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Generative Design and new designers' role in the manufacturing industry

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Abstract

Generative Design is a powerful tool allowing to fully exploit Additive Manufacturing potential. Topology Optimization, already established approach, requires an initial shape where material is removed until the desired result is reached. Generative Design presents a more complex approach, receiving several inputs such as objective, constraints, material and manufacturing technique used, it proposes a series of possible outcomes. Designer's role moves from creating the component shape from scratches to choose the best fitting option for the specific application. Using a reference case study, a plausible framework, describing how to properly select the final model, is investigated.

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Keywords: Additive Manufacturing; Generative Design; Outcome Selection; Computer Aided Engineering

1. Introduction

Today Additive Manufacturing (AM) is experiencing a growth in popularity in almost every manufacturing field. AM offers the possibility of creating components with a significant degree of geometrical complexity without the need of bespoke tools, transforming the whole component value chain. ASTM F42 committee, demanded to follow the standardization of this technology, defines AM as "*Computer-aided design to build objects layer by layer. This contrasts with traditional manufacturing, which cuts, drills, and grinds away unwanted excess from a solid piece of material, often metal*" [1].

Metal additive manufacturing has the potentiality of being a key element of Industry 4.0 thanks to its flexibility and efficiency [2]. Nowadays few sectors lead the growth of AM market, such as the aeronautical, automotive, and medical ones. The former aiming to obtain more efficient components, with a lower buy-to-fly ratio, i.e. a lower material waste during part realization, the latter due to the high degree of customization allowed by process flexibility itself [3]. Process constraints have been forcing designers to adapt their components, sacrificing design optimality. The difficulty of obtaining undercuts while casting a part, or side holes while forming it, seem to belong to the past. These new processes easily overcome most of well-known manufacturing constraints, characteristics of the procedure involved [4]. Being set free from widespread constraints, designers must face new and more uncertain limits. Hence, the already existent knowhow, related to conventional processes, is not suitable for AM. Design for Additive Manufacturing (DfAM) is the natural evolution of Design for Manufacturing and Assembly (DfMA), since it collects all the major rules necessary to exploit AM processes [5]. New supporting software tools have been created accordingly, helping to correctly explore a wider solutions space of existence.

Generative Design (GD) is one of the upcoming design tools allowing to increase the value of AM components. GD simulations accept inputs, divided into constraints and objectives, and through the use of growth algorithms propose different possible geometries. Whenever a GD simulation is performed, several outcomes are proposed by the software, offering the variety of choice which makes GD dramatically useful. The key role of GD has been suggested by several studies in the last decade. Krish [6] stated, already in 2010, that the main objective of GD is to help engineers exploring a larger range of initial possible designs than usual practice. More recently, several studies have shown how to take advantage of GD simulations to produce leaner, more robust and betterlooking components. Maricic *et al.* [7] rethought the frame of a drone, decreasing its mass from 705 g to 586 g (around 17% mass reduction), consequentially increasing the take-off mass. Similarly, Bright *et al.* [8] obtained two alternative drone frames, weighing only 227 g and 267 g from an original burden of 330 g (respectively 31% and 19% mass reduction). Moreover, Pomazan and Sintea [9] in their study applied GD simulation to re-design the base of a lifting arm, achieving a final mass of 417 g (27% mass reduction). Finally, Hyunjin [10] underlined the importance of GD and Artificial intelligence (AI) in the manufacture of tomorrow, and claimed the lack of studies applying GD to the manufacturing environment.

To the author's knowledge, the problem of how to choose between the multiple GD outcomes is not addressed. More work needs to be done not to leave this last and sensitive operation completely without guide. Considering the high number of models, the designer is working with at this stage of the process, some meaningful results could be overlooked, reducing the effectiveness of the work. In this paper an innovative outcome selection framework is proposed and validated, based on the analysis of a case study taken from the aeronautical field.

