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Towards a Framework for Self-Evolving Products in Additive Manufacturing

Jyrki Savolainen[a/b], Michele Urbani[c/d], Heidi Piili[e]

[a]LUT University, LUT School of Business, Lappeenranta, 53850, Finland (jyrki.savolainen@lut.fi)
[b]CSC – IT Center for Science, Kajaani, 87100, Finland

[c]Sustainable Energy Center, Fondazione Bruno Kessler, Trento, 38122, Italy (murbani@fbk.eu)
[c]University of Trento, Department of Industrial Engineering, Trento, 38122, Italy
[e]University of Turku, Department of Mechanical Engineering, Turku, 20520, Finland (heidi.piili@utu.fi)

Abstract: In critical industrial applications, enhancing existing custom-designed products throughout their life cycles is crucial for improving user value while managing the costs of continuous design iterations. Additive manufacturing has demonstrated significant improvements in product performance through optimized designs, but implementing these improvements in scale requires excessive design efforts. In this paper, we address this gap by presenting a digital twin (DT)-based product design framework for additively manufactured parts that makes the design of the physical parts independently to adapt into their industrial application environments. The methodology is based on efficiently utilizing data in the intersection of application-specific DT model and the CAD (Computer-Aided Design). It is proposed that with the smart utilization of Evolutionary Algorithms (EA), most of the manual labor involved in drafting performance-improving revisions of design of part geometry could be eliminated. The proposition is evaluated from the business model point of view highlighting the potential for novel, mutually beneficial supplier-customer relationships in advanced industrial equipment solutions.

Keywords: Additive Manufacturing; Simulation-based Design; Evolutionary Algorithms; Digital Twins

1. INTRODUCTION

Additive manufacturing (AM), also known as 3D printing, is used to create a wide range of products, with a particular focus on tailored high-end applications. While the ability to produce performance improvements through customized products with AM is acknowledged as a major business opportunity, designing them cost-effectively in scale has not been widely addressed.

The key challenge, as noted in Xiong *et al.* (2019), lies in finding optimal design solutions from an almost infinite design space provided by AM. The issue can be further extended to the business model (or managerial) perspective on how the optimal designs, once found, translate into revenue of the OEMs, in a way that the additional costs of AM are outweighed. As Hällgren and others (2016) note, the willingness to pay for optimal performance is subject to specific applications and customers stressing the importance of identifying those products that generate the highest value when produced using AM. For example, optimizing heat exchangers designs can yield significant business value, as demonstrated in Sabau *et al.* (2020) and Moon *et al.* (2021). Already, accounts of automated design approaches exist from Biedermann *et al.* (2020) where users input “only” the product’s functional requirements, and the algorithm generates an optimal part shape within AM-design constraints.

This paper deals with the trade-off between achieving maximum performance through design while keeping the costs at the minimum for single customers with a scope of large-scale, plant-level industrial applications that utilize plant-wide simulation models. The first contribution is developing a scalable design framework for AM that make the products self-evolve to suit individual applications. The word “framework” here is used in the meaning of conceptual guide, or a set of guiding principles, to structure thinking and development rather than a rigid methodology. At the center is the topical concept of DTs and more specifically DT-based product design. DT as a term, refers to "a virtual dynamic representation of a physical system, which is connected to it over the entire lifecycle for bidirectional data exchange” (Trauer *et al.*, 2020). DTs should allow for enhanced system control and optimization. For a more in-depth explanation of DT principles, the reader is advised to refer to Rosen *et al.* (2015); Negri *& al.* (2017).

The second contribution of this paper is to establish a business model (BM) idea on top of the described design approach to address the lack of disruptive BMs discussed in the meta-study of Savolainen & Collan (2020) (see also (Ryan *et al.*, 2017). That is, despite sky high expectations about AM that were articulated famously by Berman (2012), the AM-technology is often merely utilized as a means of complementing traditional manufacturing to gain incremental business benefits rather than putting it in the center of the business. Here, it is envisioned that the data feed of physical operations combined

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with the use of EAs paves a way towards a new type of ironclad supplier-customer relationship, where the performance-critical product in a customer application gets replaced by a series of constantly improving product instances.

