How will additive manufacturing impact materials inventory? – A system dynamics simulation

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Abstract

Additive Manufacturing (AM) is a manufacturing technique which allows the direct fabrication of three-dimensional design models using an additive approach by adding layer after layer. This does not only open new design possibilities but also constitutes a chance to reduce materials usage. The aim of this research paper is to simulate the potential reduction of materials inventories in the manufacturing industry and to point out possible implications for supply chains. For this purpose, a system dynamics model was created and applied on actual sales data of industrial AM units.

Keywords: Additive Manufacturing, Materials Inventory, System Dynamics

Introduction

Additive Manufacturing (AM) is a manufacturing technique which allows the direct fabrication of three-dimensional design models using an additive approach. This means parts are made by adding material in layers as opposed to conventional subtractive manufacturing techniques (Gibson, Rosen, and Stucker, 2015). This does not only open new design possibilities but also constitutes a chance to reduce materials usage. Waller and Fawcett (2014), Huang, Liu, Mokasdar, and Hou (2013), Kietzmann, Pitt, and Berthon (2015), Ford and Despeisse (2016), and Wohlers (2014), address a potential reduction. It arises through the additive character of the manufacturing technology that reduces waste, the potential consolidation of separate parts into one complex part, the possibility of new design approaches with organic lattice like structures that reduce weight, the reduction of materials inventories due to the higher responsiveness of the technology, or the easier recycling of raw materials.

Even though AM may have its origins in the 1980s or even earlier, the mainstream adoption of this innovative technology is just now really taking off. Bass (1969) described the adoption of such new ideas in his diffusion model. It assumes that the timing of a consumer's initial purchase is related to the number of previous buyers. The rate of adoption follows a normal distribution while the number of total adopters will resemble an s-shaped growth function. The theory is intended to apply to a broad range, of distinctive classes of products.

The aim of this research paper is to simulate the potential reduction of materials inventories through the adoption of AM in the manufacturing industry and to point out possible implications for supply chains. While research addressing the adoption of AM and the potential materials reduction exist separately, no research combining the two aspects has so far been conducted. This paper aims at closing this gap and at analyzing mutual effects. Existing research considering the potential of AM to reduce materials usage was predominantly focused on isolated design or manufacturing aspects. Trends regarding the manufacturing industry as a whole have mainly been neglected, therefore in this paper materials saving will be looked at from a more holistic and general point of view. For this purpose, a system dynamics simulation was created, combining the Bass Diffusion Model with a Materials Inventory Model. Necessary parameters were estimated through a literature review. After a thorough validation process the model was applied on real sales data of industrial AM system units and the results were presented in a way that expands insights into the field of AM and its impact on manufacturing.

Literature Review

In the system dynamics model later described in this paper the potential overall materials saving is composed of three sub-components: the degree of adoption of AM, the proportion of total manufacturing that could potentially be substituted by AM, and the so-called saving factor which stands for the potential materials saving. The following literature review will analyze and present the relevant literature according to those three sub-categories and then briefly review the literature about the effects of materials saving through AM on supply chains.

Degree of Adoption

Schniederjans (2017) explains that even though there are several obvious advantages of AM and despite the fact that it has been around for decades, the technology adoption is still in its infancy. A gradual adoption of AM and especially the direct digital manufacturing is predicted by Holmström, Holweg, Khajavi, and Partanen (2016) as manufacturing firms will introduce the new technology to improve their current operations. This is supported by Rogers (1983) who states that most innovations, in fact, diffuse at a surprisingly slow rate as even advantageous innovations do not sell themselves automatically.

Interest in the new technology is constantly increasing. Waller and Fawcett (2014) analyzed search engine results for AM and found an exponential growth in the time frame of 2004-2013. Furthermore, a Bibliometrics search using the Google Scholar data base conducted by Steenhuis and Pretorius (2015) showed the same trend but additionally found a much higher cumulative trend when including the term "industrial". Apart of academia several practitioners performed research on that topic. In a global survey led by Ernst and Young (2016) a strong cross-industry trend toward the adoption of AM was identified for the next five years. Stratasys, one of the world´s leading producers of AM equipment predicted additive metal use to nearly double over the next 3 years (Stratasys Direct Manufacturing, 2015). The rising adoption of AM is well reflected by a compound annual growth rate (CAGR) of 27% over the last 25 years. From 2011 to 2013 it was 32.3%. to reach a market volume of 3.07 billion USD in 2013 (Wohlers, 2014).

