,n} = 1) \wedge a_{2,n} = 1 \tag{14}$$

with $r = i_{1,n} + i_{2,n} + a_{1,n}$. The derivation follows the same line of reasoning as for $\Omega_{1,n}(\mathbf{i_n}, \mathbf{a_n})$. To further clarify the backorder costs computations, we provide a numerical example in Appendix A.2.

3.5. State transitions

The state transitions depend on the current state, the actions, and the demand realization. To clarify the underlying logic, we discuss possible transitions for one state and two actions. Other transitions follow the same logic and are determined by the algorithm presented in Appendix A.3. For both examples, we have the following state at the start of period n: one CM item is in stock (and no AM item), tooling is available, and the AM process has not been prepared, i.e. $\mathbf{i_n} = (1, 0, 1, 0)$. Fig. 2 shows the possible transitions for the two selected actions.

On the left side of Fig. 2, we order one part from the AM supplier, discard tooling and prepare AM, i.e. $\mathbf{a_n} = (1, 1, 1, 1)$. For this example, it is important to realize that we always move to the state $\mathbf{i}_{n+1} = (0, 1, 0, 1)$ but not to state $\mathbf{i}_{n+1} = (1, 0, 0, 1)$ if $D_n = 1$. As explained in Section 3.3, by default we always use the CM part first if both part versions are in stock. On the right side of the figure, we illustrate possible transitions for the action where we do not order any part, use CM for emergency supply, discard tooling and do not prepare AM, i.e. $\mathbf{a_n} = (0, 0, 1, 0)$. As illustrated, despite discarding tooling at the beginning of period n, we still may end up in state $\mathbf{i}_{n+1} = (0, 0, 1, 0)$, i.e. with tooling. This transition is a consequence of the assumption that the OEM solves a stock-out as soon as possible and thus, for this example, reproduces tooling if $D_n > 1$. Only in the next period $(n+1)$ is it possible to discard tooling again.

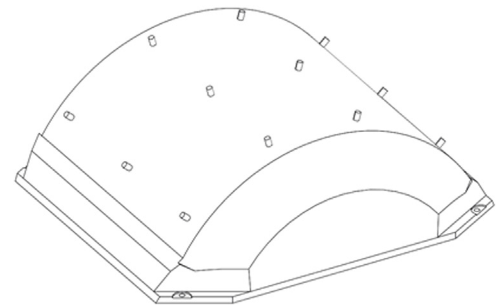

Fig. 3. Design protection cover.

4. Analysis

In Section 4.1, we evaluate the protection cover case. Next, in Section 4.2, we carry out a sensitivity analysis to evaluate the value of moving to AM technology for more general settings.

4.1. Business case

The protection cover is used for shielding electronic components from moisture, heat, and accidental damage in radar systems and has a dimension of 63.97 cm × 22.7 cm × 56.8 cm. Fig. 3 shows the design of the protection cover.

Originally, the protection cover is built with molding technology using carbon epoxy. In case of a failure, usually caused by external factors such as extreme weather conditions or imprudence during maintenance activities, the protection cover has to be replaced. Otherwise, the risk of damaging expensive components would be too high. In case of a stock-out, the exposed electronics is normally covered with a temporary solution that, at least, offers some protection. Overall, the company management translates the associated risks to backorder costs of approximately 43,800 euro per year (120 euro per day). Provided experience with AM technology is lacking, such low-risk cases are often preferred by companies or sometimes even enforced by regulations as, e.g. in the aerospace industry. Nevertheless, in Section 4.2, we also consider high backorder costs scenarios that are not uncommon in the capital goods spare parts business. The CM replenishment lead time of the protection cover is relatively long and takes approximately seven months, which is caused by low demand quantities (<1 per year), and the fact that the company is the only customer for the protection cover. For the latter reason, the company also owns the mold, which causes tool holding costs.