This study is structured as follows: Section 2 reviews the literature on optimized product design for AM and introduces relevant concepts. Section 3 introduces the results of this study outlining the algorithmic basis of the proposed self-evolving products, and economic potential. Finally, Section 4 concludes and summarizes the findings of this study.

2. RELATED WORKS

The literature around the topic of digital twinning has been growing steadily over the past years. Notably, the literature survey shows no earlier research efforts that would explore self-evolution of physical part design with the help of DT-modeling and AM not to mention its BM implications. Some of the closely related works include, Lin *& al.* (2021) who study the possibility of self-evolutionary development of operating policies for intelligent industrial products. Their approach, without a detailed account on how, suggests the use of simultaneous multiple cyberspaces and reinforcement learning to adopt optimal actions. As presented in Trauer *et al.* (2020), DTs cover an emerging role in rapid product development and validation (Huang *et al.*, 2022). In a recent DT review of Lo *& al.* (2021), these are acknowledged as a role to create a universal physical prototype. That is, an uncharacteristic physical product that would be automatically developed in the process of multi-phase field testing and simulation by adjusting gradually towards user. However, Lo *et al.* (2021) do not specifically mention AM in their work.

AM is a concept that is used in this paper broadly to encompass various technologies and materials that are reviewed in, e.g., Ngo *et al.* (2018). Gibson *et al.* (2021) identifies seven sub-categories of AM with dozens of technical solutions. Depending on the equipment, the dimensions of the product can range from nanometers to meters. AM can produce parts with lattice or cellular structures to create light-weight products with optimized performance without significantly increasing manufacturing costs (Tang *& al.*, 2015) or having multiple versions of the same product in a single run. As a result, AM has found its way to several industry applications producing lightweight, flow-optimized, and geometrically complex yet durable products, including automotive (Savastano *et al.*, 2016), aerospace (Singamneni *et al.*, 2019), and medical applications (Sandström, 2016).

In most cases, the existing parts have to be redesigned to take the advantage of the AM-technology features: for example, Tang *& al.* (2015) note that customized lattice structures, while offering superior performance, remain underutilized due to the additional design efforts required. A Design for Additive Manufacturing (DfAM) approach has been developed to capitalize on the design flexibility provided by AM technology. DfAM involves a trade-off between achieving multiple design targets such as dimensional accuracy, density, hardness, and mechanical properties while focusing on the most critical process variables (Krol *& al.*, 2013). Despite the potential flexibility, AM presents several limitations in geometric freedom - e.g., overhangs, minimum wall thickness, and the size of holes and channels (Mirzendehdel and Suresh, 2016) that can lead in the worst case to, e.g., need of heavy supporting, and the subsequent removal of these supports in a laborious post-processing phase. Some of the pitfalls can be detected by modern process simulation software and suggest alternative ways to complete the design (Bandyopadhyay and Traxel, 2018; Wang *et al.*, 2018). A comprehensive review of product design for AM is provided by (Yang and Zhao, 2015).

Considering these limitations, the design of an AM component is a difficult problem, which entails a set of design, operational, and manufacturing requirements. Summarily, the literature survey indicates that the existing works are exploratory in nature and often concentrated on the ICT-infrastructure implementation rather than the evolutionary mechanics or business implications. There is a gap in the literature on how to utilize user data of DTs to steer the design selection process. These topics will be addressed in the next sections.

3. RESULTS

The central proposition of this paper is that by a reconnection of the design with the application domain, the data-intensive fine-tuning of part characteristics could be automated as illustrated in **Figure 1**. A standard version of the component is put in service, and process data starts to be collected (left-bottom corner of Figure 1). Data feeds the DT serves as the source of updating design requirements. This process with design-application feedback allows the initially installed one-size-fits-all embodiment design to evolve towards an application-optimized design that takes into account asset-specific digital data. After the new design is accepted, AM machinery produces the new customized product from the same underlying, embodiment design. That is, AM enables minor, application-specific, geometrical improvements in the part structure. We refer to these products as "self-evolving" to highlight the automated nature of the design process.

