Topology Optimization and Machine Learning based Parametric Optimization Techniques: A Comparative Study With Physical Validation

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Abstract—**Topology optimization (TO) and Parametric Optimization (PO) are two fundamental structural optimization (SO) techniques. The aim of this study is to understand how these two techniques (TO and PO) stack up against each other from a variety of perspectives - (1) time taken for optimization, (2) manufacturability, (3) real-life adherence to simulated results, and (4) overall stiffness - by using the problem case of a cantilever beam as the basis of comparison. For this cantilever beam application, both TO and PO are evaluated and compared in a systematic manner on 3 different volume fractions (VF) of beams - 30%, 50%, and 80%. PO is conducted using surrogate optimization as opposed to simulation in-the-loop optimization.**

Most importantly and uniquely, the results achieved via software simulation for both PO and TO are then validated in a real-world physical setting. The simulated versus physically validated results are compared for all six TO and PO optimized cantilever beams. Through this comparison, it was found that the percent errors between the simulated and physical displacement for the 30%, 50%, and 80% TO/PO beams were 45.5%, -6.6%, -1.5%, 33.7%, 2.4%, and -0.1%, respectively.

It was found that - for the chosen cantilever beam application - (1) TO is faster and shows better compliance, (2) PO is more manufacturable and shows better predictability between software simulated and physically validated results. Moreover, for both TO and PO, the 50% and 80% VF beams show good alignment between simulated and physical results.

I. Introduction

Structural optimization (SO) is a crucial aspect of any engineering design. Numerous techniques can be used to improve material efficiency, structural integrity and performance. Topology Optimization (TO) and Parametric Optimization (PO) stand out due to their distinct approaches: (1) TO allows for innovative designs and solutions to very complex problems, while PO allows for refinement and precise control over design aspects, (2) TO allows for more versatility, utilizing organic shapes and more innovative designs, whereas PO is suited for making small, specific tweaks, and refining designs.

This study addresses the challenge of determining which optimization technique (TO versus PO) is better suited to the particular application of applying stress to a cantilever beam (a generally representative structure used for this study), and how each method aligns with physical, real-world outcomes. Unlike previous studies that either layered TO and PO together or applied them concurrently, this research uniquely provides a direct comparison of the two methods in the context of the chosen application. The fully optimized beams are then constructed through Fused Deposition Modeling (a popular low-cost Additive Manufacturing technique) and experimentally evaluated to determine which optimization method adheres the most to simulation results. Additionally, a unique approach to PO is employed, combining the output of SolidWorks (a CAD software) with machine learning (ML).

II. Overview of Sections

The following is a quick overview of the sections to come. Section III conducts a review of the existing literature ranging from the basics of TO and PO to various works in the field, including comparisons/combinations of TO and PO, integration of ML into engineering design, and the selection of appropriate software simulation packages. Section VI details the methods used for TO and PO, including specifics of how ML was integrated to refine and optimize the PO performed by SolidWorks. Section VII, details the findings which are summarized here

1) TO is faster than PO (refined with ML). TO takes less time to perform.
2) TO shows better compliance in both computer simulated and experimentally validated results.
3) PO (refined with ML) is more manufacturable than TO.
4) PO shows better predictability and lesser variation between simulated and experimentally validated results.

III. Relevant Work

A. Foundational concepts in Topology and Parametric Optimization

TO is the process of determining the optimal material distribution within a given design space for a specified set of loads, boundary conditions, and constraints with the objective of optimizing performance metrics like stiffness, strength, or compliance.The primary goal of TO is to find the best layout of material within a design domain that maximizes or minimizes an objective function (e.g., stiffness, weight) subject to constraints. [1]. TO can be effectively integrated into the design process for additive manufacturing (AM), focusing on achieving optimal lightweight structures, improving manufacturability, and addressing constraints inherent to AM [2]. The study [2] demonstrates how TO methods can be applied systematically to achieve optimal designs for AM, focusing on mass reduction and improving structural performance.

PO involves adjusting design parameters, such as dimensions and geometric features, to improve the mechanical performance of additively manufactured (AM) structures. The aim is to find optimal configurations that maximize energy absorption while meeting manufacturing constraints. Machine learning (ML) is increasingly being used for process-property optimization in AM. ML models can be trained to predict the mechanical properties of AM parts based on process parameters, enabling designers to quickly identify optimal settings without extensive experimentation. ML-based techniques also assist in real-time optimization during the manufacturing process, enhancing accuracy and efficiency [3].

B. Prior Comparison and Combination Studies Between TO and PO; Hybrid Optimization Approaches

Many prior studies have been run where TO and PO are either compared against each other or combined in order to create a new optimization algorithm. While minimizing von Mises stress in a rectangular sample under tensile load for AM processes, Hassani et al., concluded that PO offers higher flexibility and can achieve better structural performance in some cases. PO produces simpler configurations that are more feasible for manufacturing, whether through AM or conventional methods, and result in fewer complications related to support structures [4]. Yi et al., [5] propose a method for translating complex TO results into simpler, manufacturable geometric models using PO features and suggest extending their method to 3D structures and more complex geometric shapes as future work. Tyflopoulos et al., [6] demonstrate that a two-stage optimization process combining TO and PO can lead to significantly improved designs in terms of weight reduction and mechanical performance.

