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For Review

An Additive Manufacturing Process Model for Product Family Design

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Additive Manufacturing (AM) is projected to have a profound impact on mass customization. In order to benefit from this new technology, we need to incorporate AM into design processes. This paper addresses that need by introducing an AM process model for product family design. The proposed model reflects the ability of AM to produce customized and complex parts without tooling efforts. By utilizing AM, we eliminate all constraints which arise in conventional product family designs from finding a compromise between commonality and performance. The proposed model starts by identifying design requirements and constraints. In the second step, we use topology optimization to determine an optimal design for each product. Subsequently, Finite Element Analysis (FEA) and cost analysis are performed. The analysis results are interpolated such that they form both a performance and a cost graph. We combine these two graphs in one three dimensional plot, which displays the merits of the individual component realizations. Thus, a fair and competitive evaluation of the components is possible and the most suitable product family design can be selected. The final designs are fabricated using Fused Deposition Modeling (FDM). A case study is conducted to illustrate how the proposed model facilitates the benefits of AM. The results show that the model has the potential to provide affordable customization.

Keywords: Additive manufacturing; Product family design; Fused deposit modeling; Topology optimization; Finite element analysis

1. Introduction

During the decade from 1980 until 1990, competition in the global market place lead to the advancement of platform-based product families. The result of these advancements was a product family paradigm which introduced product proliferation while taking advantage of mass production efficiency (Pine and Davis 1999). Even today, many companies invest in product family development practices in order to provide sufficient variety to the market while maintaining the economies of scale and scope within their manufacturing capabilities (Robertson and Ulrich 1998). Conventional product family optimization focuses on exploiting the commonality between individual products (Moon *et al.* 2010). The fundamental assumption is that common components cost less than distinctive ones (Silva and Alves 2006). According to Kusiak (2002), process planning is a prerequisite for harvesting the benefits of product family design. A special focus is needed on keeping the production process as stable as possible (Zhang and Rodrigues 2009). In addition, process family planning requires complex considerations that take into account marketing information and manufacturing restrictions, such as limited resources existing on shop floors (Zhang *et al.* 2013). Thus, a fundamental issue in process family planning is the modelling of production processes (Lei *et al.* 2013b).

The production process describes routines, operations and manufacturing resources (e.g., machines, tools, fixtures and jigs) that are adopted to materialize a design (Zhang and Xu 2011). From the production process perspective, Additive Manufacturing (AM) is a manufacturing resource that produces shaped parts by gradual creation or addition of materials. The gradual creation method is fundamentally different from traditional forming and material removal manufacturing techniques (Kruth *et al.* 1998). A major benefit of AM is the ability to manufacture parts of virtually any geometric complexity without the need for tooling (Ponche *et al.* 2012). *The Economist* predicts that these beneficial properties have a profound impact on the way manufacturing businesses operate and indeed on how they generate revenue (Anon 2001). For product family design, AM is used to add value by customizing selected features (Hopkinson *et al.* 2006). Hague *et al.* (2004) predicted that AM will profoundly influence the product family production process. The new realities on the shop floor must be reflected in new or updated design concepts that incorporate AM based process models (Ponche *et al.* 2012, Mansour and Hague 2003). These concepts should exploit the flexibilities, offered by AM, in an optimal way (Yao *et al.* 2016). To achieve customization through AM requires an update or indeed an upgrade of the design methods, such that a practitioner can translate the flexibilities, available through the new manufacturing method, into tangible advantages in the global market place.