This study considers industrial applications that can generate significant savings or revenues for the end-users through improved operational performance, which would justify the high material and production costs associated with AM. Also, in the industrial context, there is typically more regulatory flexibility regarding the implementation of AM-induced design freedom for physical assets compared to consumer products, or some specific industries such as aviation with maximal safety requirements (Singamneni *et al.*, 2019).

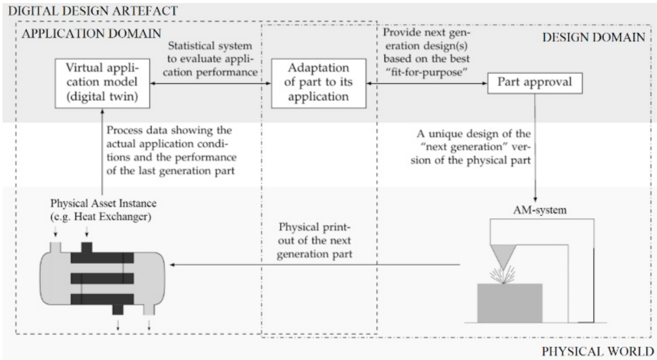

Figure 1. Schematic illustration of the self-evolutionary component development process through a digital design artefact.

3.1. Design framework – a formal description

The self-evolutionary design process occurs entirely in the virtual domain of the DT and is made of four phases, as depicted in Figure 2. Gathering and analyzing historical use data is the first step of the process (step (1) in Figure 2), which aims to produce (i) performance analytics of the actual design for comparison with new designs, and (ii) uncertainty estimates of the user environment parameters. While ensuring that the desired durability is maintained, the EA searches for an optimal design based on this historical data during step (2).

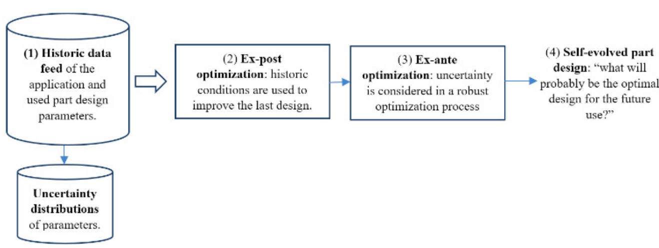

Figure 2. The self-evolving part design process.

The uncertainty distributions gathered in (ii) are used to feed further optimization of the component during step (3), whose objective is to improve the design in a robust sense. To evaluate the component in a robust setting, a Monte Carlo simulation can be used as well as other techniques, see, e.g., Beyer & Sendhoff (2007), whose aim is to explore the behavior of the component in far-from-nominal working conditions based on the experience. Finally, an optional step (4) is given to push the evolutionary concept to its limit and validate the new design under conditions that are considered probable in the future. This analysis is an extension of step (3) where uncertainty distributions of parameters are arbitrarily changed, and the component's design evolves accordingly. The practical purpose of this step is to verify the so-called safety margins of the component, e.g., through extreme value analysis as discussed in (Doorn and Hansson, 2011). Interestingly, real biological evolutionary designs that have evolved through natural selection (Diamond, 2002): the safety factors fall in the range of 1.2 – 10 depending on the environment variability and criticality of the biological "part". Evidently, the same logic of part criticality holds here for the "man-made" industrial processes, but delving deeper into the safety margins falls beyond the purview of this research.

Due to the uncertainty inherent in the simulation of parts in the operative environment, robust design principles (Beyer and Sendhoff, 2007) are exploited in topological optimization of the proposed self-evolutionary part model. The design problem is formalized by defining a quantitative measure $f(\boldsymbol{x})$ of the goodness of the current set of design parameters $\boldsymbol{x}$; in the context of EAs, $f(\boldsymbol{x})$ is the so-called *fitness function* to describe how much the current design $\boldsymbol{x}$, also named *individual*, fits the current use environment. The goal of the automated design process is to maximize the fitness of the individual to the environment by minimizing the value of $f(\boldsymbol{x})$. A generic formulation of the problem is the following:

$$
\begin{aligned}
\text{minimize} \quad & f(\boldsymbol{x}), && (1)\\
\text{subject to} \quad & g_i(\boldsymbol{x}) \leq 0, i = 1, \dots, I, && (2)\\
& h_j(\boldsymbol{x}) = 0, j = 1, \dots, J, && (3)
\end{aligned}
$$

where $g_i(\boldsymbol{x})$ and $h_j(\boldsymbol{x})$ are inequality and equality constraints, respectively. The purpose of constraints is to formalize the design requirements that an object is subject to. For example, the fitness function could be a simulation model of the new design, whose aim is to evaluate a performance metric of interest. Constraints formalize both design limitations such as, e.g., overhang angles or wall thickness, and environmental conditions like temperature and pressure experienced during the past use of the component.