Tyflopoulos et al., [7] present a quantitative comparison of ten different TO, PO, or combined TO and PO based design processes using three structural examples: A Hollow Plate, an L-Bracket, and a Messerschmitt–Bölkow–Blohm Beam (MBB-Beam), and conclude that there is no clear answer to the question about what the best process was (TO, PO or combined TO/PO processes). This depends on the designer's criteria. If the most crucial optimization criterion is the mass reduction (regardless of the optimization time), the simultaneous size/shape PO and TO optimization process gave the best results. On the other hand, if time is essential, the TO process gave the quickest design solutions. Concerning the maximum stress, it is not clear which process was better, and it is something that depends on the tested structure. The authors suggest experimental validation of these design solutions as being of high interest, and recommend experimental validation as one of the steps to advance this research.

C. Integration of Machine Learning into Engineering Design

There are many key benefits of integrating ML with engineering design methods. Integrating artificial intelligence (AI) and machine learning (ML) into engineering design can lead to reduced design time, enhanced accuracy, optimized design parameters, seamless data integration, and can help with generative design [8].

To expand on these:

1) Reduced Design Time - ML can help automate routine tasks such as identifying geometric features, optimizing material distribution, or even predicting the performance of parts under load. This reduces the time designers spend on manual work and iterations.
2) Enhanced Accuracy - By training models with data from previous designs and simulations, AI can help designers avoid common mistakes, improving the accuracy of the design and reducing costly errors during manufacturing.
3) Optimization of Design Parameters - ML models can suggest optimal configurations for various mechanical parts, significantly improving the efficiency and functionality of designs. This is especially beneficial in areas like aerodynamics or structural integrity.
4) Seamless Data Integration: AI allows for the integration of large data sets directly into the design process. This can include historical performance data, material properties, or even external environmental factors, enabling more informed design decisions.
5) Generative Design: AI tools can help generate design alternatives based on predefined constraints, offering a range of innovative solutions that a human designer may not think of. This is particularly relevant when working with complex components or in additive manufacturing scenarios.

ML can also be utilized in predicting structural performance, a crucial aspect of both engineering design and SolidWorks. One such approach utilized an automated machine learning (AutoML) approach to predict structural performance of complicated structures, such as bicycle frames [9]. AutoML was shown to be an effective method for predicting structural performance specifically in specifically in surrogate modeling tasks for performance prediction and design optimization [9].

D. Integration of ML and TO

ML has already been worked into TO SolidWorks algorithms to facilitate Generative Design [10]. A framework is presented where new designs are iteratively generated, first through TO and then refined through deep learning models, until a diverse set of designs has been conceived [10]. ML can also assist in the full creation of Topologically Optimized structures, and TO problems can be solved efficiently and quickly [11]. With the use of a Convolution-Neural-Network, as opposed to traditional FEM methods, researchers in [12] found that the process was able to be sped up almost 30x.

E. Comparisons to and Furtherment of Existing Methods

Existing methodologies have discussed the possibility of ML for SolidWorks [10]–[12]. However, only TO and Generative Design have been studied with ML integration.

This paper builds upon the concepts, methods, and conclusions from the previous works by comparing two optimization methods to each other - (1) TO - which is a pure TO

SolidWorks algorithm, and (2) PO - which is actually a layered PO-TO algorithm facilitated by ML.

Additionally, one crucial aspect of furthering simulation (which is recommended as next steps [7]) is experimental physical validation to understand how close software simulations predict real world results, and which method predicts physical results more closely. This paper discusses the validation of simulation results through physical means. This work thus helps achieve a new outlook on the value of studied optimization methods, by shining a light on the predictability of optimized structures generated from these TO and PO methods.

IV. Structural Optimization Methods

Structural Optimization (SO) is defined as ”the rational establishment of a structural design that is the best of all possible designs within a prescribed objective and a given set of geometrical and/or behavioral limitations” [13]. In simpler terms, SO is the process of finding the best possible design for a structure, while staying within defined constraints. Possible constraints include mass constraints, deformation constraints, stress constraints, and size constraints.

Srivastava et al., [14] describes the differing basic methods of structural optimization: size optimization, shape optimization, and topology optimization. Size optimization consists of finding the optimum size for parts of the structure, while shape optimization addresses the geometry of the structure [15]. Both size and shape optimization fall under the umbrella of parametric optimization (PO) [7].

Topology optimization (TO) can be done via different approaches. These include the Density Approach (SIMP), Level Set Method (LSM), the Homogenization Approach, the Evolutionary Structural Optimization (ESO), the Phase-Field Method, and Topological Derivatives [7].

Other methods such as Topometry, Topography, and Lattice optimization are also prevalent within the sphere of SO. However, they do not pertain as much to this paper as PO and TO do, and therefore will not be explained here in depth.

The most popular TO method is the Solid Isotropic Material with Penalization method (the Density Approach - SIMP) [16]. The approach used for TO in this paper is SIMP, facilitated by SOLIDWORKS.