Saving Factor

Table 1: Estimations of Saving Factor for AM

Source	Estimation of Saving Factor for AM	Sector
Thiesse et al. (2015)	>30%	Aviation / Automotive
The Economist (2011)	<90%	Aviation
Despeisse and Ford (2015)	<60%	Aviation
Lušić et al. (2015)	<72%	Tooling

AM certainly uses less material in the production process. This has implications for inventory management, transportation, warehousing, and purchasing, as lower order quantities mean less transportation, and less space for raw materials required (Waller and Fawcett, 2014). Ford and Despeisse (2016) add that as AM mimics biological processes by creating products layer-by-layer it is inherently less wasteful. Despeisse and Ford (2015) mentioned that material input to final component ratios of 4:1 are common using traditional milling processes. In aviation, where 20:1 is not uncommon, materials savings of up to 60% have already been realized. Additionally, in case that there is unused material after an AM build, most AM variations allow for the unused material to be recycled after each build (Pour, Zanardi, Bacchetti, and Zanoni, 2016).

Thiesse, Wirth, Kemper, Moisa, Morar, and Lasi (2015) also explain potential materials savings through weight reduction as material is only applied in those areas where it is required for its purpose. The Economist (2011) went as far as to say that in aviation AM can reduce the material needed by up to 90%. According to Lušić, Barabanov, Morina, Feuerstein, and Homfeck (2015), tools used for internal company production processes, such as molds, can also be manufactured by means of additive manufacturing. Faludi, Bayley, Bhogal and Iribarne (2015) compared several AM methods with CNC milling, and results indicate that AM is indeed more sustainable than subtractive manufacturing because it does not waste as much material.

Proportion of Manufacturing

AM is due to various technological solutions and the wide array of possible materials a very versatile technology. Therefore, and because of the rapid technological advancements and the unconsolidated market structure, predictions about the possible extent to which AM could substitute traditional manufacturing technologies are seemingly hard to make. Even Wohlers (2014), the probably most important source about AM, addresses the problem of quantifying the potential market penetration of AM. An actual penetration of 1% was mentioned by experts, while Wohlers estimates that AM could capture a share of more than 2% of global manufacturing industry. This fraction could although even be significantly higher.

Decreasing costs and new materials on offer could further boost AM's infiltration among manufacturers (Pour et al., 2016). Rayna and Striukova (2016) argue that AM is clearly advantageous for customized products, but is still very likely to remain uneconomical for mass-consumed objects unless a real demand for mass-customized products would emerge. Eyers, Naim, Potter, and Gosling (2016) also explain that AM is well-known for low-volume, high variety prototyping. Several applications have already demonstrated the potential to achieve a wide range of production volumes, whilst still retaining high variety in the products produced. Similarly, Holmström et al. (2016) describe that direct digital manufacturing so far lags behind by several orders of magnitude compared to traditional manufacturing methods. Yet they also found that direct digital manufacturing clearly is on an improvement trajectory. Cassaignau, Baillais, Wargny, de Melchior, and Lonjon (2016) say that the integration of AM within the organizations increased by 6% from 2015 to 2016. Comparable results were achieved by Kianian, Tavassoli, Larsson, and Diegel (2016), whose main findings show that the majority of AM users, namely 65%, are expanding their AM applications beyond rapid prototyping.

Effects on Supply Chains

While a fair amount of research exists concerning the effects of AM on supply chains, research assessing the effects from a material saving point of view is somewhat limited. The most relevant contributions for this paper will be briefly outlined here. Huang et al. (2013) point out that AM can improve the efficiency of a lean supply chain through just-in-time (JIT) manufacturing and waste reduction. The inventory management advantage is also brought up by Kietzmann et al. (2015), as firms can save space and cost by on-demand replication of stock items through AM rather than keeping items stockpiled in anticipation of a future need. Waller and Fawcett (2014) think that AM will cause a near shoring – that is, the return of offshore manufacturing – due to its various advantages. AM´s influence on logistics and supply chain management is likely to be transformational. First, it can be used by a consumer who downloads a design and then prints a product allowing for the ultimate in postponement and customization. Second, AM can also be used by a component supplier to print highly customized parts which in turn allows for fast feedback cycles at a lower echelon in the supply chain. Thiesse et al. (2015) explain that logistics processes can be digitalized through location independent manufacturing reducing the physical flow of material.