Evaluations showed that a selective laser sintering (SLS) process, using glass-filled nylon, technologically qualifies for the production of the protection cover. Further, preliminary analyses by technical staff indicated that only minor design changes would be required (and desired) to provide functionality comparable to the CM version. Unfortunately, consultations with a supplier of glass-filled nylon prints revealed an estimated piece price of 13,300 euros, which is approximately 7500 euros higher than the price of the CM version. As we discussed, such price differences are the norm rather than the exception today. To model the AM piece price decrease over the service horizon, we follow the explanations in Appendix A.1 and assume an AM piece price reduction by about 30% (i.e. $cf = 0.15$) within the next five years. The resulting AM piece price development is shown in Fig. 4.

Overall, the AM piece price remains higher than that for the CM version of the protection cover (5768 euros) during the entire service horizon. Hence, at first sight, the value of moving to AM technology appears doubtful — in particular if we consider that about 10,000 euros are required for the preparation of AM.

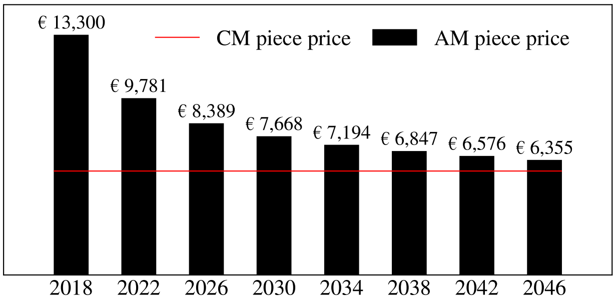

Fig. 4. AM piece price development compared to CM.

Table 2
Input parameter case study.

$c_{A,1}$	13,300 euro	l_A	14 days
c_C	5768 euro	l_C	196 days
c_P	10,000 euro	l_P	28 days
c_T	5900 euro	l_T	65 days
b	43,800 euro/year	κ	0.1 euro/euro/year
λ	0.01 failure/system/year	κ_T	0.1 euro/euro/year
IB_n	60 systems	δ	−0.1 euro/euro
N	30 years	δ_T	−0.1 euro/euro

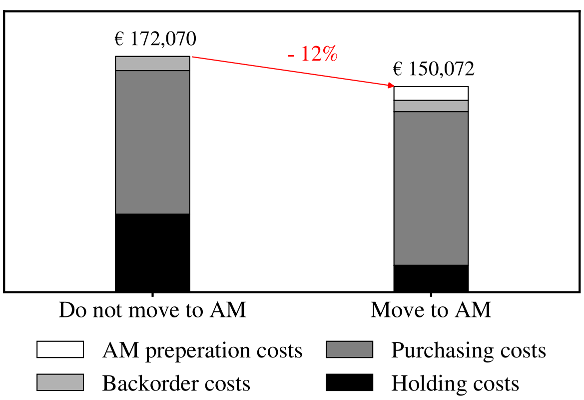

Fig. 5. Cost-saving potential.

Currently, the case company possesses the mold, has one spare part in stock and has not prepared AM yet. Furthermore, based on contractual agreements, it is expected that the installed base size remains constant over the service horizon. All parameter values are presented in Table 2.

Using the model described in Section 3, we quantify the extent to which a transition to AM may influence the remaining service costs. Fig. 5 displays the cost difference between servicing the installed base solely with CM (Do not move to AM) and the approach where a transition to AM is possible (Move to AM). Additionally, we show the cost composition where we omit cost factors that do not contribute more than 0.01% to the overall costs.

As we observe in Fig. 5 moving to AM turns out economically valuable with cost savings of more than 12% over the course of the remaining service horizon. This finding relates to holding cost savings that are obtained by discarding tooling and by reducing stock level and stock-out risk. The latter is a direct consequence of the relatively short AM replenishment lead time. Moreover, in Fig. 5, we observe that holding costs reductions compensate for higher piece price and additional AM preparation cost.

To secure these cost savings, we find that the OEM should prepare AM in the first year and always use AM for emergency supply, i.e. $a_{2,n} \in \{1, 2\}$. Fig. 6 reveals more insights about the transition policy and, for each year n, shows the probabilities of CM tooling in stock, $Pr\{i_{3,n} = 1\}$, and of regular supply with AM, $Pr\{a_{2,n} = 1 | a_{1,n} > 0\}$.