This paper addresses the need to model AM as part of a product family design process. We recognize that the unique properties of AM will fundamentally alter considerations about commonality, customization and ultimately profitability. We highlight the opportunities for AM based product family design to operate in a much broader design space that is free from constraints which arise in conventional product family designs from finding a compromise between commonality and performance. To translate the benefits of AM into customization and cost reduction, we propose a novel product family design model. The model allows practitioners to evaluate the performance of an infinite number of product designs and select the most suitable ones. To be specific, we used topology optimization and Finite Element Analysis (FEA) to generate a performance graph for individual component groups. This performance graph is combined with the result of a cost model. Therefore, we are in a position relate the manufacturing cost to the prod-

uct performance. Having established that relationship opens up the possibility for a fair competition between individual component realizations. A designer can exploit that competition and select the most suitable product family design. To verify the proposed model, a case study was conducted and the determined product family designs were fabricated with **AM**. The results of the case study confirm the fitnesses of the proposed model.

The rest of the paper is organized as follows: Section 2 reviews the product family design methods and state-of-the-art **AM** technologies. Section 3 introduces the methods which are used to realize the proposed process model. Section 4 introduces a case study with detailed results and discussion. The paper closes with conclusions, limitations of the study and suggestions for further work.

2. Literature Review

Many enterprises use product family design strategies to increase product customization and reduce time-to-market while keeping the cost under control. The design of platforms, within a product family, enables manufacturers to maintain the economic benefits of having common parts and processes (reduced system complexity, reduced development time and costs) while still being able to offer variety to customers (Moon *et al.* 2010). Thevenot and Simpson (2006) developed a product variety trade-off evaluation method to help designers resolve the trade-off between platform commonality and individual product performance. Jiao and Tseng (1999) developed a product family architecture model to handle the trade-offs between diverse customer requirements, design reusability and process capabilities. Lei and Moon (2015) introduced a system that utilizes advanced data mining and machine learning techniques, to provide designers with a objective decision support at the beginning of the product family design stage. Williams *et al.* (2007) proposed an optimization-based platform design approach, called the augmented product platform constructal theory method. The proposed method enables designers to systematically manage modularity and commonality in the design of both product and process platforms. Common to all the research is the realization that a successful product platform must balance the component performance the commonality of individual products in the family. However, performance and commonality are two conflicting objectives. A shared platform, for all products in the family, means to compromise on either component performance or communality. Furthermore, product variety induced manufacturing complexity has become a significant problem (Wang *et al.* 2011). Offering affordable customization is the most demanding challenge that enterprises face when they follow the product family design paradigm. The majority of product family design literature focuses on methodologies that optimize processes in a traditional manufacturing technology context. However, new technologies, especially new manufacturing technologies, can be game changers. Porter (1985) was among the first researchers who realized the transformational power of technology. In his influential work on competitive strategy, he suggested that technology is the most important single source of major market share changes among competitors and it can lead to the demise of an entrenched dominant firm.

With the unique capabilities for fabricating components with high complexity in shape, function, and material, **AM** technologies have greatly increased the design freedom in product development (Gibson *et al.* 2010). Over the past two decades, the research community has developed novel **AM** processes and applied them in aerospace (Thomas *et al.* 1996, Moon *et al.* 2014), automotive (Ding *et al.* 2004) and biomedical (Rengier *et al.* 2010) fields. These **AM** processes and applications differ from each other in terms of

