Generative Truss Optimization for Support-Free Fused Filament Fabrication

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***Abstract*—Fused Filament Fabrication is currently among the most commonly used Additive Manufacturing technologies but is highly reliant on temporary support structures during production. Implementing a generative optimization algorithm for support-free Fused Filament Fabrication could streamline the manufacturing process in terms of labor, time- and material use. Despite the current relevancy of Additive Manufacturing, there is a lack of research on structural optimization customized for support-free Fused Filament Fabrication. This research applies a generative optimization algorithm consisting of a multi-objective evolutionary algorithm and a local search algorithm to generate and optimize rigid-jointed 3D truss structures. The results show the capacity to generate and optimize support-free rigid-jointed truss structures with promising solutions to a multi-objective optimization task. This paper suggests that support-free structural optimization algorithms can impact how we design robotic bodies and parts in the future.**

***Index Terms*—Generative 3D Rigid-Joint Truss Optimization, Mechanical Strength**

I. INTRODUCTION

In its prime, Additive Manufacturing (AM) technologies, commonly known as 3D printing, were mainly applied in the professional sector. In recent years, AM technologies have been increasingly applied by hobbyists for rapid prototyping tasks [1]. The most widely used AM technology today is Fused Filament Fabrication (FFF), also known as Fused Deposition Modeling (FDM), due to its availability and affordable price on the consumer market. Consequently, FFF technologies have become a significant area of interest for research. However, FFF technologies pose challenges: 3D prints may be time- and material-expensive if a design does not satisfy the *overhang-constraint*. A. Guido, O. Adam and D. Zimmer specified geometrical limitations of FFF in [2]. The work by Y. Wang, J. Gao and Z. Kang in [3] suggests that a design can not be printed defect-free on an FFF 3D printer without support structures when the design does not satisfy the overhang-constraint. The works in [3] and [4] successfully incorporated the overhang-constraint in design optimization tasks of existing 3D shapes.

The *constrained* structural optimization of 3D truss structures is a complex problem that likely can not be computed by an exact algorithm without better insight into the field of Additive Manufacturing. Therefore, we want to employ a heuristic method to generate a population of candidate solutions to implement the truss generation and optimization of support-free truss structures. This paper incorporates the overhang-constraint in a generative optimization algorithm. A significant incentive for applying generative optimization algorithms to design tasks is to utilize computational resources to support human designers and automate parts of the design process [5]. Generative optimization algorithms allow for rapid testing of many different variations of truss structures through evolution, optimization, and simulation. The generative truss optimization algorithm's results may even yield design solutions that human designers would not be able to imagine. As design problems get increasingly complex, the required design time is expected to be substantially less for an automated generative optimization algorithm compared to a human designer. Furthermore, we argue that minimizing material waste is of environmental benefits, especially in large scale production. Therefore, a successful result of the proposed design process can yield economic and environmental benefits.

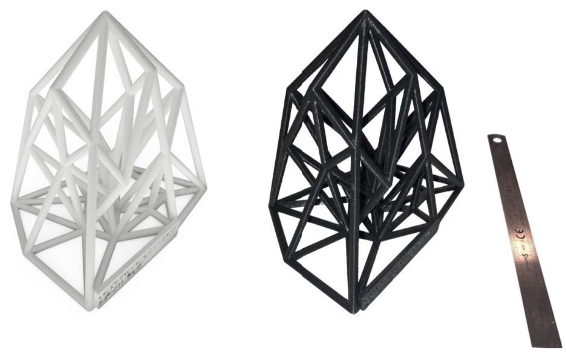

Fig. 1: Rendered simulation model (left) and physical 3D printed model (right) of a generated support-free truss structure.