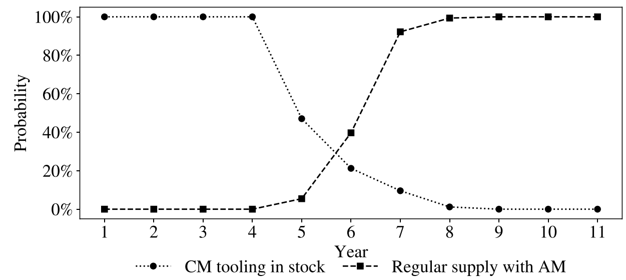

Fig. 6. Transition policy.

Despite preparing AM in the first year, we find that it is not recommended to discard tooling before Year 4 in any case. Instead, depending on the demand realization, we may use CM for regular supply up to Year 9. This observation supports the proposal in the literature that using AM and CM methods in parallel may turn out beneficial at the current development stage of AM technologies, see Section 2. Interestingly, according to our cost predictions, the piece price of AM will still be about 2400 euros higher than with CM after the transition to AM is completed.

For the company, the result clarifies that the economical valuation of AM should not be based on the AM piece price exclusively. Also, the awareness that an investment in AM technology provides immediate benefits stimulated a more extensive search for AM applications in the company. In fact, the case study exemplified that the value of AM technology — in particular in the spare parts business — often appears to be underestimated. We conclude that conceptual insights alone appear insufficient to motivate the adoption of AM in the service business. Currently, business-specific use cases seem paramount to convincing management about the value of using AM technology for their spare parts operations.

4.2. Numerical experiments

Some characteristics of the protection cover are rather specific and may deviate from other applications. In this section, we perform a sensitivity analysis to draw more general conclusions about the value of moving to AM technology. Therefore, we justify chosen parameter ranges first and then discuss the results.

4.2.1. Experimental design

In the spare parts business for capital goods, we often encounter long service horizons. For example, Van Houtum and Kranenburg [25] consider a service horizon between 10 and 40 years realistic. For our experiments, we analyze instances with a remaining service horizon (N) between 10 and 20 years. The choice to analyze a shorter time horizon is motivated by several aspects. First, today, it is likely that AM is considered in situations where the regular production phase ended several years ago. Second, in preliminary experiments we found that a transition to AM is typically considered in the first half of the service horizon, or not at all.

The installed base size in period n, IB_n, influences the demand rate and demand development over the service horizon. For the scenario encountered in the case company, we assumed a constant installed base size motivated by contractual agreements. After the regular production phase, a decreasing installed base size is also considered to be realistic in several cases, see e.g. Inderfurth and Mukherjee [26] or Dekker et al. [27]. Thus, we will regard both options in our experiments, a constant installed base size and a decreasing installed base size. In order to model the installed base size reduction, we use a decreasing function of the form $IB_n = \lceil IB_1 - (n/x)^c \rceil$ with $c > 1$, yielding a concave decreasing curve with increasing n (see Fig. 7). The value for x is set to obtain a desired final installed base size, i.e. $x = N/(IB_1 - IB(N))^{1/c}$. Fig. 7 illustrates

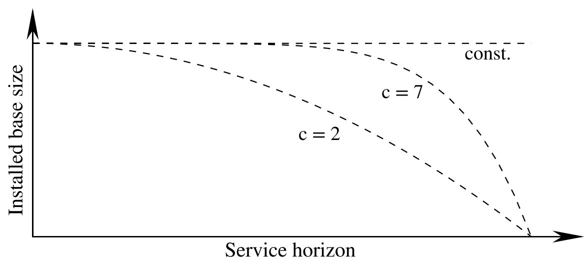

Fig. 7. Installed base development.

