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33rd CIRP Design Conference

# A data-driven topology optimization approach to handle geometrical manufacturing constraints in the earlier steps of the design phase

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## Abstract

This paper improves on the performance of the Deep Learning Additive Manufacturing driven Topology Optimization (DL-AM-TO) approach that was proposed in [4]. DL-AM-TO is a data-driven generative method that integrates the mechanical and geometrical constraints concurrently at the same conceptual level and generates a 2D design accordingly. Furthermore, DL-AM-TO tailors the design's geometry to comply with manufacturing criteria, which facilitates the designer's interpretation phase and prevents him/her from getting stuck in a loop of drawing the CAD and testing its performance. The geometry needs less support structure and hence is printed faster. Consequently, DL-AM-TO accelerates the Design for AM process.

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**Keywords:** Topology Optimization; Additive Manufacturing; Generative Design; Deep Learning.

## 1. Introduction

Along with their development, manufacturing systems replaced human involvement in the process one step at a time. Nowadays, humans are still present in the product lifecycle, from design to manufacturing. This process is known as the design for Additive Manufacturing (DfAM) process. Finding the solutions to blend this interaction is the only guarantee of a performant manufacturing system. Indeed, computer-aided technologies in the design, analysis, manufacture, and assembly phases optimized manufacturing systems regarding time and costs. Nevertheless, the phase with the highest impact on the overall product cost ( $\geq 70\%$ ) is the design phase; it allows handling defects at a lower cost. From this, the concept of "first-time correct" has emerged. The goal is to find the most optimal and free-from-defects design at an early phase of the product's lifecycle [7]. Thus, much research has been put into exploring new approaches to accelerate the DfAM process.

We classify the state-of-the-art approaches proposed to accelerate the DfAM process into four major approaches.

The first one consisted of creating AM guidelines for design

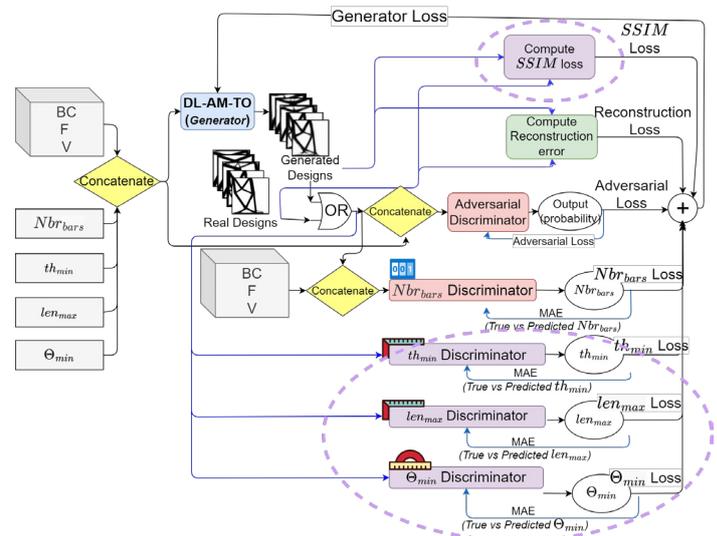


Fig. 1: DL-AM-TO's training procedure. The difference between this figure and the figure 3 in [4] consists of the addition of the structural similarity loss ( $L_{SSIM}$ ) and the  $th_{min}$ ,  $len_{max}$ , and  $\theta_{min}$  geometrical discriminators' architecture (in purple); in this work, they were converted from regression models to classification models.

engineers to help them in the re-interpretation phase to draw AM-compliant designs. While this approach was a significant step into the adoption of design for AM, the designers still got stuck in the drawing phase due to the mechanical performance deterioration induced by updating the shape to comply with AM constraints [1, 8, 12].