We consider the boundaries of the FFF 3D printer when implementing the constraints in the generative truss optimization algorithm. Additionally, we aim to optimize two objectives with the proposed algorithm. The motivation behind the objectives originates from 1: the aspiration to provide strength optimized rigid-jointed truss structures on an FFF 3D printer, i.e., fitness objective: F_D. And 2: We hypothesize that truss structures with denser connections

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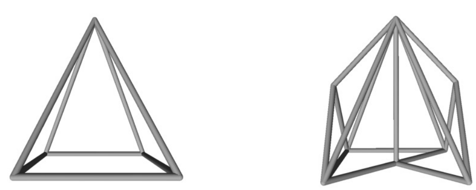
between beams, as opposed to sparse connections, can minimize defects during 3D printing on FFF printers. We want to minimize truss structures' beams' length to optimize printability, i.e., F_B. We assume that short-beamed structures must contain a higher concentration of beams compared to most long-beamed truss structures. Consequently, we hypothesize that structures containing shorter beams are more rigid during 3D printing. The presented generative optimization algorithm shall optimize truss structures given the objectives:

1. Minimize the uppermost node's deflection (F_D)
2. Minimize the longest beam length (F_B)

This truss optimization task involves finding the optimal topology and shape for a 3D printed truss structure given 40 grams (g) of Polylactic Acid (PLA) material. How can we find an optimal truss structure considering the constraints of the FFF printer, and the force load application task? The research in this paper involves incorporating the overhang-constraint to both synthesize and optimize overhang-free truss structures cf. Figure 1. This paper emphasizes the efficiency of the generative optimization process regarding performance, cost, time, and labor.



(a) Concept-seed (b) Synthesized topology

Fig. 2: Growth from half-octahedron (pyramidic) concept-seed

This paper presents the performance of generated and 3D printed truss structures, considering the efficiency of the 3D printed trusses concerning fitness performance, material-, and time use.

II. Background

Conventional truss optimization approaches discretize the design space with a nodal mesh of a ground structure, where every node connects to almost every other node in the structure [6]. The structural optimization of trusses have been implemented by many means over the past years, including Genetic Algorithms [7], Simulated Annealing [8], Particle Swarm Optimization, [9], [10], Harmony Search [11], Mine Blast Algorithm [12], Adaptive Dimensional Search [13], Symbiotic Organisms Search [14], Colliding Bodies Optimization [15], and several improved or hybrid optimization techniques. Additionally, the increased focus on shape optimization in the field of Evolutionary Robotics [16] excites the relevancy of structural optimization. Continuous shape optimization of robotic bodies during operation is a powerful technique in many applications [17].

The extensive work on structural optimization facilitates the optimization of trusses for different purposes. P. W. Christensen and A. Klarbring describe truss optimization as a combination of three optimization problems, namely: sizing, topology, and shape optimization [18].

1. The objective of *Sizing* optimization is to find the optimal cross-sectional area of structural elements.
2. *Topology* optimization aims to find the optimum existence and connectivity of the nodes.
3. *Shape* optimization is concerned with finding the optimum nodal coordinates of joints in a truss structure.

This paper focuses on topology and shape optimization exclusively to simplify the scope of the optimization task. Therefore, we standardize the size of truss structures by defining a fixed truss height, $h = 120$mm, and uniform beam diameter, $d = 4$mm, when implementing the proposed generative optimization algorithm. This paper develops a two-phase algorithm implementing the topology synthesis and shape optimization separately. O. Hasançebi, S. Çarbaş, E. Doğan, F. Erdal, and M. P. Saka indicate that Simulated Annealing (SA) is among the most effective truss shape optimization algorithms in [19]. The SA algorithm has been applied in many structural optimization tasks: L. Lamberti implemented a Modified Simulated Annealing (MSAA) algorithm in [8]. The work by L. Lamberti in [8] focuses on global optimization by generating random truss structures before optimization by SA. J. Suarez, C. Millan, and E. Millan implemented an Improved Modified Simulated Annealing algorithm (I-MSAA) for truss structure optimization [20] introduced in their work in [21]. We note that the SA approaches in [8] and [21] are devoted to the optimization of *2D* structures, while the work in [19] concerns 2D and 3D *pin-jointed* truss structures. The work in this paper focuses on synthesizing and optimizing *rigid-jointed*, *3D* truss structures exclusively. The shape optimization phase of the proposed generative optimization algorithm bases on work by O. Hasançebi et al. in [19], J. Suarez et al. in [20], [21], and L. Lamberti in [8].