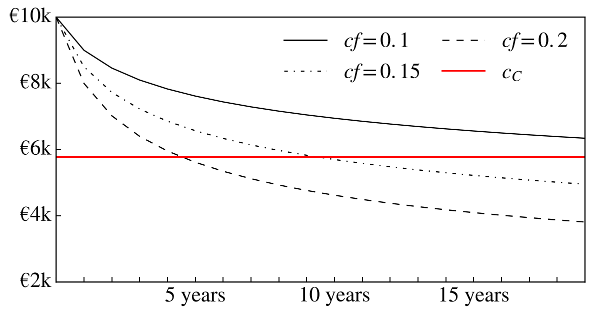

Fig. 8. Unit costs development with $c_{A,1}$ = 10,000 euro.

the different installed base development profiles we consider in the sensitivity analysis.

AM technology was identified to be the most valuable for low-volume production, i.e. for production where economies of scales do not play a significant role, see, e.g. Khajavi et al. [6] and Liu et al. [11]. Accordingly, we chose the installed base size in combination with the failure rate such that the demand rate is low. However, compared to the case study where we encountered less than one demand arrival per year on average, we also investigate possible effects of higher demand rates.

The backorder costs (b) for the protection cover are minor if compared to other examples in the industry. For instance, in the semiconductor industry, failures leading to a standstill of the production line may cost tens of thousands of euros per hour [28]. In the numerical experiments, we will consider backorder cost between 36,500 and 1,825,000 euros per year. The reason behind the exclusion of higher backorder costs in this study is twofold. First, companies might be inclined/forced to refrain from printing very critical parts, see Section 4.1. Second, in case of very high backorder costs, other solutions such as redundancy, design improvements, or predictive maintenance strategies become more attractive.

As we motivated for the protection cover, in case of low demand rates the replenishment lead time with CM methods is typically long, say several months. Liu et al. [11] assume lead times between 1.5 and 8 months, whereas the AM lead time is typically assumed to be less than a month. In our experiments, we consider a comparable range.

For the AM piece price in the first period, $c_{A,1}$, we use three values which, in combination with three values for the cost development factor (*cf*), lead to nine costs profiles. In Fig. 8 we show the three cost profiles in case $c_{A,1}$ = 10,000 euros. The six other cost profiles exhibit the same pattern.

As is depicted, we study both: scenarios where AM remains more expensive over the entire service horizon and scenarios where, at a certain point in time, AM becomes less expensive than CM. Depending on the choice of the cost development factor (*cf*), the cost decline is faster or slower. Overall, we decided to investigate this wide range of possible cost developments, because various cost profiles are perceivable, depending on features such as material type, AM process, and geometric complexity. Finally, we vary the holding cost rate with $\kappa = 0.1$ and $\kappa = 0.15$. Remaining model parameters remain unchanged compared to the protection cover case.

4.2.2. Sensitivity analysis

To evaluate the results, we use four performance indicators:

1. $\mathbf{\Delta C_0}$ describes, as an average over associated instances, the relative cost difference between the scenario where we limit ourselves to solely using CM, i.e. $a_{2,n} = 0$, for $n = 1, \ldots, N+1$, and where transitioning to AM technology is possible.
2. $\mathbf{\Delta S}$ describes the difference between the maximum stock level in case we use CM and AM. For scenarios where it is optimal to never use AM, i.e. $a_{2,n} = 0$, for $n = 1, \ldots, N+1$, we define $\mathbf{\Delta S} = 0$.
3. **Prep** denotes the time horizon that has passed before AM is prepared, averaged over all instances where preparation occurred. Instances where AM is never prepared are excluded (~6% of instances).
4. **Dis** describes the average time horizon that has passed before tooling is discarded. We consider the same instances as used for the calculation of the performance indicator **Prep** to allow for comparability between **Prep** and **Dis**.

Table 3 shows the full factorial experimental design and the results for the performance indicators as average over all other parameters. Recall that parameters not mentioned in Table 3 remain unchanged compared to the case study discussed in Section 4.1.

Over all instances, we find average cost savings of about 35%. The results in Table 3 show that the cost-saving potential ($\mathbf{\Delta C_0}$) is most sensitive to (i) the lead time difference between the AM and CM method, (ii) the backorder costs, and (iii) the AM and CM piece price difference (including the rate at which the AM piece price decreases). Subsequently, we interpret these findings.