The workflow of EAs is organized in two parts: first, the algorithm is initialized by providing the parameters $\boldsymbol{x}$ that describe the part design and the user's historical track of records. A set of solutions is generated by randomly perturbing the provided solution $\boldsymbol{x}$ to diversify the available part design. Second, the search procedure is iterated until a stopping criterion is met; the latter could be, e.g., the elapsed time, the number of iterations, or the convergence of results. During an iteration of the algorithm, the best-known solution $\boldsymbol{x}_{best}$ is stored for comparison with a new solution $\boldsymbol{x}'$, which is obtained by the so-called *genetic operations* of mutation and crossover. Genetic operations, similar to the recombination of genes in natural processes, modify a solution $\boldsymbol{x}$, or recombine it with another solution to obtain a new (possibly better) solution $\boldsymbol{x}'$. The process is iterated multiple times: at the end of each iteration, solutions are evaluated by employing a fitness function $f(\cdot)$, and the best ones are sent to the next iteration. The fitness function can be anything from a linear sum of terms to a complex simulation model; its evaluation can be long and computationally demanding to the expense of the execution time of the algorithm.

The evolutionary process governed above is not straightforward. It only makes sense to modify a part's design when the application data changes, or when a high-performing part has not yet been installed. However, many small mutations in the part's design may have a negligible impact on its overall performance. Therefore, it is essential to optimize the "amount of design randomness," which determines the extent of change in the design variables. If the mutation rate is too low, the designs may evolve slowly, whereas excessively high mutation rates may not produce feasible designs.

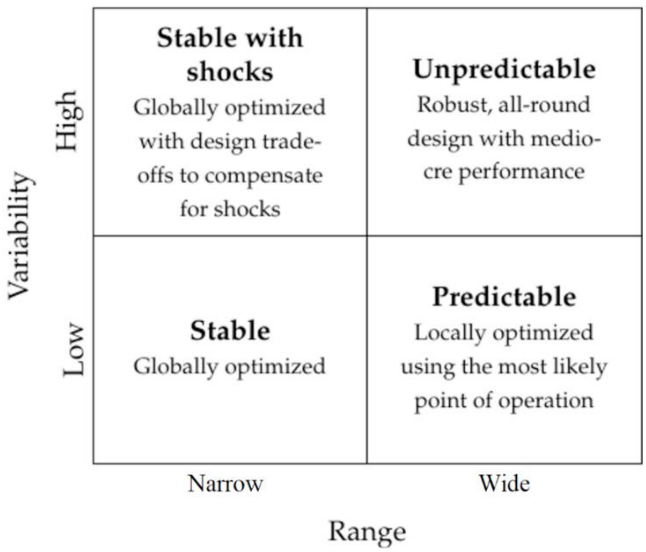

Figure 3. Anticipated direction of the self-evolutionary design process within different environments. Environment type refers to the range and variability of parameters in the dynamic application simulation model.

The above discussion implies that the direction of self-evolutionary design may be dependent on the environment variability as summarized on a high-level in **Figure 3**. High variability (Fig 3 / y-axis) of the application to drive the evolution towards robust designs, even if they do not deliver optimal performance. However, fully optimized performance designs may be appropriate for the most stable environments where both the variability and range (Fig 3 / x-axis) are low. Diamond (2002) adds that also the deterioration and the cost of failure are factors that should be accounted for in the safety factors.