M. A. Rosenman emphasizes that generative evolutionary algorithms can be potent catalysts for design synthesis where the optimal solution is not known a priori, in [22]. P. Bentley and J. Wakefield present relevant literature on generative optimization in their paper on *Generic Evolutionary Design* [23]. P. Bentley and J. Wakefield describe a generative evolutionary design system as capable of evolving a wide range of solid structures from scratch. This paper proposes a generative evolutionary design approach for truss topology synthesis, before truss shape optimization, based on work by P. Janssen in [24]. P. Janssen bases his generative evolutionary design method on earlier work by J. Frazer and J. Connor in [25], and J. Frazer in [26]. J. Frazer's approach relies on a set of design ideas for a design problem. These design ideas form a set of constraints

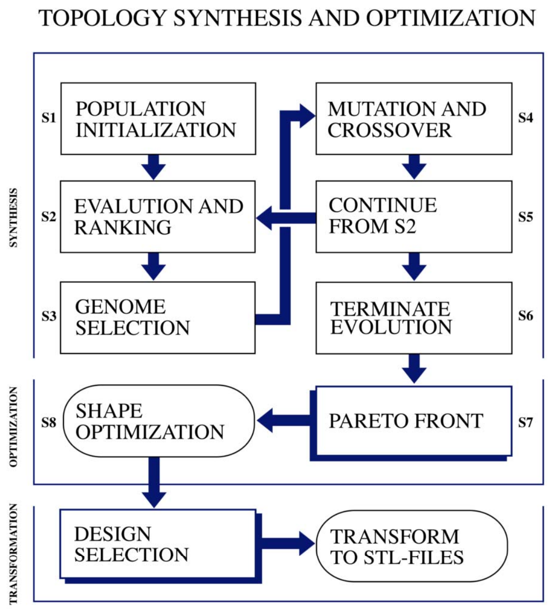


Fig. 3: Generative process, where step S8 refers to Figure 4

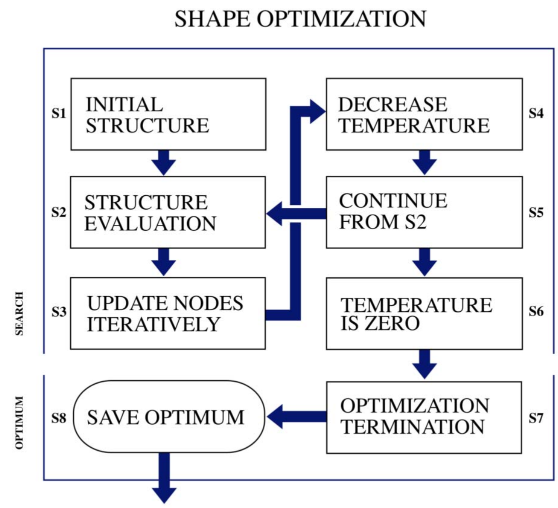


Fig. 4: Shape optimization by Simulated Annealing

that are encoded and implemented in generative optimization algorithms. The generative optimization algorithm allows a concept with a set of properties to be transformed into an improved solution to a design task [25]. Similarly, this paper aims to synthesize well fit truss structures by transforming a simple (concept-seed) structure over numerous generations, cf. Figure 2. Generative truss optimization algorithms were employed in similar works by S. Degertekin in 2007 [27], and A. Pejman, J. Mohamad, A. Abazar, G. Amir, and E. Milad in 2011 [28]. S. Degertekin compares SA and a genetic algorithm for optimum design of space frames in [27]. S. Degertekin found that the SA algorithm took longer to converge, but also found better optima than the genetic algorithm. A. Pejman et al. combined a genetic algorithm with SA to create a predictive algorithm in [28]. However, a generative truss optimization algorithm for support-free Fused Filament Fabrication is yet to be recognized. This paper proposes a novel, two-phased generative truss optimization algorithm for support-free Fused Filament Fabrication by combining a genetic algorithm and SA.