properties, such as stock material types, material bonding mechanisms, dimensional accuracies and post-processing requirements (Robertson and Ulrich 1998). The differences open up a wide range of options for product designers. As a consequence, Rosen (2007) put forward that in order to take advantage of these unique technologies, we have to re-think Design for Manufacturing (DFM). Gibson *et al.* (2010) defined the goals of Design for Additive Manufacturing (DFAM) as “maximize product performance through the synthesis of shapes, sizes, hierarchical structures, and material compositions, subject to the capability of AM technologies”. This sparked lots of research and design studies related to AM. For example, Hague *et al.* (2004) studied and summarized design rules for Stereolithography (SLA) and Selective Laser Sintering (SLS), based on DFM guidelines for injection molding. They found that some DFM rules for injection molding are not applicable to AM. In other words, AM overcomes many limitations of conventional manufacturing processes. Su *et al.* (2013) suggested a set of design guidelines of non-assembly mechanism built in one piece using Selective Laser Melting (SLM). Bin Maidin *et al.* (2012) constructed a design feature database for AM, which enabled users to visualize and gather information during the conceptual design stage. Ko *et al.* (2015) proposed a design for AM-facilitated personalisation method to identify the interrelations between AM constraints, user’s desire and product’s customised features. Xu *et al.* (2001) developed generic models that help designers to select the most suitable AM process for a specific part creation. As the capabilities of AM techniques increase, it is easier to realize optimized design approaches, such as topology optimization. In many cases, designs based on topology optimization, although optimal, may be impossible to manufacture, because the possibility for producing such parts in additive ways has not been available in the past. In recent years, topology optimization has emerged as a promising approach to utilize the benefits of this manufacturing tool (Lei *et al.* 2013a). For example, Rezaie *et al.* (2013) developed a methodology that conceptualizes the use of topology optimization for designing parts, which are built by Fused Deposition Modeling (FDM). The risen grade of design freedom of AM facilitates a more radical implementation of topology optimization into the design process and allows completely new approaches for designing functional parts. It is therefore possible and even necessary to incorporate AM directly into the product family design process. However, most research analysed singular part designs, with a special focus on geometric design freedom and limitations. There is few study that investigates how AM and product family design could benefit from each other, so as to achieve affordable customization. A key assumption in product family design is that increased standardization leads to reduced cost, while increased variety requires significant cost increases. This assumption is no longer valid when AM is used to manufacture components in the product family.

The present study attempts to achieve both economic and performance advantages by introducing an AM based process model for product family design. With the beneficial properties of AM, changes to product family variant geometries, be they subtle or substantial, may be introduced without the penalty of additional delays and costs due to tooling. This reduces the development cost significantly. The objective of this study is to provide affordable customization without compromising individual product performances. The advantages of AM have prompted us to consider mass individualization instead of mass customization and these thoughts crystallized in a new product family design paradigm.

3. An AM Process Model for Product Family Design

This section introduces an **AM** process model for product family design, along with the formulation for a scalable product family design problem. **AM** is used for mechanical part fabrication. Figure 1 shows a block diagram of the proposed model. The model starts by defining the primary requirements and constraints that will define the product family. In the second step, topology optimization is used to generate optimized individual designs which completely utilize the design freedom provided by **AM**. In a subsequent step, both performance and cost measures are investigated. **FEA** is employed to verify the fulfilment of the performance requirements. The **AM** cost analysis allows us to identify potential commonalities in order to reduce the product family development cost further. Once the requirements are fulfilled and the cost is further reduced, a customized product family is established. **AM** is used to realize the customized designs and mechanical verification is carried out. The test results are compared with **FEA** simulation results.

[Figure 1 about here.]

3.1. Product Family Design

The proposed model incorporates **AM** technologies into the design of a scalable product family. The idea of the scalable product family is that the platform is adjustable by changing values of dimensions or other parameters to adjust the sizes of components in the platform. This is in contrast to modular product families or platforms where modules are swapped in order to generate variety.

The processes basis is the identification of the product family design requirements and constraints, which have to be met to fulfill the product functionalities.

3.2. Topology Optimization for Additive Manufacturing

Topology optimization solves material distribution problems by generating optimal topologies, for a given set of requirements and constraints. Topology optimization algorithms distribute finite elements of material within a predefined space, so that boundary conditions, posed by loads and supports, are satisfied (Papalambros 2002). In most cases, each finite element, within the design domain, is defined as a variable (Bendsøe and Sigmund 2003). These design variables model a variation in density within the design domain. In general, these variables have values in the range from 0 to 1, where 0 indicates void and 1 indicates solid (Huang and Xie 2010). Using topology optimization, a designer can quickly and easily determine the most efficient material usage in order to create an optimized design that is strong, lightweight, and with minimal material usage. With the beneficial properties of **AM**, the optimized design can be realized.