3.2. Business Model

From the monetary perspective, the *value* of additively manufactured parts for the customer should be broadly recognized as the improved performance of products that stem from the design optimization of its standard version. The business logic of the self-evolutionary products addresses the needs of specific high-end industrial applications where the system performance is closely linked to topology of its components. Here, the major improvement to the current practice is to provide minor, valuable product improvements through automation. That is, the monetization of the idea comes from the performance-design cost trade-off resolution through the described highly automatized DT-based product design. Nowadays, it is common that standard products tend to become sub-contracted in the long-term with ever-decreasing margins, whereas, in the proposed model, the supplier (usually OEM / Original Equipment Manufacturer) can induce increasingly bulletproof customer lock-ins once the performance is connected to the stream of optimized product instances.

AM undoubtedly provides a wide range of prospective use-cases, but so far, many of the opportunities have been mostly contributing on the element of *value creation* rather than *value capture* where, as defined by (Baden-Fuller and Haefliger, 2013), the latter refers to extracting monetary benefits for the product/service supplier and not just “giving away” the additional value. This, excluding the fact being expensive, might be the key reasons why AM-produced parts haven’t yet found their way to many applications where they could deliver obvious benefits.

In capturing the value of self-evolutionary parts, in theory, a customer suffices to fulfill its production lot size of one. However, as the revenues induced by performance gains ultimately accrue to the customer and not to the producer, additional incentives would have to be put in place to enable value capture. These can be in the form of performance-based premiums or pay-per-use. Since many of the applications are unique and work only as a part of a larger industrial system(s), neither creating nor signing such contracts is straightforward. In the absence of such contracts, the only benefit for the OEM would originate from the manual design work saved that might not be sufficient for maintaining the previously described system for a small customer base. Due to the evident reluctance of customers to agree on performance premiums on individual products, the likely initial invoicing model of self-evolutionary products would launch as an additional subscription-based, premium performance service model within reach for large or very large companies with a critical mass of customers.

3.3 Challenges

Another dimension to consider is the disruptiveness of the BM referring to the extent to which the current market would be altered. The self-evolutionary design logic, as indicated previously, would be targeted to a (very) high-end segment looking for low-cost improvements. Following the insights of Schmidt & Druel (2008), emergence of such an innovation would lead other market incumbents to adopt similar type of product offerings to avoid losing their highest paying customers while the question remains whether the competence of producing self-evolving parts can be reached before the market gets redistributed. A good example of AM use case is given by Sandström (2016) hearing aid industry that swiftly transitioned from traditional manufacturing to additive once the first market actors succeeded in technology adaptation. As one of the main insights Sandström finds that even though the technology would be disruptive it does not always necessitate disruption in market shares.

As discussed in Schmidt and Druehl (2008), there is a trickledown effect of high-end products towards lower market segments. The scope of this study has been limited to the aforementioned one with AM, but evidently, a possibility exists that self-evolution could spread into more everyday products. However, it is suggested that in this case the ability to pay for performance would be limited at the cost of convenience and the optimization would be more about discrete version revisioning based on data involving large production runs to different segments using the means of conventional manufacturing. Therefore, such cases start to have an evident resemblance with the topics of mass customization and further discussion is left out of the scope of this study.

4. CONCLUSIONS

This study is an exploratory work to put together a structure of a self-evolutionary design framework that automatically steers the physical shape (design) into the direction that best suits the needs of the unique user-specific application and thus provides improved application performance with every new part instance installed. The business potential lies in selected high-value applications where topologically optimized parts could be produced without human intervention which, as such, is a radical AM-based business model that has not been presented before.

An analytical presentation of the automated self-evolutionary design process was formalized. It was suggested that the approach has solid business potential in applications where the customer is motivated to pay extra for increased performance and the performance is tied to the part topology while several issues remain for real-life implementation.

Despite potentially significant benefits, self-evolutionary optimization faces several practical limitations. One evident caveat of this work is using a single case study that is by nature context-dependent. Secondly, the acceptance process for new manufacturing technologies and materials, particularly for critical components that require third-party verification, remains a major obstacle. Thirdly, the current technical limitations of AM mean that certain processing phases required for finalizing self-evolved component designs were not included in this research. However, there are promising developments in design tools that may soon overcome these limitations, see, e.g., Liu and Shin (2019). Lastly, the design computation presented in this paper, and the simulation artifacts beyond the scope of this paper, are expected to be computationally intensive, necessitating operation in a cloud computing environment. Related to the last point, the availability, amount, and quality of data are critical to the success of the proposed algorithm. While this study assumed that important process variables would be reliably measured and continuously stored, practical challenges arise in monitoring wear and tear processes that cannot be constantly observed. In such cases, proxy variables such as vibrations or observed performance may be used, or inspections and scheduled maintenance stops may be necessary to assess the part state only qualitatively.