III. Methods

We implement the proposed generative truss optimization algorithm through a non-dominated sorted genetic algorithm (NSGA-II) [29] for topology synthesis and a modified Simulated Annealing algorithm (MSAA) [8] for shape optimization. We evaluate each truss structure through the Finite Element Method (FEM) for 3D rigid-jointed space frames. The multi-objective fitness is based on a candidate truss' simulated vertical deflection on the uppermost node in the structure and the length of the truss structure's longest beam. The goal of the optimization is to minimize the fitness function for both of the objectives. The presented truss structures are manufactured on a Creality Ender-3 (CE3) FFF 3D printer [30]. Subsequently, we inspect the quality of the printed truss structures regarding defects in the 3D prints. Lastly, we load-test the 3D printed truss structures on the load-testing rig. The load-testing rig consists of a steel frame with an attached podium for placing and testing 3D printed truss structures. An FC23 Compression Load-Cell [31] is connected to a hydraulic press on the rig, that can be adjusted vertically up and down. The load-cell connects to an aluminum pipe that loads the truss structures, cf. Figure 6. Figure 6 displays the test rig frame in blue, load-cell in red, and aluminum pipe in grey. A 3D printed truss structure is placed underneath the aluminum pipe and loaded when it is lowered with the hydraulic press. The FC23 compression load-cell measures the load resistance from the truss structure.

We require a fitting representation of the force load application task when simulating the real world. The works in [32], [33] and [6] show that one can enhance the design process by considering insight into the direct relation between load flow and deformation behavior. D. W. Kelly and M. Elsley introduce the term load path in [33]. Force loads flow through a structure from the applied input point(s) to the reaction output point(s). Truss structures carry axial loads exclusively; therefore, the load paths are simple to compute.The mathematical formulation of the load paths is popularly carried out with the Finite Element Method (FEM) [6], [34], cf. Figure 5. This paper applies a FEM for the simulation of loaded trusses structures.

A. Constraints

This section sums up the constraints we implement in the complete generative truss optimization algorithm. We specify the boundaries of the truss topology synthesis and shape