The sensitivity of the cost-saving potential on the lead time difference and backorder costs are explained with holding cost savings. As we observe in Table 3, the lead time difference between AM and CM method significantly influences the stock level difference $\mathbf{\Delta S}$. That is, the stock level difference increases, in case the AM lead time becomes shorter or the CM lead time becomes longer. On the other hand, the backorder costs affect $\mathbf{\Delta S}$ only marginally (cf. Table 3). However, by increasing the backorder cost, the relative importance of saving holding cost increases. As explained during the case study, saving holding cost is a primary benefit of transitioning to AM technology. In fact, the relative holding cost fraction more than doubles if we compare b = 36,500 euro/year and b = 1,825,000 euro/year.

This result stresses the prospect of printing critical parts for the spare parts business. Currently, however, companies are reluctant (or not allowed) to consider high backorder costs cases. In particular, high AM process variability raises concerns about part reliability and, for the time being, renders the certification of critical parts cumbersome. In the near future, closed-loop control mechanisms which support online adjustments and corrections of the printing process may significantly decrease process variability, see, e.g. Craeghs et al. [29] or Everton et al. [30].

In Table 3, we also observe cost savings increasing if the holding cost fraction (κ) increases. Further analysis revealed that this result follows the same rational as for the backorder costs: the higher the holding costs factor, the higher the relative importance of holding costs saving. We infer from these results that high inventory and backorder costs indicate the profitability of moving to AM technology in the low-volume spare parts business.

The initial AM piece price ($c_{A,1}$) is most influential on the cost savings (cf. Table 3). This result is explained by the fact that, in case

Table 3
Results sensitivity analysis.

Parameters	Parameter values	ΔC_0	ΔS	**Prep**	**Dis**
N	10 years	30%	2.5	17%	28%
	20 years	41%	2.4	4%	24%
IB_1	50 Parts	35%	1.5	13%	14%
	150 Parts	33%	2.4	10%	28%
	300 Parts	38%	3.4	8%	36%
Installed base development	$c = 2$; $IB(N) = 0$	35%	2.7	12%	22%
	$c = 7$; $IB(N) = 0$	35%	2.4	11%	27%
	const.	36%	2.3	9%	29%
b	36,500 euro/year	29%	2.4	10%	18%
	365,000 euro/year	32%	2.5	13%	28%
	1,825,000 euro/year	45%	2.6	9%	31%
l_C	60 Days	23%	1.8	10%	29%
	180 Days	48%	3.1	11%	23%
l_A	5 Days	40%	2.8	6%	23%
	15 Days	31%	2.1	15%	29%
κ	0.1 euro/euro/year	32%	2.6	14%	28%
	0.15 euro/euro/year	39%	2.3	7%	24%
$c_{A,1}$	6000 euro	74%	2.3	0%	0%
	10,000 euro	23%	2.5	6%	26%
	14,000 euro	9%	2.6	28%	57%
cf	0.1	25%	2.5	17%	36%
	0.15	34%	2.5	11%	26%
	0.2	46%	2.4	5%	17%

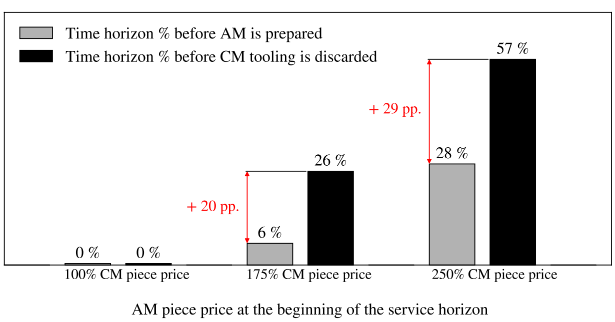

Fig. 9. **Prep** and **Dis** for different values of the starting AM piece price $c_{A,1}$.

the starting AM and CM piece price are comparable, CM becomes inferior quickly (equal or higher piece price and longer resupply lead time). Thus, a fast and complete transition to AM has few drawbacks and leads to immediate holding and purchasing cost savings. On the other hand, in case the AM piece price is high (which is more likely today), purchasing cost increase and solely the reduction of holding costs may justify the transition to AM. Hence, in case the initial AM piece price is very high, cost savings are limited.