Methodology and Model

The chosen methodology for this paper is system dynamics, a research approach which allows the simulation of feedbacks and time delays in complex and dynamic systems. For these features system dynamics was chosen over agent-based or discrete-event simulation. Sterman (2000) points out that feedback loops make systems self-organizing and adaptive, therefore dynamics arise spontaneously from their internal structure, while time-delays may make the behavior unpredictable. Forrester (1961) explained that mathematical analysis in general is not powerful enough to provide analytical solutions to such complex situations. Experimental approaches are alternatives, but they cannot always be performed in real-life. Simulations can handle time-delays and thus policies and assumptions can be evaluated. In this paper, the impact of AM on the materials inventory will be analyzed using system dynamics. A model, combining two sub-models, a Diffusion Model and a Materials Inventory Model, was created using the specialized Vensim software. In Figure 1 the Materials Inventory Model can be seen to the left while the Diffusion Model is on the right. In the mid-section, here depicted in orange color, are the feedback mechanisms as identified in this paper. A simplified work-in-process model was included to indicate a possible extension to this model. In the following section, the two sub-models will be briefly described, as both are well established an in depths analysis is at this point not necessary and more emphasis will be put on the feedback loop connecting the two.

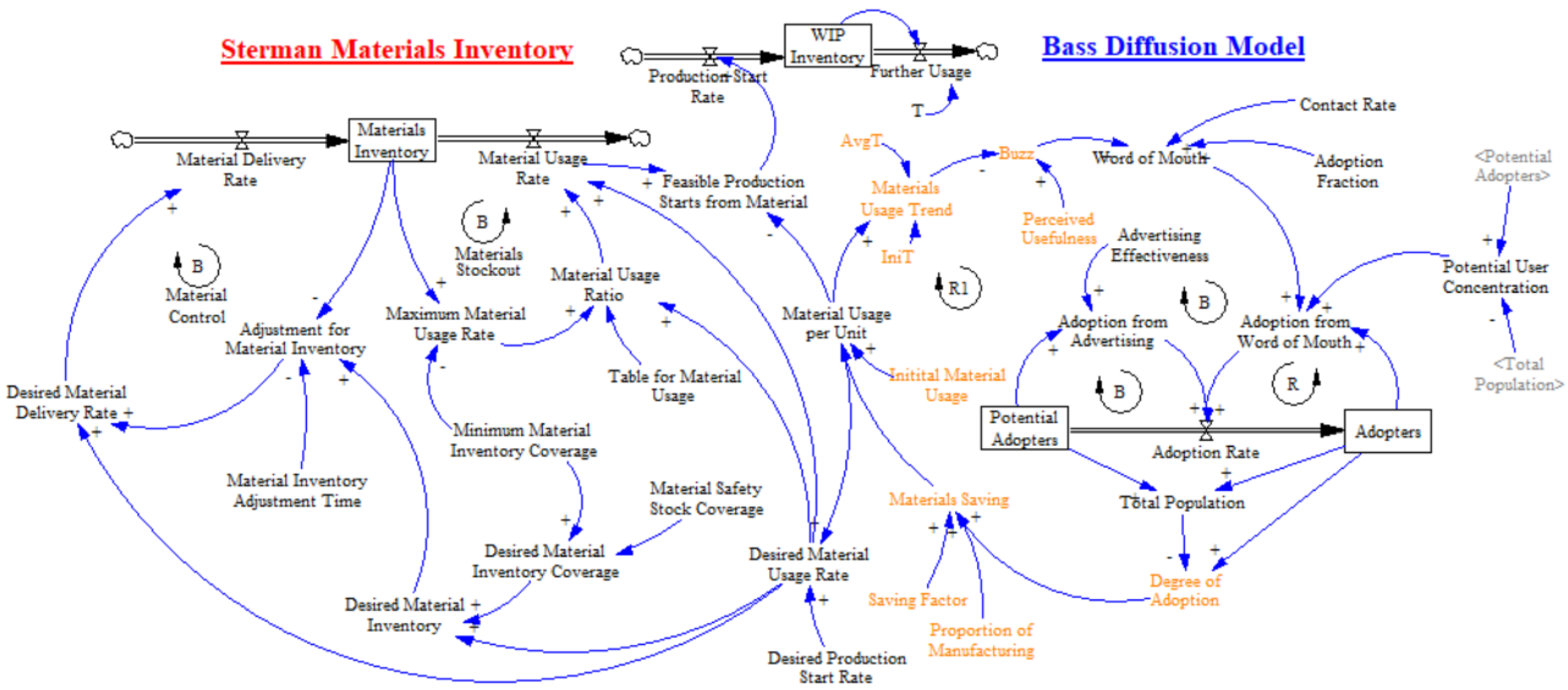

Figure 1 – The combined model as described in this paper

Bass Diffusion
Diffusion is the process by which an innovation is communicated through certain channels over time among the members of a social system (Rogers, 1983). Building up on that Bass (1969) established a Diffusion Model with the basic assumption that a consumer's initial purchase is related to the number of previous buyers. The model implies exponential growth of initial purchases to a peak and then exponential decay. This will result in a significant s-shaped growth function of total adopters. Phaal, O´Sullivan, Routley, Ford, and Probert (2011) stress that defining the phases and transitions associated with industrial emergence is important for understanding the underlying dynamics, and for providing guidance for organizations concerned with technology emergence. Sterman (2000) took up the original Bass Model and slightly adapted