In this study, topology optimization was performed individually for all variants in a product family. Mathematically, the family design problem with q products can be formulated as follows:

$$\begin{aligned} \min_{\mathbf{p}_i} c(\mathbf{p}_i) &= \sum_{e=1}^N (p_{i,e})^\alpha \mathbf{u}^T K \mathbf{u} \quad \text{for } i = 1, \dots, q \\ \text{s.t.} \quad &v(\mathbf{p}_i)/v_0 = m, \\ &K \mathbf{u} = \mathbf{f}, \\ &\mathbf{0} < \mathbf{p}_{\min} \leq \mathbf{p} \leq \mathbf{1}. \end{aligned} \tag{1}$$

where c is the compliance function, $\mathbf{u}$ and $\mathbf{f}$ are the global displacement and force vectors, respectively, K is the global stiffness matrix, $\mathbf{p}$ is the vector of design variables, $\mathbf{p}_{\min}$ is a vector of minimum relative densities (non-zero to avoid singularity), N is the number of elements used to discretize the design domain, α is the penalization power, $v(\mathbf{p})$ and v_0 are the material volume and design domain volume, respectively and m is the prescribed volume fraction.

We use the Solid Isotropic Material with Penalization (SIMP) optimization method which was originally proposed by (Bendsøe 1989). A compact Matlab implementation of the topology optimization was done in 99 lines of Matlab code (Sigmund 2001). The topology optimization algorithm yields a matrix O , for each of the different force requirements. The matrix entries define the amount of material at a specific element location. For example, $o_{80,10} = 0.5$ indicates that the element at location $x = 80$ and $y = 10$ has 50% material. The optimization algorithm stops when the change in material is less than a prescribed tolerance, for example 0.01%.

For our case study, we formulate and solve a 2D problem. We recognize that commercial software, such as Altair OptiStruct®, can perform topology optimization in 3D. However, for the prove of concept, 2D Finite Element Method (FEM) modelling is sufficient. The topology optimization step produces 2D matrices that represent a slice of the 3D component. The 2D to 3D conversion step extrapolates these slices to form 3D objects. This extrapolation is done with a Matlab routine which stacks N slices on top of each other. The resulting `stl` files are input to a FEA program and an AM file definition program.

3.3. Finite Element Analysis and Cost Analysis

This section investigates both mechanical performance and cost of the components. These two measures are often used to assess the product family design. In our work, we measured the component performance as deflection in the direction of a force, because it is a common measure to reveal whether or not a particular component is suitable for a specific application. If the chosen design does not meet the deflection requirements an iterative redesign process takes place which aims to improve the structure until it is suitable.

The generated structures were split into finite elements in order to quantify the deflection performance. The FEA starts with volume meshing. We use Gmsh to establish the interior volume of the component (Geuzaine and Remacle 2009). Calculix is used to define the boundary conditions and for FEA solving as well as result analysis (Dhondt 2004, Wittig 2011).

The product manufacturing time and cost are measures of resource consumption associated with each variant in the product family (Williams *et al.* 2006). The costs for producing parts with AM processes can be broken down into four categories: (a) machine purchase, (b) machine operation, (c) material costs, (d) labor costs (Gibson *et al.* 2010). The cost model can be expressed with the following formula:

$$C = C_{\text{machine}} + C_{\text{operation}} \times T + C_{\text{material}} \times M + C_{\text{labor}} \quad (2)$$

where C_{machine} is the machine purchase cost which is allocated to the build, C_{material} is material cost per kg, M is the total mass of the material used, $C_{\text{operation}}$ is the machine operation cost, T is the manufacturing time, C_{labor} is the labor cost for both preparing the build as well as the post-processing.

The time required to fabricate the parts is an important factor which influences the operation cost. The manufacturing time per build can be expressed as the sum of pre-

processing and printing time. The total manufacturing time t is calculated as:

$$T = T_{\text{setup}} + T_{\text{preheat}} + T_{\text{buildtime}} \quad (3)$$

where T_{setup} is the machine setup time, T_{preheat} is the preheat time, $T_{\text{buildtime}}$ is the build time. $T_{\text{buildtime}} = \sum_{j=1}^n t_j$, where t_j is the time to build the j^{th} layer and n is the total number of layers used to build the parts.