The trade-off between holding cost decrease and purchasing cost increase also influences the transition strategy. Fig. 9 illustrates the situation by comparing the time horizon % before AM is prepared, **Prep**, and the horizon % before CM tooling is discarded, **Dis**, for different values of the starting AM piece price ($c_{A,1}$).

As observed, if the initial AM piece price is low, tooling is discarded at about the same time as AM is prepared. Hence, a dual sourcing approach as described in the case study is usually not profitable under these conditions. On the other hand, the higher the AM piece price becomes, the longer the time horizon where both sourcing methods are used in parallel (AM is prepared before tooling is discarded, cf. Fig. 9). During the time horizon where dual sourcing is applied, we typically use CM for regular and AM for emergency supply ($a_{2,n} = 2$). Consequently, we are able to reduce stock while the purchasing cost increase is maintained within limits. Similarly, as shown in Table 3, a large installed base size (IB_1) and high backorder costs (b) increase the time horizon where both methods are used in parallel. Remarkably, in case a transition to AM is profitable, AM preparation takes place relatively early during the service horizon (**Prep** = 10% on average, cf. Table 3). This observation motivates the conclusion that an investment in AM technology should not be postponed. Instead, before a complete transition to AM is economical, one could use both sourcing methods in parallel. Apart from the economical perspective, an early AM preparation also enables the accumulation of experience which appears beneficial prior to a full transition to AM technology.

Finally, we observe that an increasing demand rate (determined by multiplying installed base size with failure rate) has a positive, though less predominant, effect on the value of AM. It remains an open research question when economies of scale reverse this trend. Here, we refrain from further analysis on this matter given that our model choices are tailored to a low-demand environment.

5. Conclusion and future research

Based on a case observed at an OEM of radar systems, we developed a finite horizon stochastic dynamic programming model. We selected this approach because we identified that the change of characteristics through time, such as AM production cost reductions and installed base size changes, are deterrents to the transition strategy. Furthermore, we wanted to understand how the existing CM production capacities may affect the investment decision in AM technology. Utilizing the case from the OEM and numerical experiments to study more general settings as well, we were able to derive various crucial insights that can be summarized as follows:

1. We find average cost savings by moving to AM of about 35% despite a typically higher AM piece price and additional AM preparation costs across all instances. The cost-saving potential increases predominantly with increasing backorder costs, increasing AM and CM lead time differences, and decreasing piece price differences between AM and CM.

2. The costs reduction is primarily achieved by holding cost savings with AM that are caused by decreasing stock levels, a reduced stock-out risk and the option to use a tool-less AM process. In case the backorder and inventory costs are high, the holding cost reduction becomes most beneficial.
3. If AM becomes competitive during the remaining service period, the preparation of AM should not be postponed. Instead, before a complete transition to AM is profitable, it is beneficial to use both sourcing methods in parallel for several reasons. A dual sourcing with AM enables holding cost savings while the purchasing cost increase (due to a typically high AM piece price) is kept within reasonable limits.
4. We find a long dual sourcing period if the AM piece price is high, the demand rate is high, or if the backorder costs are high. During this period, CM is used for regular supply and AM is preferably used for emergency supply.
5. It appears that the value of AM for spare parts supply is underestimated. Company-specific business cases seem necessary to convince management about the value of moving to AM technology for spare parts supply. In particular, the opportunity to invest in AM technology at this early stage appears to be disregarded.

To further support our findings it might be valuable to extend the proposed model by also considering stochastic AM piece price developments. Even though we base our analysis on predictions made in the literature, it is well-perceivable that uncertainty regarding piece price development will influence the investment decision. Similar extensions are perceivable for the installed base development and the service horizon length. Finally, one may consider a scenario where supply disruptions occur during the service horizon. A straightforward extension in this regard might be to model an occasionally occurring loss of tooling. While conducting the case study, we were several times confronted with scenarios where the tooling was lost due to operational inadequacies.

Conflict of interest

None declared.