A. SIMP method

In this paper, the SIMP method was chosen due to it's ease of use and accessibility, coming prebuilt into SOLIDWORKS CAD and simulation software. The following is an explanation of the SIMP method, facilitated by [16]:

The traditional approach to TO is breaking up a design space into a space of finite elements, known as isotropic solid microstructures. Each element is either filled or void of material, and the density-distribution p is discrete.

A continuous relative density function can help avoid this binary nature. This function allows for assigned density to vary between a minimum value (which helps ensure numerical stability of the final finite element analysis) and a full 1. These intermediate densities are referred to as porous elements.

As material density varies, so does the material's Young's Modulus. The following law relates material density (P_e) to Young Modulus (E_0) for an element e.

$$\mathrm{E}\left(\rho_e\right)=\rho_e^p E_0$$

The “Penalty” factor in SIMP aims to diminish (or penalize) elements with intermediate density values, and tries to get the optimized solution to be completely binary. A penalty value of 3 has been indicated to work well.

As an element's material Young modulus decreases, stiffness decreases. The SIMP method of modulating global stiffness is the following:

$$K_{SIMP(\rho)}=\sum_{e=1}^N\left[\rho_{\min}+\left(1-\rho_{\min}\right)\rho_e^p\right]K_e$$

K_e represents element stiffness, P_{min} is the minimum element density, P is the penalty factor, and N is the number of elements.

1) *Maximizing Stiffness:*

The SIMP algorithm mainly aims to maximize the stiffness of a structure (in other words, to minimize the compliance of the structure). SIMP iteratively finds element densities that minimize compliance, utilizing the following equation:

$$\min C(\{\boldsymbol{\rho}\})=\sum_{e=1}^N\left(\rho_e\right)^p\left[u_e\right]^T\left[K_e\right]\left[u_e\right]$$

u_e is the displacement, K_e is the stiffness, and vector p is comprised of the elements' densities.

In each iteration, the mass constraint, force-stiffness equation, and required functional constraints:

$$\min C(\{\boldsymbol{\rho}\})=\sum_{e=1}^N\left(\rho_e\right)^p\left[u_e\right]^T\left[K_e\right]\left[u_e\right]$$

$$\sum_{e=1}^N\left\{v_e\right\}^T\rho_e\leq M_{\text{target}}$$

V_e is the element volume, M_{target} is the target mass.

$$[K\{\boldsymbol{\rho}\}]\{u\} = \{F\}$$

K_p is the global stiffness matrix, u is the displacement vector, and F is the external force vector.

2) Sensitivity Analysis: In each iteration, sensitivity analysis is conducted to evaluate material density variation.

This analysis is expressed as the derivative of the objective function with respect to material density:

$$\frac{dC}{d\rho_e} = -p\left(\rho_e\right)^{p-1}\left[u_e\right]^T\left[K_e\right]\left[u_e\right]$$

During this analysis, elements with low material density factors will lose structural importance and become null in future iterations. These optimization iterations continue until they converge and reach an optimum solution.

V. Methods Background

This section covers the background surrounding the specific research methods.

A. Research Design and Approach

This research paper compared TO and PO (a layered PO-TO facilitated by ML) and explored the pros and cons of each method for Structural Optimization. The approach of this paper was largely based off the study conducted in [17]. Similarly to those researchers, the study conducted in this paper was an exploratory study meant to expand the current body of knowledge on different optimization methods. The design of experiment (DOE) of the research presented in this paper is inspired by [7]. This paper utilized an experimental-based research methodology.

B. Variables and Subjects

This paper uses an experimental-based methodology with different variables.

Specifically, there were the independent variables of the two optimization workflows (TO and PO). These independent variables led to the dependent variables of optimized mass, optimized deflection, and optimized stiffness. These two independent variables were experimented on in three different groups: the beam VF's 30%, 50%, and 80%. The subjects in the research were cantilever beams. A basic cantilever beam was created, and was then subjected to 6 different optimization workflows: the 30% TO, 30% PO, 50% TO, 50% PO, 80% TO, and 80% PO. The reasoning behind choosing the cantilever beam was twofold. Firstly, this beam is a common and general test case for structural optimization problems and to that extent the results of this research can be generalized. Secondly, the cantilever beam was among one of the more feasible problem cases to mechanically test on a homemade testing setup.

VI. Research Methodology

This section details the experimental methods followed to conduct the research described in this paper. In subsection VI-A, the original beam constraints and TO are discussed. The PO is discussed in subsection VI-B, and the final TO is discussed in subsection VI-C. Finally, the physical validation is discussed in subsection VI-D.

A. Original Beam Constraints and Topology Optimization

This subsection discusses in detail the original beam constraints and original TO.

a) Original Beam Constraints: To create the original beam, SolidWorks CAD software was used. In SolidWorks, a simple cantilever beam was constructed as shown in Figure 1.