2. Methodology

The proposed GD workflow is depicted in Fig. 1. The first task is the creation of an initial 3D CAD model based on the maximum envelope and the part requirements (i.e. hole locations, mating features, etc.). Any GD simulation requires several inputs, such as component materials, applied loads, and geometrical constraints. Some software packages are also able to take into account manufacturing techniques, embodying technologies constraints inside the simulation. This way, starting from the same set of constraints, designers can achieve different geometries according to the manufacturing process to be used later. Moreover, every simulation needs an objective to be provided in the setup phase, commonly either mass minimization or stiffness improvement. In this second case, both minimum mechanical performances and part weight should be defined into the software. At this stage, the simulation can be launched, trying to solve the optimization problem yet introduced. Genetic algorithms try to sculpt valid options, in the starting domain, proposing several possible geometries, whose number mainly varies according to the list of materials and manufacturing processes selected.

The process of outcome selection is one of the most critical points of the chart, if not strictly applied, it could lead to leaving out the most interesting outcomes, precluding the designer to get the best fitting solution. It is easily understandable that defining a unique algorithm, valid in all engineering fields, is a trivial task since many variables have different influence in different fields. Once the minimum requirements are satisfied, mechanical performances, such as mass and stiffness, improve inversely with respect to the cost of the component. Weights attributed to these parameters change accordingly to the field and to the specific application. It is important to point out the key aspect of defining the weight of different parameters beforehand, for the sake of making an aware choice of the outcome. Outcomes are then sorted according to weights and criteria, finally the first one is selected for further investigation.

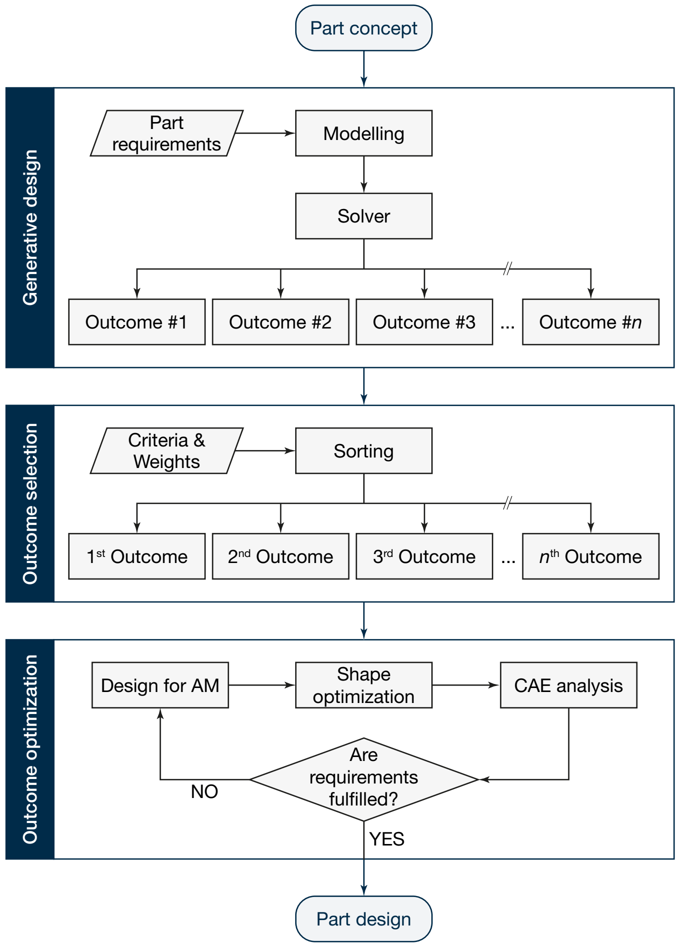

Fig. 1. Generative Design workflow.

After this selection phase, the chosen outcome is then further processed to apply design rules for AM and optimize the shape of the part, at the same time CAE analyses are performed to verify the requirement on the modified geometry. Thus, an iterative phase should be always present, allowing the software to rework the same volume to sculpt a better geometry, either with a lower mass or a better distribution thereof.