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Appendix A

A.1 AM piece price predictions

Fast market growth, rapid technological advancements, patent expiration, and decreasing raw material prices are only some indicators that the production costs for AM parts will reduce significantly over the next years. A comparable effect for CM parts is unlikely. To account for this discrepancy, we model the AM piece price $c_{A,n}$ as a decreasing function over time. A widely accepted approach to forecast technological costs, see e.g. Nagy et al. [31] or Magee et al. [32], is the use of an experience curve with the underlying logic that the costs reduce by a constant every time the experience doubles. Alberth [33] explains that using experience curves qualify to obtain insights into potential prices during the growth phase in competitive markets which significantly resembles the AM market. For our model, we assume that experience is gained in every period and rely on estimated price reductions (see below) in order to specify the experience curve. More explicitly we have:

$$c_{A,n} = c_{A,1} n^r$$

where r describes the elasticity of the cost reduction to the experience, defined as

$$r = \frac{\log(1 - cf)}{\log(2)}.$$

An analysis conducted by Roland Berger [34] forecasts an AM production cost reduction potential of about 30% between 2018 and 2023. A study sponsored by the German government [35] and a report from Siemens [36] support these predictions. For the case study conducted in Section 4.1, we utilize the same cost development, i.e. $cf = 0.15$. Nevertheless, in order to understand the impact of more conservative or optimistic cost development predictions, we include the factor cf in the sensitivity analysis conducted in Section 4.2.

A.2 Backorder costs

Before we give a numerical example, we explain the calculation of $\Omega_{1,n}(\mathbf{i_n}, \mathbf{a_n})$, $\Omega_{2,n}(\mathbf{i_n}, \mathbf{a_n})$, $\Omega_{3,n}(\mathbf{i_n}, \mathbf{a_n})$ and $\Omega_{4,n}(\mathbf{i_n}, \mathbf{a_n})$ for sourcing with CM only ($a_{2,n} = 0$) and where we apply a dual sourcing approach ($a_{2,n} = 2$).

In case $a_{2,n} = 0$, the calculations remain the same as for the case $a_{2,n} = 1$ except that the associated lead times change. Therefore, we have to replace l_A by l_C and l_P by l_T in Eqs. (10)–(14). Furthermore, in case of $\Omega_{3,n}(\mathbf{i_n}, \mathbf{a_n})$, we have to account for the possibility that we may decide to discard tooling in period n, i.e. $a_{3,n} = 1$. Accordingly we have:

$$\Omega_{3,n}(\mathbf{i_n}, \mathbf{a_n}) = Pr\{D_n \geq i_{1,n} + i_{2,n} + 1\} l_T \left(1 + \frac{\lambda_n l_T}{2}\right),$$
$$\text{if} \quad a_{1,n}, a_{2,n} = 0 \wedge (i_{3,n} = 0 \vee a_{3,n} = 1)$$

In case ($a_{2,n} = 2$), $\Omega_{1,n}(\mathbf{i_n}, \mathbf{a_n})$ is calculated similar to the case where $a_{2,n} = 0$. The values $\Omega_{2,n}(\mathbf{i_n}, \mathbf{a_n})$, $\Omega_{3,n}(\mathbf{i_n}, \mathbf{a_n})$ and $\Omega_{4,n}(\mathbf{i_n}, \mathbf{a_n})$ are calculated as if $a_{2,n} = 1$.

Next, we give a numerical example to clarify the backorder costs calculations. Assume we are in state $\mathbf{i}_n = (2, 0, 1, 0)$ (two CM items, no AM items, tooling available, AM not prepared) and take action $\mathbf{a}_n = (2, 1, 1, 1)$ (order 2 items with AM, discard tooling, and prepare AM). We encounter backorders of type $\Omega_{1,n}(\mathbf{i_n}, \mathbf{a_n})$ if $3 \leq D_n(t) \leq 4$ and have

$$\Omega_{1,n}(\mathbf{i_n}, \mathbf{a_n}) = Pr\{D_n(t) = 3\} \frac{1}{4} t + Pr\{D_n(t) = 4\} \left(\frac{2}{5} + \frac{1}{5}\right) t$$