Thus, for a reason mentioned previously, the second approach proposed integrating AM constraints into finite elements based TO (FE-TO) methods so that generated designs would be compliant with both mechanical and AM constraints simultaneously; the top common AM constraints are the minimum overhang [13, 6] or support structures [24], the thin features [10, 22]. Nevertheless, this approach faced several challenges. AM constraints are contradictory [25], informal [11], and geometrical), making formulating them analytically challenging, especially with FE-TO, the geometry is unknown beforehand. Moreover, FE-TO identifies the shape at early iterations, restraining it from changing to account for other constraints. Finally, FE-TO has a hard time converging [18] (i.e., finding the optimal design complying with all the constraints) with the increasing number of constraints, and when it converges, the computational power needed can be significantly expensive.

The third approach modeled a hybrid TO method; they replaced some FE blocks with Machine (ML) or Deep Learning (DL) techniques [16, 21, 9, 15]. Unfortunately, this approach focused on the design phase and not the whole DfAM process and inherited the convergence and computational flaws of FE.

The fourth approach replaced FE with ML/DL models [19, 14, 17]. This last approach accelerated TO and eliminated all FE-TO setbacks but did not integrate any AM constraints and did not impede getting stuck in a loop in later phases of the DfAM process.

We aim to accelerate the entire DfAM process and have the best quality/cost ratio. Indeed, the design phase is the least costly and the most impactful on the overall product cost [7]. Nevertheless, more than accelerating this phase is required, as we have seen with state-of-the-art approaches. Moreover, while AM-driven FE-TO methods aim to accelerate the whole DfAM process by preventing repetitive iterations, the analytical formulation of AM constraints, the methods' convergence, and their computational costs are still a hurdle. Conversely, the introduction of ML and DL only accelerated one phase. Thus, we propose to get the best of both worlds in this work; this new DL approach allows manufacturing constraints' integration within mechanical ones concurrently at the same level, and any constraints, even ones lacking a mathematical definition [23] like experts' rules and knowledge while benefiting from DL's speed and scalability advantages. Thus, DL-AM-TO, a TO approach based on DL that integrates AM and mechanical constraints concurrently at the same level, was proposed in [4]. DL-AM-TO is a generative model that takes as input the mechanical (Boundary conditions  $BC$ , loads  $F$ , volume fraction  $V$ ) and geometrical (number of bars  $Nbr_{bars}$ , minimum thickness  $th_{min}$ , maximum length  $len_{max}$ , minimum overhang  $\Theta_{min}$ ) constraints and generates a 2D image-like design. The training designs and constraints come from the open-source dataset, Geometrical and Mechanical CAD (GMCAD) dataset [3], which

was inspired by designs outputted by the top common industrial TO method, Solid Isotropic Material with penalization (SIMP) [5]. In [4], DL-AM-TO showed poor performance regarding the generated designs' quality. This behavior was identified to be tied to several criteria, the most impactful one being the geometrical discriminators' performance. The better the discriminator predicts the geometrical condition, the more informative the generator's loss function is; hence, DL-AM-TO is more reliable. We note that it is trained within GAN frameworks known for their unstable oscillating losses, which explains its sensitivity to the losses delivered by its discriminators. This phenomenon is observed with the  $th_{min}$  variable; integrating the latter into the model deteriorated its performance. The  $th_{min}$  discriminator should have been more precise. As a matter of fact, the image-like designs in GMCAD are CAD models converted to images with computer vision filtering techniques, which can easily alter the thicknesses of the design.

Consequently, to improve on the previous results, several actions are taken into consideration in this paper: (1) Improve the performance of the geometric discriminators, for their performance dramatically impacts the generator's performance. (2) Retrain DL-AM-TO with the new geometrical discriminators (Fig. 1). (3) Propose several geometries for the same mechanical conditions using DL-AM-TO, draw these geometries, print them, and compare their manufacturability.

The major contribution of this article is validating the capability of DL-AM-TO to accelerate the whole DfAM, not simply the design phase. The article is organized as follows: section 2 details the geometric discriminators' improvement. DL-AM-TO's training is summarized in section 3. Sections 4 and 5 outline DL-AM-TO's performance. Section 6 presents DL-AM-TO's limitations. Finally, section 7 summarizes the methodology and its outcomes and presents future perspectives.