3. Case study

A real case scenario was selected to prove the feasibility of the proposed methodology: an existing aeronautical component was redesigned for AM, to improve its mechanical performances. The assembly to be redesigned is part of the tail landing gear of an ultralight single-seater aircraft, Fig. 2, the Zigolo MG12 by Aviad, made of several parts joined through bolted connections. Fusion 360, commercial software by Autodesk, was used as GD design tool. From a designer perspective, it is common in the industrial practice, not to have access to unlimited different software packages [11]. Hence, design activity should take place in the lowest possible number of programs. Fusion 360 allows designers to perform their whole activity, offering different environments according to their specific needs. *Design environment* was used to translate

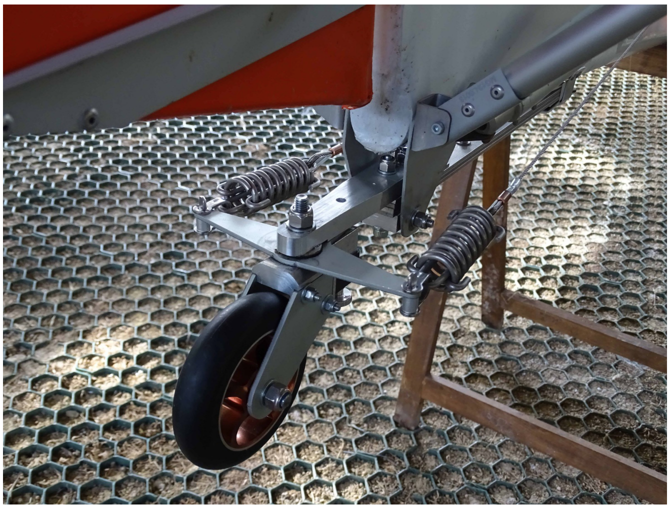

Fig. 2. Original assembly as provided by Aviad (overall dimensions:72 × 41 × 70 mm³).

the technical drawings, provided by the customer, into a 3D CAD model, *Simulation environment* for static simulations and *Generative Design* for GD simulations. Simulation constraints were imposed by Aviad itself, requiring a minimum Safety Factor (SF) of 1.5 and a lower mass than the original one. The production process considered for the realization of the component is laser powder bed fusion (L-PBF). It is chosen since it is economically suitable for small production batches, allows relatively small features, and ensures a good surface finishing, if compared to other AM processes [12]. Moreover, since the original alloy of the assembly, Al2020, is not suitable for AM processes [13], the material exploited in this study is EOS Aluminum AlSi10Mg, common alloy in AM field, especially in the aeronautic field [14]. AlSi10Mg has a high strength to weight ratio, with a good thermal conductivity and corrosion resistance, making it a perfect material for similar aeronautical applications [15].

The assembly was constrained as close as possible to the real case, and after loads were applied, taking advantage of the Finite Element Method (FEM), it was analyzed in a linear static case, trying to detect its most critical issues. Three load cases were considered (Table 1), landing, right steering, and left steering, supposed not to occur at the same time. The two steering cases had the same intensity but opposite directions.

The volume standing for the original assembly is divided between *Preserve Geometry*, accounting for the volumes GD will not change, such as connections with other components or assemblies; *Obstacle geometry* accounting for the part of working volume the software will not add material into; and *Starting Shape*, which is optional, helping Fusion 360 to connect different elements of *Preserve Geometry* one another by reminding Fusion of the original shape of the assembly. In this specific case, *Starting Shape* was introduced due to the complexity of setup. These three different volumes, as represented in Fusion 360, are reported in Fig. 3, interpenetrating volumes, i.e. *Starting Shape* and *Preserve Geometry*, do not represent a problem. Once the domain is defined by all these constraints, the objective of the simulation is defined the same way, leading to either mass reduction or stiffness improvement. In this paper, simulations were performed aiming to reduce components mass. The most compelling requirements to satisfy is the minimum SF of 1.5, as required by Aviad.