it to be used in system dynamics modelling. The *Adoption Rate* AR is composed of the *Adoption from Advertising* (external sources) and the *Adoption from Word of Mouth* (social exposure and imitation). The necessary input parameters are *Advertising Effectiveness* (a) and the *Adoption Fraction* (c). Formula 1 shows AR in mathematical notation which can then be modelled in system dynamics, as in Figure 1 to the right-hand side.

$$AR = a * (N - A) + ciA - \frac{ci}{N} * A^2 \tag{1}$$

When it comes to AM there is a big uncertainty about the size of the potential total market of additive manufacturing (Wohlers, 2014), hence the value for *Total Population* (N) in this model was set at 100, while *Advertising Effectiveness* (a) and *Adoption Fraction* (c) were estimated through the analysis of real data as described later in this paper.

Sterman Materials Inventory
As the aim of this paper is to analyze the effects of AM on materials inventories the second sub-model used is the Materials Inventory Model as designed by Sterman (2000). It constitutes the left-hand part of the model as depicted in Figure 1. The materials inventory is modeled as a stock management structure where production can only begin if there is a sufficient level of materials. The central element of this model is the *Materials Inventory* stock which is defined by the following formula,

$$Materials\ Inventory = \int_{t_0}^{t} \begin{bmatrix} Materials\ Delivery\ Rate\ - \\ Material\ Usage\ Rate \end{bmatrix} ds + Materials\ Inventory_{t_0} \tag{2}$$

The model was calibrated to reach an equilibrium value of 100 for *Materials Inventory* under the premise of constant demand. Prior to reaching that equilibrium the model initially oscillates around this value when there is no initial inventory. Another important element in the Materials Inventory Model is the auxiliary variable *Material Usage per Unit*, measured as Material/Widget with an initial value of 1 but it will be decreased (or increased) by *Materials Saving*.

Materials Saving
The key input variable for this paper is *Materials Saving* which is the Product of *Degree of Adoption*, *Saving Factor* and *Proportion of Manufacturing*. It has the unit Material/Widget.

$$Materials\ Saving = \begin{pmatrix} Degree\ of\ Adoption * Proportion\ of\ Manufacturing\ * \\ Saving\ Factor \end{pmatrix} \tag{3}$$

The *Degree of Adoption* is simply the fraction of members of the population that have already adopted AM. Initially it is 0, while it will eventually reach a maximum value of 1.