The values of T_{setup} and T_{preheat} depend on the machine preparation time of a specific **AM** printer. Hence, these time measures are largely independent of the particular component design. Therefore, n and t_j are the two main contributing factors for the difference in manufacturing time across variants in the product family.

After the deflection and cost analysis for all products in the product family, we display the results in a deflection graph and a cost graph, such that they represent the deflection and the cost in the entire design space. The interpolated graphs are combined in a three dimensional plot. This combination opens up a fair competition between individual component realizations and the most suitable product family design can be selected.

3.4. Customized Product Family

Based on the **FEA** performance graph, the designers can choose the individual designs that fulfill the specific design requirements. The cost graph helps to identify potential commonalities that we can exploit in order to reduce the product family development cost further. The final designs will be chosen based on three criteria: (1) meet the design requirements, (2) comply with the **DFAM** rules, (3) achieve maximum customization without rising manufacturing cost.

The next section introduces the case study to illustrate the proposed **AM** process model for product family design.

4. Case Study

Section 3 introduced a model that helps practitioners to realize the topology optimized product family design directly via **AM**. To evaluate this model, we created a product family design problem and subsequently solved it with the **AM** process model. **FDM** was used to fabricate the physical parts. Once the parts were manufactured, their mechanical deflection were tested. The testing results were compared with the **FEA** results.

4.1. Product Family Optimization

The product family consists of ten components. These components take the form of $v_0 = 100 \times 20 \times 20 \text{ mm}^3$ cantilever beams. All beams are fixed at one end, and a static force of 10 N is applied at the opposite end. Figure 2 shows both boundary and load conditions. According to the product family design requirements and constraints, these 10 cantilever beams need be designed such that each beam has 10%, 20%, ..., 100% material respectively. The objective is to minimize the cost for up to 10 distinct components. The compliance optimization problem for the family of cantilever beams can be expressed as:

$$\begin{aligned}
\min_{\mathbf{p}_i} \quad & c(\mathbf{p}_i) = \sum_{e=1}^N (p_{i,e})^\alpha \mathbf{u}^T K \mathbf{u} \text{ for } i = 1, \dots, 10 \\
\text{s.t.} \quad & v(\mathbf{p}_i)/v_0 = m, \text{ for } m \times 100\% = 10\%, 20\%, \dots, 100\% \\
& K \mathbf{u} = \mathbf{f}, \text{ for } |\mathbf{f}| = 10 \text{ N} \\
& \mathbf{0} < \mathbf{p}_{\min} \leq \mathbf{p} \leq \mathbf{1}.
\end{aligned} \tag{4}$$

[Figure 2 about here.]

We used topology optimization to produce structures for 10%, 20%, ..., 100% material. The optimization problem, defined in Equation 4, was solved using the so called standard optimality criteria method (Bendsøe and Sigmund 2003). Figure 3 shows the result of the optimization step. An approximately linear graph can be observed which relates the ten samples to the amount of material used. The five objects above the graph indicate the results of the topology optimization step for 20%, 40%, 60%, 80% and 100% material respectively. As part of the case study, we simulated ten different beams with different amounts of material. As for the graph in Figure 3, these beams are mere samples, indicated by black dots, on the linear graph.

[Figure 3 about here.]

The topology optimization results must comply with FDM related design rules such as the minimum wall thickness. FDM is an AM process that deposits thermoplastic polymer filaments in a layer-by-layer manner. The main advantages of FDM technology are the fabrication of low cost parts, water dissolvable support structures and the possibility of coating the surface to improve its quality. For this case study, a Panowin F321 FDM printer was used to manufacture a family of cantilever beams (As of August 30, 2015, the Panowin F321 printer listed on website <http://panowin.com>). The feedstock material was Polylactic Acid (PLA) which is bio-degradable and widely used in FDM machines (Drumright et al. 2000).