Table 1. Load Cases, z-axis vertically oriented, y-axis along the longitudinal direction of the plane.

Load case	Intensity (N)	Direction
Landing	1069	z
Steering	854	±x

After GD simulation were run, outcome selection phase took place. In order to make a conscious choice about proposed geometries, parameters to judge and relative weights must be made clear before the selection itself. Three parameters have been considered during the outcome-selection phase: component's weight, cost and component maximum displacement. Outcomes were ordered according to these three criteria, and a ranking system for their evaluation proposed. For each single criterion, i.e. mass reduction, maximum displacement and cost, every outcome received a score computed as in Eq. 1:

$$\text{Score }(i) = \frac{x_{\max} - x_i}{x_{\max} - x_{\min}} \cdot (r-1) + 1 \qquad (1)$$

where x_i is the value of the considered parameter for the *i*-th outcome, x_{max} and x_{min} are the maximum and minimum values, respectively, of all the outcomes and r is the maximum score ascribable to the criterion. In this work r is equal to 6.

Each score is then multiplied for the corresponding weight. Mass is weighted one, while cost and displacement 0.5. This difference was chosen to remark the importance of mass reduction above all parameters.

Costs are computed thanks to the contribution provided by aPriori, tool specialized in simulation-driven cost estimation. Starting from a generic batch, aPriori returns two costs, the Piece Part Cost, and the Finally Burden Cost, adding to the first one also fixed costs such as tooling, fixtures, and programming. Aiming to give an accurate estimation, aPriori refers to manufacturing related data distinguishing between nine geographical areas, which strongly influence both raw materials and labor costs. Both Piece Part Cost and Finally Burden Cost are supplied in a possible range, providing lower and higher

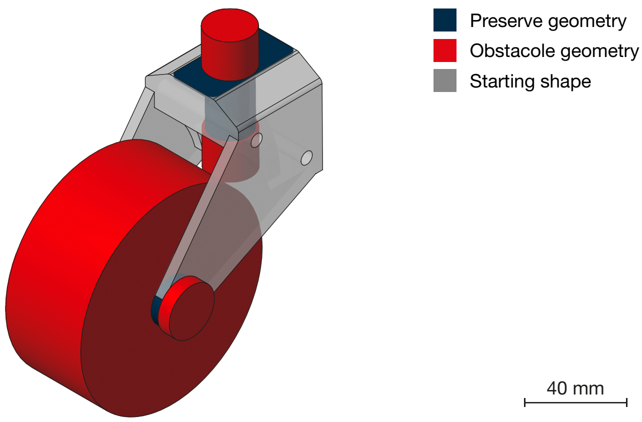

Fig. 3. Three-dimensional CAD model representing *Preserve Geometry*, *Obstacle Geometry* and *Starting Shape*.