Future research has many potential directions. An evident possibility would be to establish a test bed for self-evolutionary logic using the simplest possible part imagined with proper instrumentation and digital model. In the higher-level setting, it would be worth considering how the evolutionary design could be extended to applications beyond heat exchangers.

As the final point, the larger industrial system perspective implications of the self-evolutionary products were not considered and it remains unclear whether the self-evolving design of a single part of the system would cause a subsequent need to address the design of the other components of the system as well for the overall optimal performance. Theoretically, it would be interesting to study (a multi-agent system) simulation of several self-evolving parts to see whether this type of system would start having similar features to nature's ecosystems.

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REFERENCES

Baden-Fuller, C. and Haefliger, S. (2013) 'Business Models and Technological Innovation', *Long Range Planning*, 46(6), pp. 419–426. Available at: https://doi.org/10.1016/j.lrp.2013.08.023.

Bandyopadhyay, A. and Traxel, K.D. (2018) 'Invited review article: Metal-additive manufacturing—Modeling strategies for application-optimized designs', *Additive manufacturing*, 22, pp. 758–774.

Berman, B. (2012) '3-D printing: The new industrial revolution', *Business Horizons*, 55(2), pp. 155–162. Available at: https://doi.org/10.1016/j.bushor.2011.11.003.

Beyer, H.-G. and Sendhoff, B. (2007) 'Robust optimization – A comprehensive survey', *Computer Methods in Applied Mechanics and Engineering*, 196(33), pp. 3190–3218. Available at: https://doi.org/10.1016/j.cma.2007.03.003.

Biedermann, M. and Meboldt, M. (2020) 'Computational design synthesis of additive manufactured multi-flow nozzles', *Additive Manufacturing*, 35, p. 101231.

Diamond, J. (2002) 'Quantitative evolutionary design', *The Journal of physiology*, 542(Pt 2), pp. 337–345. Available at: https://doi.org/10.1113/jphysiol.2002.018366.

Doorn, N. and Hansson, S.O. (2011) 'Should probabilistic design replace safety factors?', *Philosophy and Technology*, 24(2), pp. 151–168. Available at: https://doi.org/10.1007/s13347-010-0003-6.

Gibson, I. *et al.* (2021) *Additive manufacturing technologies*. Springer.

Hällgren, S., Pejryd, L. and Ekengren, J. (2016) '(Re)Design for Additive Manufacturing', *Procedia CIRP*, 50, pp. 246–251. Available at: https://doi.org/10.1016/j.procir.2016.04.150.

Huang, S. *et al.* (2022) 'Toward digital validation for rapid product development based on digital twin: a framework', *The International Journal of Advanced Manufacturing Technology*, pp. 1–15.

Krol, T.A., Seidel, C. and Zaeh, M.F. (2013) 'Prioritization of Process Parameters for an Efficient Optimisation of Additive Manufacturing by Means of a Finite Element Method', *Procedia CIRP*, 12, pp. 169–174. Available at: https://doi.org/10.1016/j.procir.2013.09.030.

Lin, T.Y. *et al.* (2021) 'Evolutionary digital twin: A new approach for intelligent industrial product development', *Advanced engineering informatics*, 47, p. 101209. Available at: https://doi.org/10.1016/j.aei.2020.101209.

Liu, S. and Shin, Y.C. (2019) 'Additive manufacturing of Ti6Al4V alloy: A review', *Materials & Design*, 164, p. 107552.

Lo, C.K., Chen, C.H. and Zhong, R.Y. (2021) 'A review of digital twin in product design and development', *Advanced engineering informatics*, 48, p. 101297. Available at: https://doi.org/10.1016/j.aei.2021.101297.

Mirzendehdel, A.M. and Suresh, K. (2016) 'Support structure constrained topology optimization for additive manufacturing', *Computer-Aided Design*, 81, pp. 1–13. Available at: https://doi.org/10.1016/j.cad.2016.08.006.