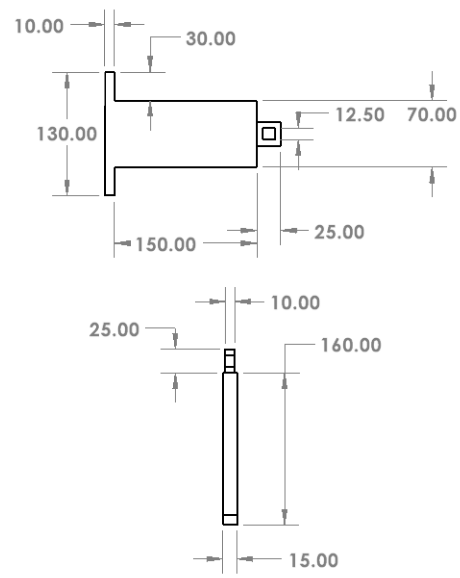

Fig. 1: Side and top views of original beam designed in SolidWorks before TO or PO was performed

On this simple beam, the two sections which jut out at the back, on both the top and bottom, were set as "fixed geometry" in the TO simulation (meaning that they are the affixation point of the beam). A force of 400 newtons was then applied inside the square hole in the front, on the bottom face on the inside.The material used for all beams and for the rest of the project used for both software simulations as well as experimental validation was Qidi Technology PC/ABS alloy.

b) Original Topology Optimization (TO): To conduct the original TO simulations, the simple beam was constrained as mentioned in the above section. The simulation was then configured to use the parameter of best mass-to-stiffness ratio, and the force applied to the beam was set to 400 newtons. Three different simulations were run, configured to retain 30%, 50%, and 80% of the material mass, respectively. These three volume fractions (VF's) were considered as the original TO beams.

B. Parametric Optimization (PO) and the Integration of ML with SolidWorks

The PO was actually a layered PO-TO facilitated by ML. To conduct this PO, the topologies generated in the TO section were first parameterized by roughly redesigning the cantilever beam to match the optimized topology. Constraints were then applied to each redesigned beam to find suitable ranges for each parameter. Using a force of 400 newtons, each cantilever beam was tested using meshes of different resolutions and SolidWorks Finite Element Analysis (FEA). Data from the stress and displacement for each mesh resolution was collected in order to determine which mesh resolution was the optimum one to use, balancing both accurate data and runtime per simulation. The mesh resolution tests are shown in Figs 2 and 3. The units are in mm. Blue represents the 30% VF, Red is the 50% VF, and yellow is the 80% VF. These tests conclude that the optimum mesh resolution to use is 0.2154-2.154 mm.

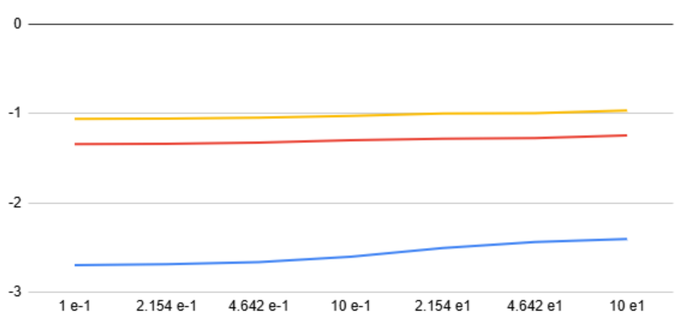

Fig. 2: Mesh resolution (mm) testing for maximum simulated y-axis deflection (mm). The minimum mesh size for each range is marked and the maximum size is 10x the marked size.

After determining the mesh resolution to use, random configurations of each parameter were generated within the ranges and constraints previously set. All of these configurations were tested, and 5000 datapoints were obtained for each volume fraction (VF) (30%, 50% and 80%) parametrization. Using these datapoints, 2 ML models were fitted for each VF parametrization, one to predict mass and one to predict displacement. The model used for each of the 6 total models fitted was determined through rigorous testing of inference time vs R2 score of each model on the testing data, after being fitted on the training data. The model finally chosen was the Polynomial Features Linear Regressor from SKLearn. Subsequently, Pymoo's NSGA-II algorithm was used to find an optimum mass-displacement solution set by feeding the configurations it tested into the mass and displacement models. Next, the point on the solution curve corresponding to the

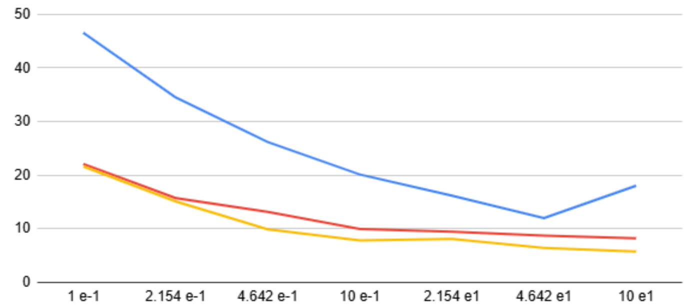

Fig. 3: Mesh resolution testing (mm) for maximum simulated Von Mises Stresses (N/mm^2). The minimum mesh size for each range is marked and the maximum size is 10x the marked size.

ideal VF for each beam was selected, and FEA analysis was conducted on those solutions using a force of 98.75 newtons.

C. Final Topology Optimization

In order to keep as many control variables as consistent as possible, a new TO was generated to match each of the final masses of each VF parametrization. These new TO's were simulated using FEA in the software for displacement and mass with a force of 98.75 newtons.