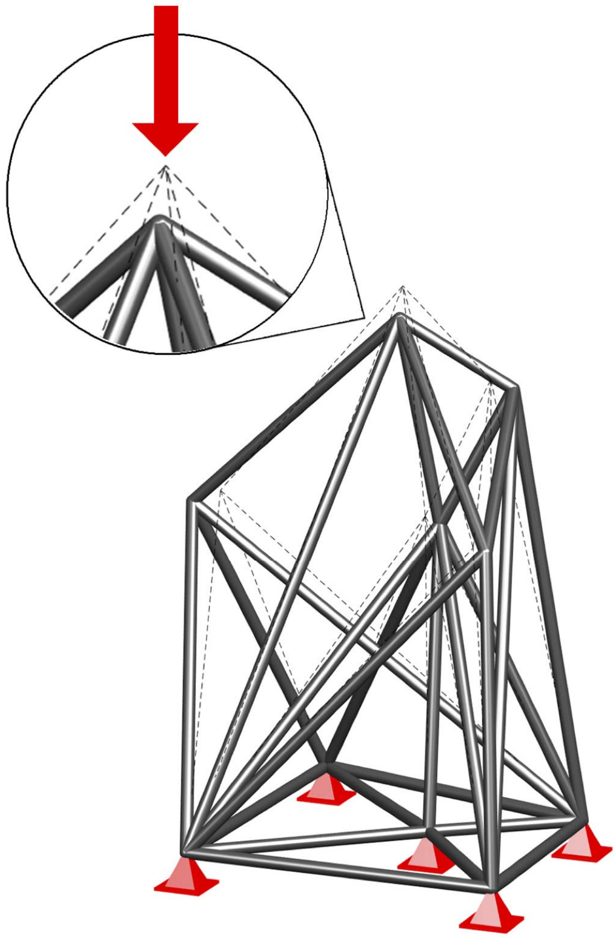


Fig. 5: Simulated force load on 3D rigid-joint truss

optimization task with the finalized boundary specification of the generative truss optimization algorithm. The proposed FEM is utilized as the deflection evaluation metric in this study. Thus, we take the FEM's constraints into account when posing the problem specification. We take the CE3 printer's constraints into account to ensure successful 3D printing of truss structures. The FFF constraints constitute the printability measure for the generative truss optimization task. Here, the angle between a beam and the ground plane, and the length of each beam affect the printability. With the successful implementation of the FEM and FFF constraints, we can begin implementing the truss topology synthesis and shape optimization algorithms. The following points specify the constraints for the implementation:

$$\text{Beam length: } L_{min} = 4\text{mm and } L_{max} = 200\text{mm:} \quad (1)$$

A printable truss shall be within a (220 x 220 x 250) mm^3 space. To ensure a successful FEM for the given application, all beams in a successful truss structure must be of minimum $L_{min} = 4$mm. We set an upper boundary to the longest beam

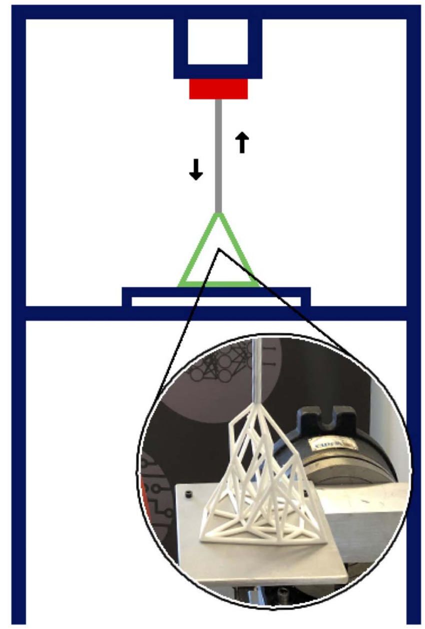


Fig. 6: Load-testing Rig Illustration

length $L_{max} = 200$ mm, as we wish to minimize the beam lengths in the truss structures.

$$\text{Truss weight constraint: } m_T = 40 \text{ grams.} \quad (2)$$

We ensure that truss structures obtain a maximum mass of $m_T = 40$ grams. We note that the maximum mass m_T constitutes a constraint for the optimization, and not an objective to be minimized in this paper. The upper mass limit m_T is specially directed towards the truss topology synthesis phase to produce truss structures with an efficient filament distribution.

$$\text{Beam angle constraint: } \theta_T = 18°. \quad (3)$$

We ensure that all accepted candidate structures contain beams with a minimum angle of $\theta_T = 18°$ between every beam. The constraint concerning the minimum angle between beams is a means to ensure successful finite element analyses during truss topology synthesis and shape optimization. As the generative truss optimization algorithm relies on the accuracy of the structural analysis, the FEM must not contain errors when analyzing a wide range of truss structures.

$$\text{Overhang-angle-constraint: } \theta_{FFF} = 45°. \quad (4)$$

Every beam in all of the support-free candidate truss structures shall be at least $\theta_{FFF} = 45°$ with respect to the ground (xy-) plane. The truss structures are printed from the ground plane and up. Consequently, all horizontal beams must lay on the ground plane for support-free truss structures.