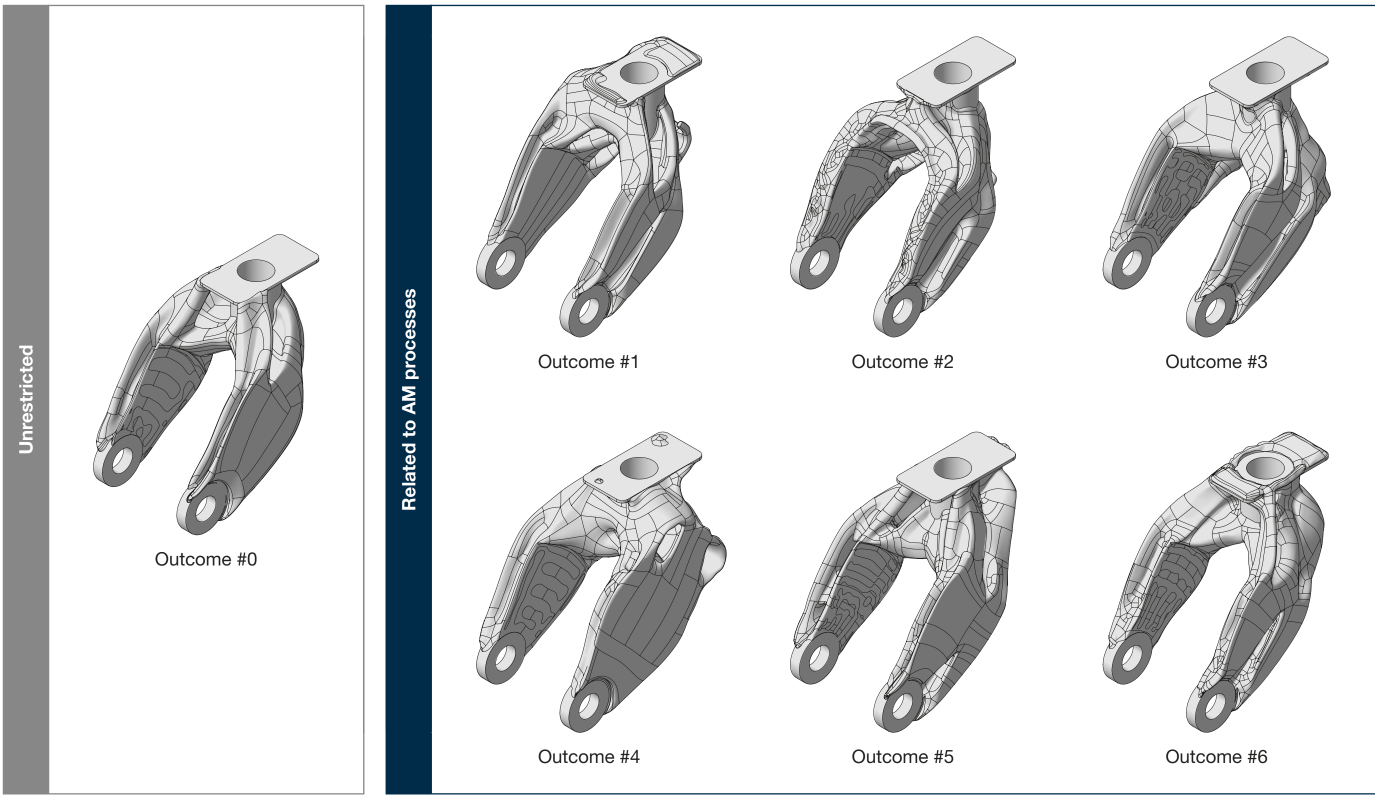

Fig. 4. Outcomes resulted from the simulations, one unrestricted and six related to AM processes.

extremes, and by the median value. The median finally burden cost is the one considered during the comparison and outcome selection phase over a production batch of fifty components. Total scores were obtained summing weighted scores ad outcomes were accordingly ordered. The outcome scoring the highest total was selected for further elaborations to respect design rules, always in Fusion 360. This process was performed iteratively, aiming to refine the result by letting the software rework the same geometry. Later, additional static simulations were performed on the selected outcomes to validate their mechanical performances. Finally, the legitimacy of these static simulations is granted by mesh convergence analysis.

4. Results and Discussion

Seven outcomes resulted from the simulations, one unrestricted and six related to AM processes, here reported in Fig. 4. The unrestricted geometry was not selected for this comparison stage since does not take into account real limits of the manufacturing process; it was used as a benchmark for Fusion 360 modelling capabilities. At first all outcomes with an eventual SF lower than the threshold would have been rejected since they did not meet part requirements, at this stage, virtually all components were still eligible of being the final solution. Outcomes were then sorted according to the sum of weighted scores in terms of mass, maximum displacement, and cost. Table 2 details the outcome selection process, bringing to the selection of Outcome #5 as the best option.