D. Physical Experimental Validation

After the 6 finalized TO beams and PO beams were designed using software simulaition as described above, they were each manufactured through the additive manufacturing (AM) method of 3D-printing, using a QIDI Q1-Pro 3d printer and QIDI PC/ABS alloy filament. These 6 3D printed beams (3 TO at 30%, 50%, 80% VF and 3 PO at 30%, 50%, 80% VF) were then experimentally subjected to a load of approximately 10 kg (exactly 22.2 lb or 98.75 newtons) by using a custom experimental setup as shown in Fig 19. The steps for this were as follows:

1) Experimental validation setup shown in Fig 19 was constructed using metal brackets, screws, a thick 2x4 wooden plank, and a flattened tree stump
2) Measurements were taken in order to create a mount for the dial gauge
3) A dial gauge mounted directly beneath the point where the edge of the beams will be located
4) Beams were secured (one at a time) to testing setup utilizing 1/4 inch nuts and bolts, making sure the outer edge lines up with the tip of the dial gauge
5) A small chain was threaded through the front hole of the cantilever beam in order to attach the weight
6) An approximately 10kg weight was secured to the the chain, such that the combined weight that the beam was subjected to (including the chain) was exactly 22.2 lb

7) The weight was slowly released so that was supported by the beam, and the deformation and displacement was recorded on the dial gauge

The actual displacement was measured using a dial gauge as shown in figure 19.

All of the 6 beams were also subjected to a simulated load of 22.2 lbs (98.75 newtons) in SolidWorks.

The physically measured Vs simulated results are documented, compared and discussed in section VII.

The following formula was used to determine stiffness for both simulated and experimental results:

$$S = F/\delta$$

Where S is stiffness, F is Force applied, and δ is the total bending deflection (displacement).

VII. Results and Discussion

As was mentioned earlier, the test case of the optimization was a cantilever beam.

A. Topology Optimization Results

The cantilever beam was designed utilizing SOLIDWORKS CAD software. The beam was fixed via bracket-style extensions at the top/bottom, and a downward force of approximately 10 kg was applied to the end of the beam. Using the SIMP method of TO, the beam was optimized through several cycles. The area where the fixture conditions were applied, as well as the area where the the load was applied, were excluded from the optimization process, The material used for simulations was a custom profile based off of QidiTech PC/ABS alloy. Mesh control was used for the entire simulation.

30% Topology Optimization: The final TO beam for the 30% VF is shown in Fig 4. The final beam massed in at a simulated 62.5 grams. Under approximately 10 kg of force load, the 30% VF TO beam had a simulated deformation of 0.5897 mm. Using the formula described in VI-D, the simulated stiffness of the beam is approximately 167.46 N/mm.

50% Topology Optimization: The final TO beam for the 50% VF is shown in Fig 5. The final beam massed in at a simulated 97.6 grams. Under approximately 10 kg of force load, the 50% VF TO beam had a simulated deformation of 0.3769 mm. Using the formula described in VI-D, the simulated stiffness of the beam is approximately 262.01 N/mm.

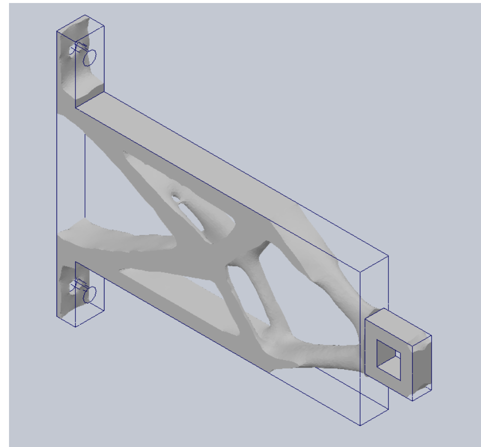

Fig. 4: Final 30% VF TO Beam

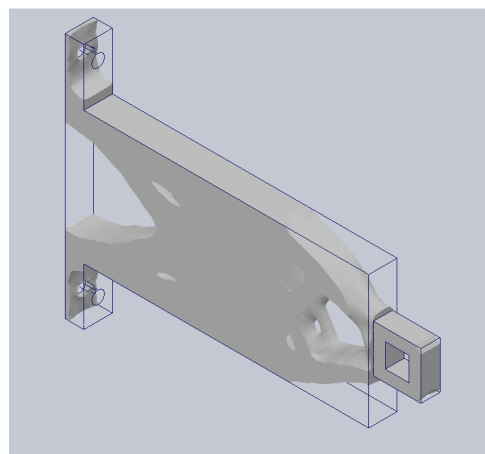

Fig. 5: Final 50% VF TO Beam

80% Topology Optimization: The final TO beam for the 80% VF is shown in Fig 6. The final beam massed in at a simulated 156.9 grams. Under approximately 10 kg of force load, the 80% VF TO beam had a simulated deformation of 0.2751 mm. Using the formula described in VI-D, the simulated stiffness of the beam is approximately 358.96 N/mm.