## 2. Improving the geometric discriminators' performance

The geometrical constraints are scalar values; thus, previously, we have chosen a regression-like architecture. Unfortunately, this architecture only convenes some constraints;  $th_{min}$  discriminator needed to be more precise. Hence, we decided to convert the regression problem into an ordinal regression one; it is a special case of classification problems. Instead of predicting the scalar value of a constraint, we will predict an interval in which it falls. The geometrical constraints that were concerned are  $len_{max}$ ,  $th_{min}$ , and  $\Theta_{min}$ .

The  $len_{max}$  constraint was divided into twenty-one classes (figure 3a). As described in [3], the  $len_{max}$  and  $th_{min}$  are measured with respect to the unit measure, with it being the width of the design space, which is equal to its height in our work.

The  $th_{min}$  constraint was divided into nine classes (figure 3b). The  $\Theta_{min}$  constraint was divided into fourteen classes (figure 3c). It is essential to highlight here that we exclude the rotational data augmentation for two reasons. First, the  $\Theta_{min}$  is the only geometrical value affected by the rotation of the design space. Also, we realized that the distribution of  $\Theta_{min}$  values after rotational data augmentation became not uniform and

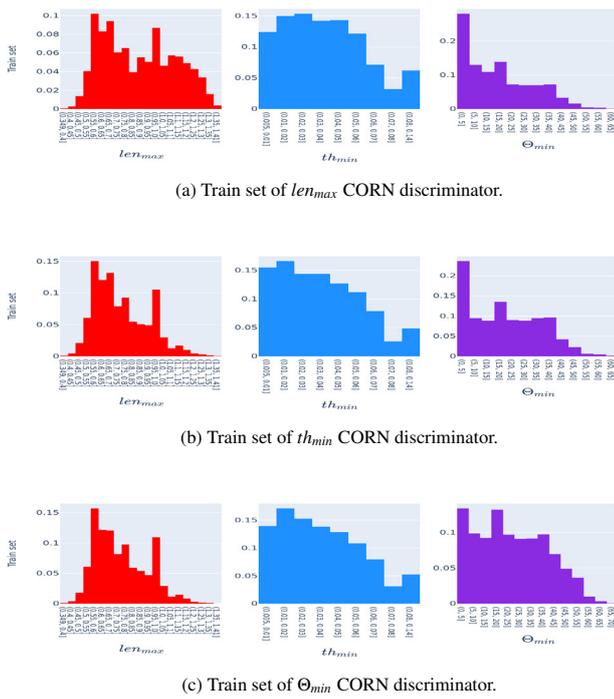


Fig. 2: Distribution of the geometric intervals of  $len_{max}$ ,  $th_{min}$ , &  $\Theta_{min}$ , from left to right respectively, in the training sets of the  $len_{max}$ ,  $th_{min}$ , &  $\Theta_{min}$  CORN discriminators, from top to down respectively.

did not include all the value intervals for the designs present in GMCAD; thus, this data augmentation will affect the representativeness of some classes in the dataset and deteriorate the model’s performance. Second, we train DL-AM-TO with no data augmentation; hence, the  $\Theta_{min}$  discriminator is only needed to predict on non-rotated designs with  $\Theta_{min}$  ranging from 0 to  $70^\circ$ .

To comply with the problem’s formulation as a classification instead of a regression, the discriminators’ architectures defined in [4] will only differ on the last fully connected layer; the output is a binary vector of  $K$  nodes with  $K$  being the number of classes of the variable described above; i.e.,  $K = 21$  for the  $len_{max}$  model,  $K = 9$  for the  $th_{min}$  model,  $K = 14$  for the  $\Theta_{min}$  model.

The geometric discriminators are trained via the state-of-the-art Conditional Ordinal Regression for Neural networks (CORN) framework [20].

### 2.1. Training dataset

To further improve the geometric discriminator’s accuracy, we have increased the number of training data samples per geometric variable to ensure that every class (i.e., every interval of values) is well represented. The distribution of the intervals of  $len_{max}$ ,  $\Theta_{min}$  and  $th_{min}$  values in the training set for every geometric discriminator is shown in figure 2.