Although load cases introduced into Fusion 360 are symmetric, outcomes do not ensure a perfect symmetry. Fig. 4 reports both almost-symmetric outcomes, such as Outcome #2 and Outcome #5, and strongly asymmetric outcomes, such as Outcome #1 and Outcome #4. For this reason, with the aim of ensuring symmetry, Outcome #5 was further edited, cut in halves, and mirrored to obtain a symmetric result. Since so, an iterative process was then carried on, concerning only the Outcome #5. The selected outcome was inserted in the simulation as *Starting Shape*, guiding Fusion 360 in its activity.

Table 2. AlSi10Mg outcome selection for a productive batch of 50 pieces.

Outcome	Mass (g)	Mass score Weight = 1	Displacement (mm)	Displacement score Weight = 0.5	Cost (€)	Cost score Weight = 0.5	Total weighted score
#5	72	6,00	0,86	6,00	114,54	1,61	9,80
#3	76	4,00	0,95	5,04	90,47	6,00	9,52
#6	72	6,00	1,02	4,30	113,71	1,76	9,03
#2	72	6,00	1,07	3,77	114,54	1,61	8,69
#1	75	4,50	1,33	1,00	117,03	1,15	5,58
#4	82	1,00	0,99	4,62	117,86	1,00	3,81

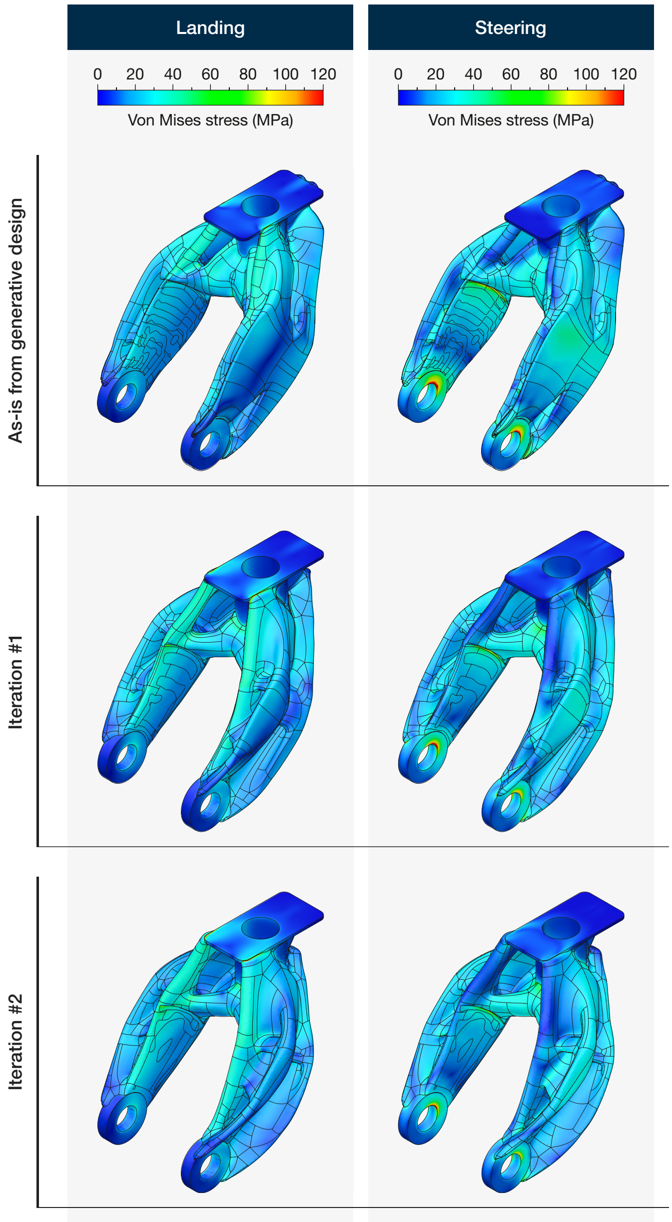

Fig. 5. Von Mises stress maps for landing and steering load cases. Geometry as-is from generative design, after Iteration #1, after Iteration #2.