The first noteworthy observation is that the topology optimized 3D model for Beam 1, having 10% material, had a very thin wall. The wall thickness was smaller than the minimum wall thickness that could be manufactured with the selected FDM printer. As a consequence, we had to adjust the product family design requirements. Conceptually, we followed the block diagram shown in Figure 1. The requirements check failed, i.e. it is impossible to manufacture a beam with only 10% material. Therefore, we had to go back and draw up new product family design requirements and constraints. Our solution to the 10% problem was to change the constraints such that beams with 20%, 30%, ..., 100% material are required.

4.2. Finite Element and Cost Analysis

From the resulting Beams 2 to 10, we conducted FEA analysis. The FEA analysis assumed linear elastic behavior of the structures and we utilized the following PLA material properties from the literature: Young Modulus of 5619 MPa and Poisson's ratio of 0.36. We analyzed the deflection in the direction of the applied force for each beam. The predefined static force was 10 N. For all tested beams, that force was not sufficient to cause plastic deformation. Hence, all tests were carried out within the elastic range of the beams.

Table 1 shows deflection results of the nine Beams. These nine results are interpolated to the deflection graph, such that it represents the deflection for any amount of material,

subjected to a static force of 10 N. This interpolation is shown as a solid line in Figure 4. The deflection behaved according to expectations. For example, we found that Beam 2 with 20% of v_0 shows a maximum deflection of 0.2976 mm and Beam 10 with 100% of v_0 shows the least deflection of 0.1 mm. There is an inverse relationship between the material used and the deflection. To be specific, more material used implies less deflection. However, as the material volume went up to 70 %, Beams 8 to 10 showed very similar deflection. Which means the increase in material use did not contribute to the performances.

[Table 1 about here.]

[Figure 4 about here.]

For the **AM** cost analysis, we focused on the relative cost between product variants. The machine purchase cost was not taken into account. We assumed that the labor cost for both build preparation and post-processing is about the same for all variants in a product family. Hence, machine operation and material costs played a major role for the overall **FDM** production cost. The **PLA** price was 300\$ per kg. From the simulation, the beam volumes are known, therefore, the material cost can be calculated. T_{setup} and T_{preheat} in Equation 3 are approximately 4 and 5 minutes respectively. The build time $T_{\text{buildtime}}$ is influenced by both the material volume and the scanning patterns. Rapid changes of the **FDM** extrusion head direction can make it difficult to control the material flow. Therefore, the outlines are drawn to represent the external feature of the part and they are built using a slower plotting speed. The internal fill pattern can be built more rapidly, since the outline represents the external features of the part that corresponds to geometric precision. With the same geometric complexity, the cost increases linearly with the material increase, which the machine cost closely relates to the geometric complexity for **FDM**. The more complex the geometry, the higher the machine operation cost.

The build time $T_{\text{buildtime}}$ was obtained from the open source software Cura¹. Table 1 lists the estimated build time and the product family component costs. The costs for Beams 2 to 10 were interpolated to cost graph that is shown as a dashed line in Figure 4. We observed that Beams 2 to 8 form a totally ordered set in terms of build time and cost. Mathematically, the totally ordered relationship between the Beam build times is modelled as

$$T_i < T_k, \text{ for } i < k \text{ and } i, k \in \{2, 3, \dots, 8\} \quad (5)$$

For the beam cost follows

$$C_i < C_k, \text{ for } i < k \text{ and } i, k \in \{2, 3, \dots, 8\} \quad (6)$$

However, both build time and cost for Beams 9 and 10 decreased, despite the fact that both beams have more material than Beam 8.