### 2.2. Results

On the test set, the global accuracy score of the  $th_{min}$  is 93.7%, of  $len_{max}$  is 86.1%, and of  $\Theta_{min}$  is 91.2%. However, when it comes to multi-class classification, the global macro accuracy score can be deceiving, and a better approach is to use the micro scores, i.e., scores per class. Thus, figure 3 plots the confusion matrices computed on the test set. We define an admissible misclassification as a point belonging to the class  $k$  classified into the class  $k \pm 1$ .

For the  $th_{min}$  discriminator, the highest percentage of admissible confusion is 16.77%, for the class (0.07, 0.08]; it is confused with the class (0.08, 0.14], which is admissible. Moreover, the class (0.07, 0.08] is the least represented class in the training set (figure 2b shows the distribution of the classes of  $th_{min}$ ). As for the remaining classes, this percentage never exceeds the 8%. The highest percentage of inadmissible confusion is of 1.8%, for the class (0.06, 0.07]; with this class being confused by 0.53% with the class (0.03, 0.04], 0.11% with the class (0.03, 0.04], and 1.16% with the class (0.08, 0.14].

For the  $len_{max}$  discriminator, the least accurate CORN discriminator, the highest percentage of admissible confusion is 82%, for the class (0.349, 0.4]; this class is the least represented class in the training dataset (0.05%, figure 2a), which makes it challenging for the model to predict the exact class. Nevertheless, the model confuses it with the exact following class (0.4, 0.45], which is admissible. Similarly, the highest percentage of inadmissible confusion is 5.17% for the class (0.45, 0.05].

For the  $\Theta_{min}$  discriminator, the highest percentage of admissible confusion is 28.6%, for the class ( $55^\circ, 60^\circ$ ]; it seems that angles belonging to ( $55^\circ, 60^\circ$ ] are highly confused with the class ( $60^\circ, 65^\circ$ ]. As a matter of fact, this confusion is understandable, for these two classes are less represented than the others (figure 2c shows the distribution of the classes of  $\Theta_{min}$ ). The highest percentage of inadmissible confusion is 1.68%, for the class ( $5^\circ, 10^\circ$ ].

Finally, the global percentage of inadmissible predictions are 1.23% for  $len_{max}$  discriminator, 0.92% for the  $\Theta_{min}$  discriminator, and 0.4% for the  $th_{min}$  discriminator. Thus, all three geometrical discriminators are precise enough to forward the training of DL-AM-TO.

### 3. Training DL-AM-TO with new discriminators

We recall DL-AM-TO’s training procedure described in section 3 in [4]. First, the mechanical (the boundary conditions  $BC$ , the loads  $F$ , and the volume fraction  $V$ ) and geometrical (the number of bars  $Nbr_{bars}$ , the minimum thickness  $th_{min}$ , the maximum length  $len_{max}$ , and the minimum overhang  $\Theta_{min}$ ) constraints are inputted to DL-AM-TO, which generates a 2D design accordingly. Second, this design is input to the  $th_{min}$ ,  $len_{max}$ , and  $\Theta_{min}$  discriminators, which predict its geometric constraints. Third, the design and the mechanical constraints are input to the  $Nbr_{bars}$  discriminator, which predicts its  $Nbr_{bars}$ . Fourth, the generated design and all input constraints are input to the traditional discriminator, which computes the



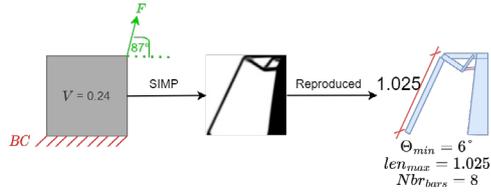


Fig. 4: Design generated by SIMP. This design is clamped on the bottom edge (BC in red), it is loaded on the top right corner (F in green), and the V