B. Parametric Optimization Results

The cantilever beam was designed utilizing SOLIDWORKS CAD software. The beam was fixed via bracket-style extensions at the top/bottom, and a downward force of approximately 10 kg was applied to the end of the beam. After the SIMP method of TO was used to optimize the beam, the optimized beam was then roughly parametrized. This rough parametrization consisted of 7-10 parameters, depending on

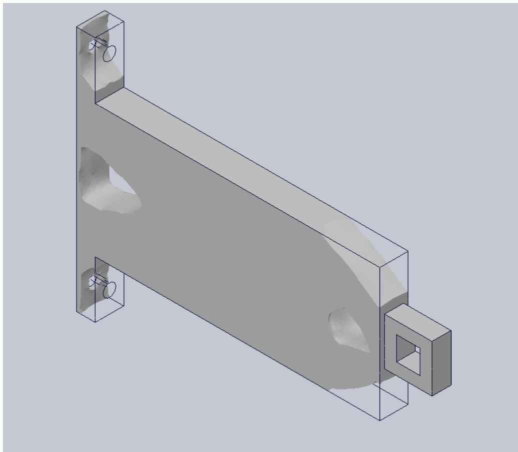

Fig. 6: Final 80% VF TO Beam

the beam's VF. 5000 random configurations of each beam were then created and simulated in SOLIDWORKS. These 5000 data points were fed into 2 predictive models for each beam to predict mass and displacement. A Genetic Algorithm (NSGA-II from [18] was then utilized in order to generate a solution curve for each beam, containing optimized solutions for different weightings of mass and displacement. These solution curves are shown in Figs 7, 8, and 9, where the y-axis is mass and the x-axis is deformation displacement. The optimal solution that most closely fitted each respective beam's original VF mass was then chosen for each beam.

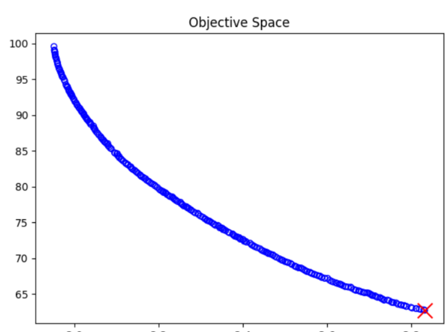

Fig. 7: 30% VF PO beam optimal solution curve

30% Parametric Optimization: The final PO beam for the 30% VF is shown in Fig 10. The final beam massed in at a simulated 62.4 grams. Under approximately 10 kg of force load, the 30% VF PO beam had a simulated deformation of 0.6969 mm. Using the formula described in VI-D, the simulated stiffness of the beam is approximately 141.70 N/mm.

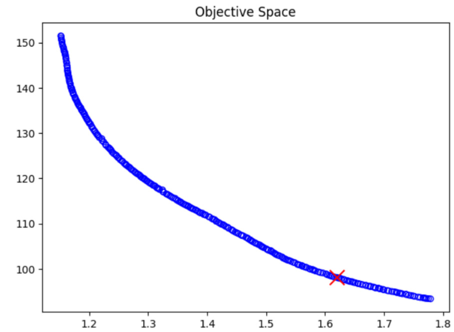

Fig. 8: 50% VF PO beam optimal solution curve

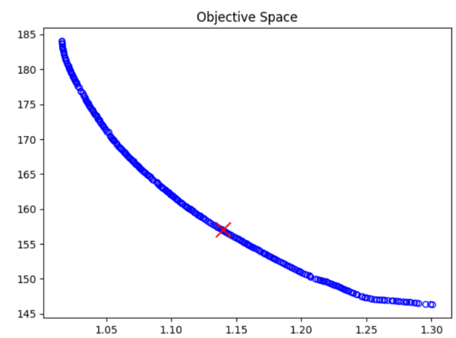

Fig. 9: 80% VF PO beam optimal solution curve

50% Parametric Optimization: The final PO beam for the 50% VF is shown in Fig 11. The final beam massed in at a simulated 97.99 grams. Under approximately 10 kg of force load, the 50% VF TO beam had a simulated deformation of 0.4004 mm. Using the formula described in VI-D, the simulated stiffness of the beam is approximately 246.63 N/mm.

80% Parametric Optimization: The final PO beam for the 80% VF is shown in Fig 12. The final beam massed in at a simulated 156.72 grams. Under approximately 10 kg of force load, the 80% VF PO beam had a simulated deformation of 0.2833 mm. Using the formula described in VI-D, the simulated stiffness of the beam is approximately 348.57 N/mm.