Beams 9 and 10 break the totally ordered set, because they have a lower geometric complexity. We establish the geometric complexity through visual inspection of the beam topology. Analysing the topology yields three distinct beam groups: $A = \{2, 3, 4\}$, $B = \{5, 6, 7, 8\}$ and $C = \{9, 10\}$, where the numbers refer to the beams. The beams within a group have a similar geometric complexity and beams in different groups have a different

¹<http://software.ultimaker.com>

geometric complexity. Group *A* is formed by Beams 2 to 4, because these beams are composed from five interconnected triangles. All beams in group *B* have a leading triangle followed by six or more triangles. The complexity of group *B* is higher than *A*, because there are more triangles and hence the outline of the shape is longer. For **FDM**, the complexity increase results in a longer scanning length and frequent direction changes of the extrusion head. The two beams in group *C* have the lowest geometric complexity. The difference in geometric complexity is especially prominent when the elements of group *C* are compared to Beam 8, because that beam has the highest geometric complexity and 80% material. To be specific, the difference in geometric complexity and the associated difference in scanning length explains the decrease in both build time and cost for Beams 9 and 10.

The above discussion was based on the **FDM** process. For different **AM** processes, the cost profiles differ. For example, in 3D printing, the bulk of each printed layer, regardless of complexity, is deposited by the same and rapid spreading process. Therefore the build time will be a constant for Beams 1 to 10.

4.3. Customization of the Cantilever Beam Product Family

The results from the previous step indicated that, though **AM** offers freedom of design, it does not always offer complexity for free. Specifically, for processes, such as jetting-based systems, the “complexity is free” statement is true; conversely it is not correct for extrusion-based systems (Gibson *et al.* 2010), such as **FDM**. The build times are higher for complex shapes than for simple shapes since the laser-based processes have to trace out the the cross section profile with laser beams.

Following the updated design requirements, Beams 1 and 2 share the same design (20% v_0) to comply with **DFAM** restriction of minimum wall thickness, Beams 3, 4, 5, 6, 7 each have distinct optimal designs that offer the individualization, Beams 8, 9 and 10 share the same design (100% v_0) to reduce the product family cost further without compromising the deflection performance.

4.4. Beam Fabrication and Mechanical Verification

A key hypotheses of **FDM** is that virtually all layered processes can deposit material in the horizontal plane much more rapidly than they can build up thickness. Therefore, we built all parts lying down so that their shortest overall dimension was oriented along the z -axis. All manufactured samples have the same horizontal built orientation, with the flat side surface touching the build platform. The main advantage of this build orientation was that no support structure was needed. The process parameters for all samples were identical and they are listed in Table 2.

[Table 2 about here.]

[Figure 5 about here.]

For the manufactured samples, the deflection measurements were performed with a dial test indicator having a scale interval of 0.01 mm. The boundary and load conditions for all samples were identical. Figure 2 depicts the measurement setup. One end of the beam was fixed with a clamp and a 10 N load was applied to the other end. The maximum deflection at the load point was measured and compared to the **FEA** results.

From the material provider, **PLA** has a Poisson ratio of 0.36 and the Young's modulus ranges from 310 MPa to 5619 MPa. Therefore, each of the **FEA** based deflection simulation for the Beams 2 to 10 yields two results, one for the maximum and the other for the minimum of the Young's modulus. Figure 6 shows the elastic properties of the samples as the deflection over the beam number, which reflects the material used. The upper curve are the **FEA** results when the lowest Young's modulus was assumed. The lowest curve indicates the **FEA** simulation results when the highest Young's modulus was assumed. The curve in-between indicates the mechanical testing results.

[Figure 6 about here.]

The actual maximum deflections of the fabricated samples fell between the two **FEA** curves, which correspond to the maximum and minimum Young's modulus values. All three curves, shown in Figure 6, indicate the same trend: the product variants with less material have a larger deflection for the 10 N load. Comparing the results indicates that **FEA** provides relevant information about the mechanical characteristics of a product family early in the design stage. A detailed analysis of the graphs shown in Figure 6 reveals that Beam 7 has a slight increment in its maximum deflection compared to Beam 6, which contradicts the **FEA** result. Such disagreement may be caused by noise in either the manufacturing process or in the deflection measurement process. However, the disagreement was small, therefore it did not affect decisions based on the **FEA** models.