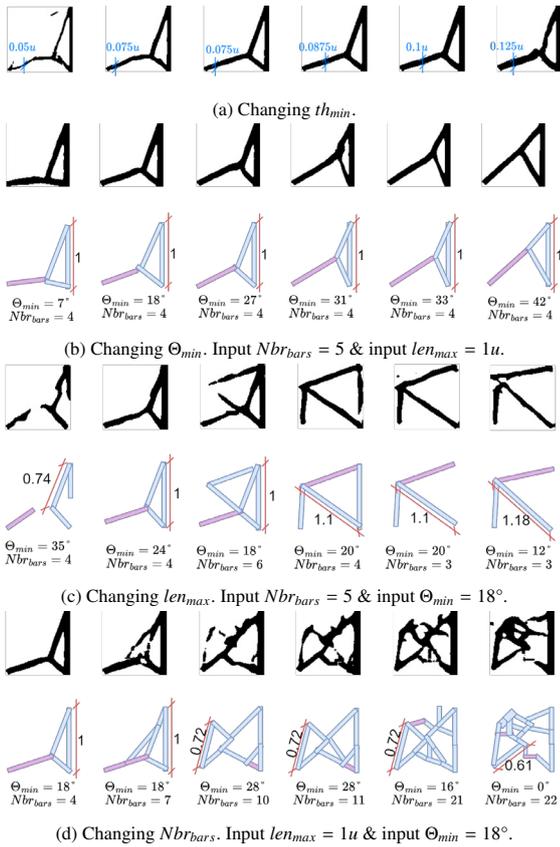


Fig. 5: Tailoring a geometrical constraint at a time.

constraint, 89.3% with the  $th_{min}$  constraint, 87.9% with the  $\Theta_{min}$  constraint, and 88.7% with the  $Nbr_{bars}$  constraint. On the computational performance, DL-AM-TO is thousands of times faster; it takes 0.03 seconds to generate a design, while SIMP needs 140 seconds to output the same design. To recapitulate, DL-AM-TO generates designs with good quality and geometrically valid within a fraction of a second.

### 5. Tailoring a design's geometry with DL-AM-TO

For the sake of this article, we limited our experiments to one set of mechanical constraints (figure 4). This experiment tests DL-AM-TO's ability to tailor a design's geometry while always complying with mechanical constraints. Thus, we fix all input constraints except for one geometrical constraint. We scan a range of values for this constraint and generate the geometries accordingly. It is important to note that modify-

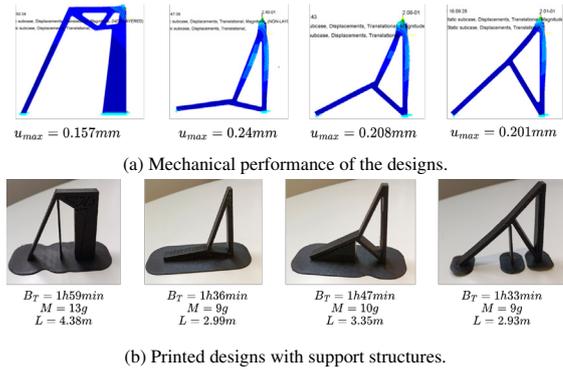


Fig. 6: Printing phase. The material used is the Polyactic acid (PLA).  $\Theta_{min_{printer}} = 60^\circ$ .  $u_{max}$  is the maximum displacement in mm.  $B_T$  is the build time.  $L$  and  $M$  are the PLA filament length and mass, respectively.

ing the  $Nbr_{bars}$  and  $th_{min}$  constraints induce modifying the  $V$ , for increasing/decreasing these two constraints requires additional/less material as demonstrated in [2].

Figure 5 shows six geometries generated by DL-AM-TO after changing a geometrical constraint at a time.

Figure 5a illustrates the geometries outputted with increasing input  $th_{min}$ . As we can clearly see, DL-AM-TO generates designs thicker with the increasing  $th_{min}$  while respecting the other constraints; the shape is conserved, in other terms the BC and F are respected, the  $Nbr_{bars}$  vary in the range  $Nbr_{bars_{input}} \pm 2$ , which is admissible, the  $len_{max_{generated}} = len_{max_{input}} = 1u$ , the  $\Theta_{min_{generated}} = \Theta_{min_{input}} = 18^\circ$ .