This process was repeated two times with good results, from 72 g to 67 g, 7% mass reduction. Two iterations were considered sufficient since mass reduction was already negligible after the second iteration. Finally, considering DfAM rules, component geometry was slightly modified accounting for a lower support need in the processing phase.

However, unavoidable modelling limits had to be faced during the work. Fusion 360 is not a single-purpose software package, it is straightforward that it does not provide for the same accuracy and modelling possibilities of other solutions. Both in Simulation and GD environments, the absence of yielding joints cannot lead to a proper representation of the real elastic behavior of the assembly. Yielding joints account for the elastic deformation of the part of the assembly not considered in the simulation. Removing these types of joints, and substituting them with rigid ones, introduced additional stiffness in the model; an over-rigid structure is obtained indeed. Although the model does not align precisely with

Table 3. Part properties of Outcome 5 after iterations

Criterion	Value
Mass (g)	67
Cost (€)	177
Max Displacement (mm)	0.14
Technology	Additive Manufacturing

reality, it provides a more conservative paradigm. Eventual mass excess, deriving from this aspect, could be removed during the redesign and CAE analysis phase of the geometry by using a Topology Optimization (TO) software for example. Finally, Fusion 360 does not provide a fatigue analysis tool, this means that any given results will not be validated from a dynamic standpoint.

Fig. 5 shows stress maps of the chosen outcome before iterations and at the two iteration steps. The upper limit of the legend is 120 MPa, around but below the fatigue limit of the material. This way it is possible to have a rough indication about part fatigue behavior.

The final geometry is more articulated, with the presence of beam like structures defining internal cavities. In this case, iterations were not only followed by a consistent mass drop, but instead material was also reorganized in the volume in a more efficient way. Indeed, different parts of geometry are highlighted in the two different load cases, meaning there are geometrical features specifically meant for each load case. AlSi10Mg outcome weights around 67 g, since the starting weight of the studied assembly was roughly 148 g, it marked a noticeable mass reduction of 52%. A similar mass reduction was allowed by a series of factors such as parts consolidation, use of state-of-the-art material and a conscious choice of the outcome to promote. Table 3 summarizes the properties of Outcome #5 after iterations. Final task of the whole activity was the realization of a prototype to check on part geometry. The conceptual prototype could help to understand critical issues on part geometry and assembly criticalities to be solved by further geometry editing and it was realized in polymeric material through Selective Laser Sintering (SLS) process. The critical issues were mainly related to the assembly with mating components and supports reduction, to be solved before the realization of the functional prototype in metal alloy. Fig. 6 shows the result of such activity.

Fig. 6. Conceptual prototype realized through SLS.

5. Conclusions

Generative Design is a useful tool in the manufacturing world, allowing designers to obtain high added-value components. Geometries coming from these simulations are quite complex, and for this reason, GD is usually coupled with AM. Consistent mass reductions draw the attention of sectors where high costs are overshadowed by possible technical gains (automotive, aerospace, medical). Although previous works featuring GD already achieved consistent mass reductions, most of the time designers were not completely aware of the hidden potentiality of this technology. Iterative processes are still not so common in literature and outcome selection frameworks are almost absent.

In the present paper a first and general method to discern outcomes quality is proposed. At first, focusing on the respect of hard constraints, later finding the component representing the best trade-off between mechanical performances and cost. This same base concept can be easily implemented, in any specific manufacturing field, attributing different weights to the discussed different parameters.

It would be beneficial to implement the result obtained by means of a TO software, further reducing component's mass, and a fatigue analysis tool, to certify the final part for the real use. Other metal alloys should be tested, such as titanium alloy, allowing designers to take advantage from state-of-the-art metal alloys, typical of AM processes.

Designers' role is changing in the manufacturing world. Taking advantage of instruments like GD and TO designers are not asked to build solution from scratches anymore, they are supposed to properly set simulations up, and to understand the critical features and potentialities of the results. Mastering these new tools will be a major requirement for designers of tomorrow.

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