5. Conclusion

In this paper, we proposed an **AM** process model for product family design based on topology optimization and **FEA**. We put forward that topology optimization provides optimal customized designs that can benefit from advanced **AM** technologies. To substantiate and discuss the proposed model, we introduced a case study design for a family of 10 cantilever beams. These beams shared the same design space, but they had different load and weight requirements. Based on these requirements, the beam realization was broken down to a material distribution problem, which was solved with topology optimization. The optimization process resolved the geometry and the structural response when the amount of beam material was restricted, such that the optimized designs could be realized with **FDM**. The beam performance and the cost measures were investigated. The combination of the performance cost graph helped identify the final product family designs. The successful sample fabrication and the mechanical test validated the proposed model.

Compared to existing methods of product family design, which find a compromise between performance and cost, the proposed model increased product customization by introducing **AM** resources. We interpolated the performance and cost in the 3 dimensional space. The resulting graph provided a visual aid for designers, enabling them to reach informed decisions regarding the specific customized product family design criteria. In the case study, ten beams with same load condition were evaluated. We found that the cost saving did not necessarily compromise performance as Beams 8 to 10 share the same design.

A limitation of the proposed model comes from the assumptions made when we incorporated **AM** into the product family design process. Both guidelines and criteria for the selection of either **AM** or traditional manufacturing technologies for part realization are needed in the research community. The case study illustrated a simple cantilever beam

product family design. During the **FDM** process, we arranged the part orientation in such a way that no support structures were needed. However, in general such support structures are necessary when using **FDM** to manufacture a part with floating overhangs. The presence of support structures increases both production time and cost. Thus, more sophisticated product family design problems need to be formulated in order to improve the proposed model. As for the cost analysis, we considered only one component per build. If we considered efficient parallel production of a mixed family of products, then the **AM** induced cost saving would be even more significant.

We predict that the importance of the **AM** resources will rise as the production costs decrease. Therefore, it will become more and more important to harvest the benefits of this production process in an optimal way. Modeling is a first step to address that problem, because it allows us to conduct ‘what if’ analysis and to extrapolate results. Both considerations are of eminent importance to change the paradigm for truly individualization in product family development.

Acronyms

AM	Additive Manufacturing
DFAM	Design for Additive Manufacturing
DFM	Design for Manufacturing
FDM	Fused Deposition Modeling
FEA	Finite Element Analysis
FEM	Finite Element Method
PLA	Polylactic Acid
SLA	Stereolithography
SLS	Selective Laser Sintering
SLM	Selective Laser Melting
SIMP	Solid Isotropic Material with Penalization

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Figure 1. Block diagram of the proposed AM model for product family design.

Figure 2. Boundary and load (10 N) condition for cantilever Beam 6 with 60% material.

Figure 3. Module dependent material use.

Figure 4. Deflection and cost for the family of cantilever beams.

Figure 5. Beams 2 to 10 realized by **AM**.

Figure 6. Elastic properties of the samples calculated from the FEA versus sample measurement.

Table 1. Deflection and cost

Beam No.	2	3	4	5	6	7	8	9	10
Material	20%	30%	40%	50%	60%	70%	80%	90%	100%
Deflection (mm)	0.297	0.194	0.152	0.129	0.116	0.108	0.103	0.102	0.100
Mass (g)	4.8	7.2	9.6	12	14.4	16.8	19.2	21.6	24
Build time (min)	59	74	86	99	111	121	128	124	123
Cost (\$)	33.04	39.76	45.28	51.2	56.72	61.44	64.96	64.08	64.4

Table 2. **FDM** process parameters

Layer thickness (mm)	Fill density (%)	Print speed (mm/s)	Track width (mm)	Nozzle temperature (°C)	Platform temperature (°C)	Support type
0.1	100	80	0.4	210	55	None