When  $\Theta_{min}$  is modified, DL-AM-TO's generated geometries respect the  $len_{max}$  and  $Nbr_{bars}$  input constraints (figure 5b).

Figure 5c shows that the  $len_{max}$  of the generated geometries increases with the increasing input  $len_{max}$ . For the other constraints, the generated designs'  $Nbr_{bars}$  vary in the range  $Nbr_{bars_{input}} \pm 2$ , and their  $\Theta_{min}$  in the range  $\Theta_{min_{input}} \pm 6^\circ$  (i.e.,  $\pm 1$  class, section 2), except for the first geometry, which is admissible.

When the  $Nbr_{bars}$  is changed, we see that DL-AM-TO has difficulty conforming with the other geometrical constraints; 3 out of 6 geometries comply with the  $\Theta_{min_{input}}$  and only 2 out of 6 comply with the  $len_{max_{input}}$ . DL-AM-TO's non-conformity with  $len_{max}$  could be justified. DL-AM-TO adds bars to respect mechanical constraints, in other words, keeping the outer geometry intact, which makes that additional bars are internal transmission ones, which affects the  $len_{max}$  constraint that is reduced. On the other hand, the non-conformity with  $\Theta_{min}$  is intriguing. This result should be further analyzed to understand the correlations between these two constraints.

To complete DL-AM-TO's evaluation, we chose the  $\Theta_{min}$  experiment of figure 5b. We picked three designs generated by DL-AM-TO (the first, third, and last) and the one output by SIMP, drawn them using FreeCAD, tested their mechanical performance (measure by the maximum displacement  $u_{max}$ ) using Patran/Nastran, and produced them using 3D printer Creality Ender 3; the support structures were added by the slicing software Cura. At every printing, we note the build time ( $B_T$ ) and the length ( $L$ ) mass ( $M$ ) of the PLA material consumed to pro-

duce the part. We compare the mechanical and manufacturing metrics of the SIMP design versus the ones proposed by DL-AM-TO.

Figure 6b shows that DL-AM-TO designs are 30.7% cheaper in material (9g versus 13g for the SIMP design) and 10 to 22% faster to print while conserving the same mechanical performance as the one shown by SIMP; DL-AM-TO's designs show the same order of magnitude of  $u_{max}$  as the SIMP one (figure 6a).

To sum up, DL-AM-TO tailors design geometry to adapt it to manufacturing criteria. The test example described above demonstrates that DL-AM-TO proposes different geometries printable up to 22% faster and 30% cheaper than the SIMP design without deteriorating the mechanical performance.

## 6. Discussion

It is imperative to note that this approach is not intended to replace robust FE-TO but to help compensate for its difficulties in integrating various complex constraints. Indeed, a better approach would be a hybrid approach with the first draft generated by DL-AM-TO and the final optimized by an FE-TO method. DL-AM-TO's capability to tailor a design's geometry was demonstrated in section 5. However, as we have noticed, when the  $Nbr_{bars}$  constraint is modified, DL-AM-TO has difficulty complying with the other constraints. This result can be explained in different ways: this constraint is correlated with the other geometrical constraints and seems to dominate over them. Hence, it would be interesting to push the analysis further and train several DL-AM-TO models with one geometrical constraint at a time to understand the influence of every constraint on the others when controlled alone to understand their correlations when controlled altogether eventually.

## 7. Conclusion

This paper improves on the setbacks reported in [4]. It proposes and validates a Deep Learning-based Additive Manufacturing driven Topology Optimization approach called DL-AM-TO. DL-AM-TO integrates the mechanical and geometrical constraints at the same level and generates 2D designs. More interestingly, it tailors the design's geometry easily to propose several geometries AM compliant corresponding to the engineer's input while keeping a similar mechanical performance as the one proposed by SIMP.

In the future, a pushed analysis of the correlations between the geometrical manufacturing-related constraints and further tests will be conducted and published to validate DL-AM-TO's performance and quantify its acceleration on the overall DfAM process. Additionally, DL-AM-TO could be enhanced to generate 3D designs. Finally, DL-AM-TO could be industrialized as a light and fast generative module in industrial design software.

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