$$Degree\ of\ Adoption = \frac{Adopters}{Total\ Population} \tag{4}$$

The *Saving Factor* is a number ranging from 0 to 1 and it stands for the amount of material per widget that could potentially be saved through the use of AM technology when compared to traditional manufacturing. During the literature review several sources addressing this component were identified (see Table 1) as no definitive statement concerning that value can be made a Monte Carlo Simulation was included (see Figure 3). The simulation comprises 2000 runs assuming the following distribution,

$$Saving\ Factor = RANDOM_{UNIFORM}(0.3{,}0.9) \tag{5}$$

The *Proportion of Manufacturing* is again a number between 0 and 1. It is the proportion of the total manufacturing market that can potentially be substituted by AM. As seen in the corresponding chapter of the literature review values are ranging quite a lot. A potential minimum, maximum, and a most likely case based on Wohlers (2014) were used for an assumed triangular distribution for the Monte Carlo Simulation,

$$Proportion\ of\ Manufacturing = RANDOM_{TRIANGULAR}(0.01{,}0.2{,}0.01{,}0.02{,}0.2) \tag{6}$$

Material Usage per Unit is, as already described, assumed to be 1 initially but will be decreased (increased) by the *Materials Saving* variable. This reduction (increase) in material required per widget will be measured in the *Materials Usage Trend*, while the *Buzz* variable will then increase the *Adoption from Word of Mouth* and in consequence the *Adoption Rate*. This closes the reinforcing feedback loop R1 (which can be seen in Figure 1 in the mid-section, where the elements added during this research are colored in orange).

Model Validation

Building confidence in system dynamics models can be done through a variety of channels. Forrester and Senge (1980) explain that there is no single test for validation, confidence rather accumulates gradually as the model passes one test after another. The tests seek disproof but as the model withstands the tests confidence develops. Qudrat-Ullah (2012) proposes a two-step iterative assessment process, where structural and behavioral validity should be tested.

For structural validity Vensim, the software application used for building the model presented in this paper, includes two testing tools. The Model Check will test the model for structural errors while the Units Check feature checks the model equation for the consistent use of units of measurement (Ventana Systems, 2016). The sub-models and the combined model underwent and passed the tests separately. Forrester and Senge (1980) identified several core tests but put a special note on the extreme-conditions test, where constants will be set to extreme values such as 0 or a very large number, then the behavior of the model should shift accordingly. The model passed various extreme conditions tests. After structural testing the behavior tests measure how accurately the model reproduces the major behavior patterns of the real system. Barlas (1994) stated that if the problem involves long-term and steady-state simulation, then standard statistical measures might be applicable. If the problem involves non-stationary behavior, as for example s-shaped growth, then such tools are practically impossible to apply, graphical or visual approaches might then be preferable. As the Bass Diffusion Model features s-shaped growth graphical tests were conducted and the model exhibited reasonable behavior patterns.

Results

As the model has been validated and its behavior analyzed it was applied using real data. Therefore, *Adoption Rate* which is a non-linear differential equation was solved corresponding to Bass (1969):

$$F(T) = \frac{1 - e^{-(a+c)*T}}{\frac{c}{a}e^{-(a+c)*T} + 1} \quad (7)$$

F(T) in this form was then used for parameter estimation using nonlinear least squares (NLS) regression. For this paper, the NLS regression was performed in 'R' which is an interpreted computer language that contains functionality for a large number of statistical procedures. An approach based on the one presented by Cowpertwait and Metcalfe (2009) was applied. For the validation of the NLS analysis the NLS regression model was applied on data originally used by Bass (1969) and later by Marković and Jukić (2013) and the results were compared.

As the NLS regression produced reasonable results it was hence applied on actual annual sales data of industrial AM system units for the time period of 1988-2013 rounded to the nearest hundreds as taken from Wohlers (2014). Through this regression the *Adoption Fraction* (0.138) and the *Advertising Effectiveness* (0.00035) parameters were estimated. Even though they are lower than the mean values (0.302 / 0.04) as estimated in a meta-analysis conducted by Sultan, Farley, and Lehman (1990) the parameters are still within a reasonable range. The low *Advertising Effectiveness* parameter can be explained by the slow adoption of the technology. It has to be noted though that the statistical significance of the results decreased when including the sales figures of the year 2013 as this year featured a rather steep increase in sales.

In Figure 2 the graph for the actual sales data is contrasted with the simulated number of *Adopters*. As can be seen they both exhibit a very slow initial rate of adoption, which is due to the low *Advertising Effectiveness* parameter as described above.