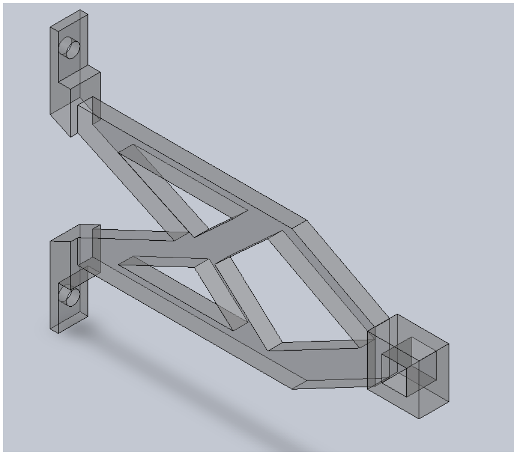

Fig. 10: Final 30% VF PO Beam

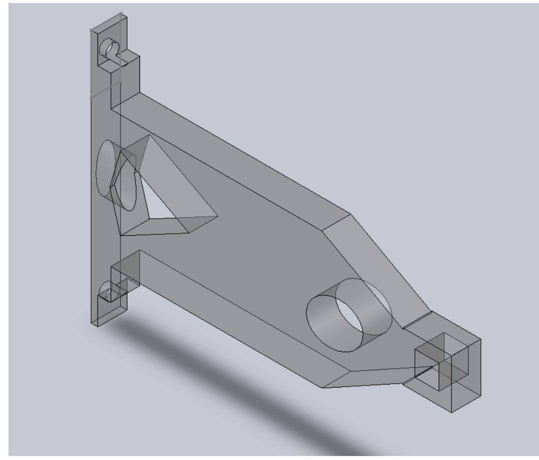

Fig. 12: Final 80% VF PO Beam

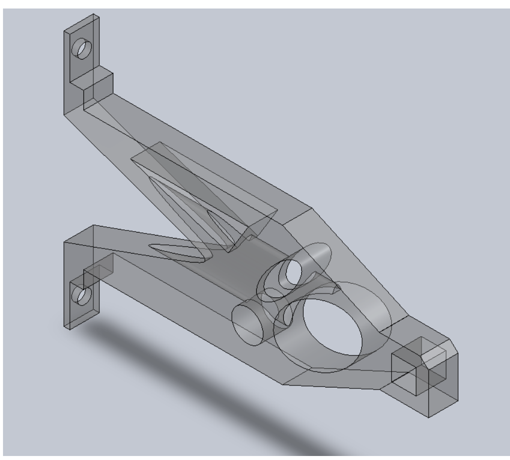

Fig. 11: Final 50% VF PO Beam

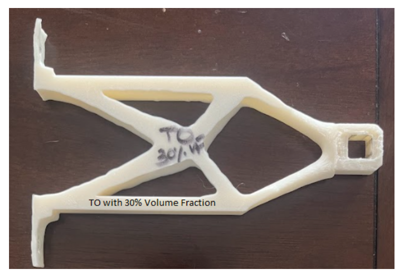

Fig. 13: 30% VF TO Beam

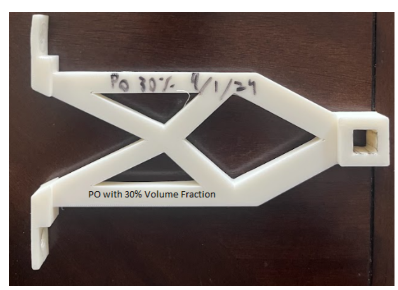

Fig. 14: 30% VF PO Beam

C. Physical Experimental Validation

After the finalized TO beams and PO beams were created, they were each manufactured through the additive manufacturing (AM) method of 3D-printing. The 3d printed beams are shown in Figs 13,14, 15, 16, 17, and 16.

These 6 3D printed beams were then physically subjected to a load of approximately 10kg, using a custom experimental setup as shown in Fig 19. The actual deformation displacement of each beam was measured using a dial gauge as shown in Fig 19. The final results of this physical experimental validation are shows in Tables I and II

As shown in Tables I and II, the data reveals many key findings (note: percent error for the stiffness data is the same as the respective beams displacement percent error). It is evident that the TO workflow led to stiffer beams across all 3 VFs. This was consistent across both the simulated results and physical results. However, while the TO beams were stiffer, they were also shown to be less predictable. As shown in table I, the 3 TO beams had physical deflection to simulated deflection percent errors of 45.5%, -6.6%, and -1.5%, compared to the respective PO beam percent errors of

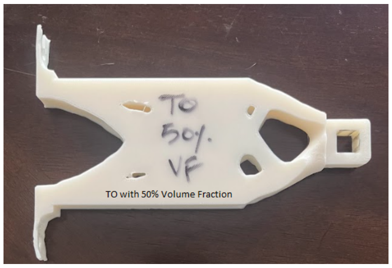

Fig. 15: 50% VF TO Beam

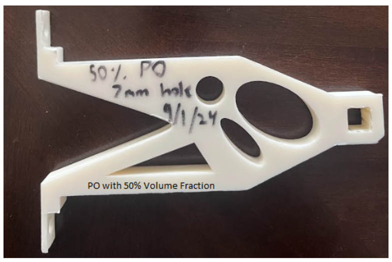

Fig. 16: 50% VF PO Beam

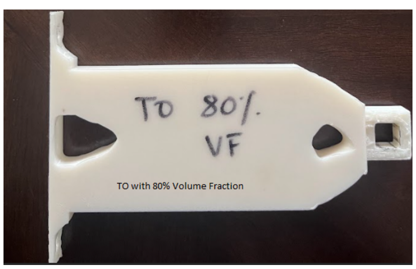

Fig. 17: 80% VF TO Beam

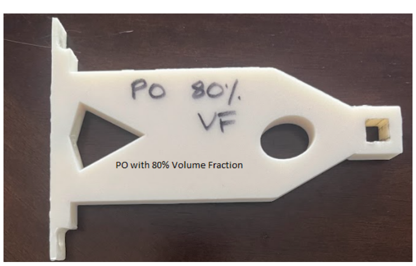

Fig. 18: 80% VF PO Beam

Fig. 19: Experimental setup for testing displacement

This table summarizes the main results of software simulations and physical experimental validation