Moon, H. *et al.* (2021) 'Ultra-power-dense heat exchanger development through genetic algorithm design and additive manufacturing', *Joule*, 5(11), pp. 3045–3056.

Negri, E., Fumagalli, L. and Macchi, M. (2017) 'A Review of the Roles of Digital Twin in CPS-based Production Systems', *Procedia Manufacturing*, 11, pp. 939–948. Available at: https://doi.org/10.1016/j.promfg.2017.07.198.

Ngo, T.D. *et al.* (2018) 'Additive manufacturing (3D printing): A review of materials, methods, applications and challenges', *Composites Part B: Engineering*, 143, pp. 172–196. Available at: https://doi.org/10.1016/j.compositesb.2018.02.012.

Rosen, R. *et al.* (2015) 'About The Importance of Autonomy and Digital Twins for the Future of Manufacturing', *IFAC-PapersOnLine*, 48(3), pp. 567–572. Available at: https://doi.org/10.1016/j.ifacol.2015.06.141.

Ryan, M.J. *et al.* (2017) '3D printing the future : scenarios for supply chains reviewed', *International Journal of Physical Distribution & Logistics Management*, 47(10), pp. 992–1014. Available at: https://doi.org/10.1108/IJPDLM-12-2016-0359.

Sabau, A.S. *et al.* (2020) 'Design, additive manufacturing, and performance of heat exchanger with a novel flow-path architecture', *Applied Thermal Engineering*, 180, p. 115775. Available at: https://doi.org/10.1016/j.applthermaleng.2020.115775.

Sandström, C.G. (2016) 'The non-disruptive emergence of an ecosystem for 3D Printing - Insights from the hearing aid industry's transition 1989-2008', *Technological Forecasting and Social Change*, 102, pp. 160–168. Available at: https://doi.org/10.1016/j.techfore.2015.09.006.

Savastano, M. *et al.* (2016) '3-D Printing in the Spare Parts Supply Chain: An Explorative Study in the Automotive Industry', in *Lecture Notes in Information Systems and Organisation*. Available at: https://doi.org/10.1007/978-3-319-40265-9.

Savolainen, J. and Collan, M. (2020) 'How Additive Manufacturing Technology Changes Business Models? – Review of Literature', *Additive Manufacturing*, 32, p. 101070. Available at: https://doi.org/10.1016/j.addma.2020.101070.

Schmidt, G.M. and Druehl, C.T. (2008) 'When Is a Disruptive Innovation Disruptive?*', *Journal of Product Innovation Management*, 25(4), pp. 347–369. Available at: https://doi.org/10.1111/j.1540-5885.2008.00306.x.

Singamneni, S. *et al.* (2019) 'Additive Manufacturing for the Aircraft Industry: A Review', *Journal of Aeronautics & Aerospace Engineering*, 8(1). Available at: https://doi.org/10.35248/2168-9792.19.8.215.

Tang, Y., Kurtz, A. and Zhao, Y.F. (2015) 'Bidirectional Evolutionary Structural Optimization (BESO) based design method for lattice structure to be fabricated by additive manufacturing', *Computer-Aided Design*, 69, pp. 91–101. Available at: https://doi.org/10.1016/j.cad.2015.06.001.

Trauer, J. *et al.* (2020) 'What is a digital twin?–definitions and insights from an industrial case study in technical product development', in. *Proceedings of the design society: DESIGN conference*, Cambridge University Press, pp. 757–766.

Wang, Y.M. *et al.* (2018) 'Additively manufactured hierarchical stainless steels with high strength and ductility', *Nature materials*, 17(1), pp. 63–71.

Xiong, Y. *et al.* (2019) 'Data-Driven Design Space Exploration and Exploitation for Design for Additive Manufacturing', *Journal of Mechanical Design*, 141(10). Available at: https://doi.org/10.1115/1.4043587.

Yang, S. and Zhao, Y.F. (2015) 'Additive manufacturing-enabled design theory and methodology: a critical review', *The International Journal of Advanced Manufacturing Technology*, 80(1), pp. 327–342. Available at: https://doi.org/10.1007/s00170-015-6994-5.