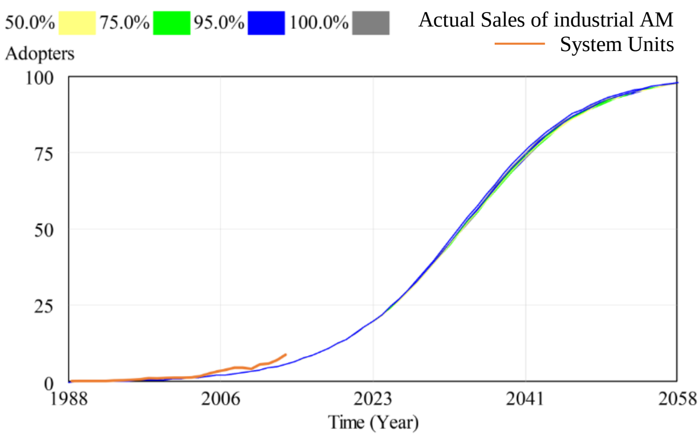

Figure 2 – Actual versus predicted Sales of industrial AM System Units

The most important simulation result, the development of the *Materials Inventory* over time, can be seen in Figure 3. It indicates a probable reduction of inventory in the single-digit percent area. Included in the graph are 4 Percentiles, where the 50% percentile (yellow) is the area in which half of the runs are located. The reduction is likely to take place gradually, corresponding to the adoption process.

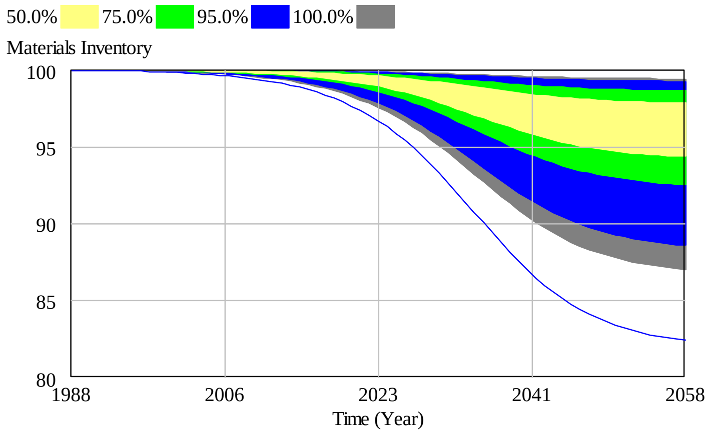

Figure 3 – Materials Inventory over Time

The statistical evaluation of this simulation results in following development over time for *Materials Inventory* (Table 2):

Table 2 – Materials Inventory over Time

Year	**1988**	**1998**	**2008**	**2018**	**2028**	**2038**	**2048**	**2058**
Median	100	99.98	99.9	99.64	98.91	97.72	96.83	96.51
Mean	100	99.97	99.88	99.56	98.68	97.21	96.14	95.77
StDev	0	0.017	0.0778	0.284	0.859	1.814	2.492	2.726

The statistical results of the simulation return a final median value of *Materials Inventory* of 96.51 which would mean a potential 3.49% reduction of materials inventory in the manufacturing industry given all model assumptions as described in the other sections of this paper. Also of importance is the timing of the reduction. According to the model the impacts of AM on materials inventories up to the year 2018 are only marginal while most of the total reduction will take place during the time frame of 2018-2048 given the model results.

Model Limitations and Further Research

The model presented in this paper provides good orientation for decision makers on how the adoption of AM will affect materials usage and materials inventories, although the list of components used in this model is far from complete. First, according to Schniederjans (2017) AM is not a single technology but rather a category of different manufacturing approaches that proliferate at different speeds, hence a separate analysis might yield more specific results. Second, the cost factor of AM has not been considered, Thomas (2016) emphasized that the costs of AM technologies and materials have decreased steadily over time. Third, the know-how diffusion is rather slow (Ford and Despeisse, 2016). Further education of designers and engineers about the potential benefits of AM could spur its implementation. Finally, the biggest limitation of the model as presented here is that it only depicts a small part of the supply-chain. An expanded view on different supply chain processes could provide deeper insights into the behavior of the system and the effects of AM on inventories and the supply chain.

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