Deflection (mm)	30% VF	50% VF	80% VF
TO SolidWorks	0.59	0.38	0.28
TO Physical	0.86	0.35	0.27
TO Percent Error	45.5%	-6.6%	-1.5%
PO SolidWorks	0.70	0.40	0.28
PO Physical	0.93	0.41	0.28
PO Percent Error	33.7%	2.4%	-0.1%

TABLE I: SolidWorks simulation and physical experimental validation results for TO and PO beams

33.7%, 2.4%, and -0.1%. These findings imply that while the TO workflow will suffice to create better designs for structural performance, designers concerned with predictability of design performance should consider a PO workflow.

Another trend evident in the data is the drop-off in real-world adherence to simulated results as VF decreases. This is seen across both the TO and PO beams, where the percent error increases slightly between the 80% and 50% beams, but experiences a massive increase from the 50% beams to the 30% beams. While the exact cause of this is difficult to explain, a few theories are proposed. The first theory is that the maximum yield stress of the material used was surpassed, as this stress was not provided on the material specification sheet and therefore was not factored into simulation calculations. Another theory is that due to the specific design of the 30% VF beams, they were manufactured in a manner leading to much less material efficiency and isotropy, which could have contributed to their unprecedented deflection.

This table summarizes the simulated and physical experimental stiffness of each beam

Stiffness (N/mm)	30% VF	50% VF	80% VF
TO Solidworks	167.45803	262.00584	358.96038
TO Physical	115.09324	280.53977	364.39114
PO Solidworks	141.69895	246.62837	348.57042
PO Physical	105.95494	240.85366	348.93993

TABLE II: SolidWorks simulation and physical experimental validation stiffness for TO and PO beams

VIII. Key Findings

The experimental results shown in Tables I and II yield several key findings:

1) Both TO and PO are proven, valid methods for SO, in the context of this chosen application (a simple cantilever beam).
2) TO was much faster than PO and easier to perform in SolidWorks.
3) The integration of ML into the PO process increased the efficiency of SolidWorks to perform PO. For PO, SolidWorks relies on manual, trial-and-error approaches. It does not ”learn” from past results, meaning that users must manually adjust parameters and rerun simulations, leading to a time-consuming process. By incorporating ML for PO, the design process became more data-driven and automated.
4) PO performed in this way was significantly slower than TO.
5) 3D printing both TO and PO led to the conclusion that PO beams were easier to manufacture than TO beams (In order to maintain their integrity during the 3D-printing process, TO beams required supports that were more complex and more in number than PO beams, resulting in a difficult support removal process).
6) TO predicted less displacement for the same volume fraction in SolidWorks. simulations, as well as resulted in less displacement in physical validation; however PO was more accurate in its prediction of real displacement (the physically validated results more closely matched the SolidWorks simulated results for PO beams).

IX. Conclusion

In this paper, a comparative study was conducted between two main SO workflows, TO and size/shape PO. In particular, the test case of a cantilever beam was used as a medium for the research. TO was first conducted on the cantilever beam for 3 different mass preserved percentages (VFs). Afterwards, PO was conducted on roughly redesigned versions of these 3 TO beams, with the assistance of data-driven optimization and machine learning. Finally, the 6 resulting beams were both simulated in FEA software and physically tested with a homemade deflection testing setup (the beams were additively manufactured through fused-deposition modeling). The results of simulated versus actual deflection for all 6 beams were then compared, and presented in Tables I and II. The results from the manufacturing of the beams and the the testing results indicate many findings, detailed in VIII.

The results substantiate the conclusion from the paper “Topology and Parametric Optimization-Based Design Processes for Lightweight Structures” [17] in which authors conclude that there is no clear answer to the question about what the best process is, and the suitability of TO Vs PO depended upon use case and end application. From this work, the following conclusion can be drawn - If better manufacturability and accuracy is desired, use PO; but if time is of the essence then use TO.

X. Key Contributions

- Direct comparison of TO and PO that evaluates both from a variety of angles, including time taken, compliance, manufacturibility, and variability between simulation and experimental results.
- Physical experimental validation of software simulated results.
- Integration of ML with SolidWorks for PO.

XI. Future Research Directions

The integration of a Machine-Learning based surrogate optimization algorithm for Parametric Optimization was utilized in this paper. However, this algorithm was only compared against the SOLIDWORKS built-in SIMP Topology Optimization algorithm. There are other methods of conducting Parametric optimization, one such being to use a Simulation In-The-Loop algorithm, where parameters are manually changed and optimized after repeated Finite Element Analysis simulations. Possible high-interest further research in this field may include the comparison of ML-based surrogate parametric optimization versus simulation in-the-loop parametric optimization.

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