with $t = l_A + l_P$. For the case that $D_n(t) = 3$, we know that the third demand arrives at $(3/4)t$ and is fulfilled after $(1/4)t$ on an average using which demand arrivals are uniformly distributed. Following the same logic, in case $D_n(t) = 4$, the third and fourth demand arrival cause a backorder duration of $(2/5)t$ and $(1/5)t$, respectively. For the case that $D_n(t) > 4$, we encounter downtime of type $\Omega_{2,n}(\mathbf{i_n}, \mathbf{a_n})$ and $\Omega_{4,n}(\mathbf{i_n}, \mathbf{a_n})$ because AM preparation is initiated at the beginning of period n.

For the sake of explanation, let us assume $D_n(l_P) = 6$. Again using that Poisson arrival are uniform distributed, expected arrival times are equal to $(i/7)l_P$ ($i = 1, \ldots, 6$). Then, $\Omega_{4,n}(\mathbf{i_n}, \mathbf{a_n}) = (2/7 + 1/7)l_P$ because the first two demand arrivals are filled from stock and the second two with regular supply.

A.3 State transitions

Algorithm 1 shows the procedure to determine $\mathbf{i}_{n+1}$ in case we use emergency supply in period n.

Algorithm 1. Determines $\mathbf{i}_{n+1}$ based on $\mathbf{i_n}$, $\mathbf{a_n}$ and D_n if $i_{1,n}+i_{2,n}+a_{1,n}-D_n<0$

```
i_{1,n+1}, i_{2,n+1} = 0, i_{3,n+1} = i_{3,n}, i_{4,n+1} = i_{4,n};
if a_{2,n} = 0 then
    i_{3,n+1} = 1;
    if a_{4,n} = 1 then
        i_{4,n+1} = 1;
if a_{2,n} = 1 then
    i_{4,n+1} = 1;
    if a_{3,n} = 1 then
        i_{3,n+1} = 0;
if a_{2,n} = 2 then
    i_{4,n+1} = 1;
    if a_{1,n} > 0 then
        i_{3,n+1} = 1;
    else
        if a_{3,n} = 1 then
            i_{3,n+1} = 0;
```

Algorithm 2 shows the procedure to determine $\mathbf{i}_{n+1}$ in case we do *not* require emergency supply in period n.

Algorithm 2. Determines $\mathbf{i}_{n+1}$ based on $\mathbf{i_n}$, $\mathbf{a_n}$ and D_n if $i_{1,n}+i_{2,n}+a_{1,n}-D_n\geq 0$

```
i_{3,n+1} = i_{3,n}, i_{4,n+1} = i_{4,n};
if a_{3,n} = 1 then
    i_{3,n+1} = 0;
if a_{2,n} ≠ 1 and a_{1,n} > 0 then
    i_{3,n+1} = 1;
if a_{4,n} = 1 or (a_{2,n} = 1 and a_{1,n} > 0) then
    i_{4,n+1} = 1;
if i_{4,n+1} = 0 then
    i_{1,n+1} = i_{1,n} + i_{2,n} + a_{1,n} − D_n and i_{2,n+1} = 0;
else
    if a_{2,n} = 1 then
        if i_{1,n} − D_n > 0 then
            i_{1,n+1} = i_{1,n} − D_n and i_{2,n+1} = i_{2,n} + a_{1,n};
        else
            i_{1,n+1} = 0 and i_{2,n+1} = i_{1,n} + i_{2,n} + a_{1,n} − D_n;
    else
        if i_{1,n} − D_n > 0 then
            i_{1,n+1} = i_{1,n} + a_{1,n} − D_n and i_{2,n+1} = i_{2,n};
        else if i_{1,n} + i_{2,n} − D_n > 0 then
            i_{1,n+1} = a_{1,n} and i_{2,n+1} = i_{1,n} + i_{2,n} − D_n;
        else
            i_{1,n+1} = i_{1,n} + i_{2,n} + a_{1,n} − D_n and i_{2,n+1} = 0;
```

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