B. Algorithm

Truss topology synthesis: The generative evolutionary algorithm (NSGA-II) is devoted to synthesizing candidate truss topologies, cf. Figure 3. The problem specifications for angle constraints, rigid and fixed nodes, maximum beam length, and the loaded node deflection are incorporated in the evolutionary algorithm. The proposed evolutionary algorithm starts with a simple half-octahedron concept-seed, cf. Figure 2a, as the baseline for the evolution of new truss structures. The proposed evolutionary algorithm generates an initial population of mutated variants of the half-octahedron concept-seed. Mutational variations include moving nodes in 3D space, swapping edge-connections, or spawning new nodes with new connections. All variations of the baseline concept-seed constitute the entire initial population of candidate solutions. The proposed FEM calculates the deflection in the uppermost node for each node mesh and determines a structure's longest beam length. The deflection F_D and maximum beam length F_B constitute the candidate solution's fitness. The truss-topology-synthesis-phase results in a Pareto front of candidate truss structures based on the fitness objectives, cf. Figure 9.

Truss shape optimization: The truss shape optimization process constitutes the second and final phase in the proposed generative truss optimization algorithm, cf. Figure 4. The goal of the truss shape optimization phase is to find the optimal node configuration for each node in a truss structure based on the objectives F_D and F_B, respectively. The shape optimization phase consists of applying the MSAA on each candidate truss from the final Pareto front presented by the truss topology synthesis phase. The shape optimization phase terminates when all candidate truss structures' shapes have converged, cf. Figure 4.

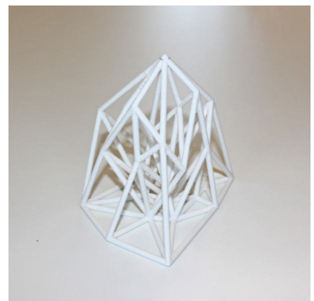
The MSAA inputs a candidate truss structure with n nodes $\in$ N and e edges $\in$ E. The MSAA iterate over the nodes in a candidate structure numerous times during the shape optimization phase. On each iteration in the MSAA, six *searches* with a defined search length T are employed along all spatial axes. Here, the *search* constitutes creating a temporary truss structure, altering the position of the given node. A candidate truss structure can be updated with a worse fitness based on the probabilistic Boltzmann equation. If the P(ΔE) $< \frac{1}{3}$, where P(ΔE) = $e^{\frac{-\Delta E}{T}}$, and ΔE = $F_D + F_B$, the MSAA updates the truss candidate with a worse equilibrium. The search step T decreases by the step size S, if the fitness of a candidate truss structure is not updated during an entire iteration. The MSAA terminates when the search step $T = 0$.

TABLE I: 3D printed truss meta data

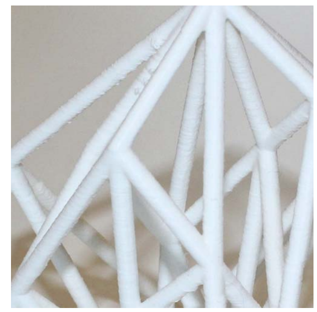
Res	F_D	F_B	T_{print}	Mass	Name
0.044kN	1000	1271	≈ 3 h	11g	Seed
0.46kN	144	842	≈ 13 h	40g	Evo 1
0.39kN	197	1214	≈ 10 h	39g	Evo 2
0.24kN	229	776	≈ 7 h	30g	Evo 3

(a) Seed: Full figure

(b) Close up on defects



(c) Evo 3: Full figure



(d) Close up on defects

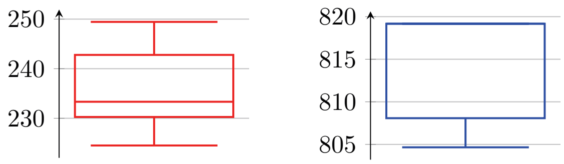
Fig. 7: Comparing defects in 3D printed trusses

IV. Experiments and Results

The 3D printed truss structures were manufactured without support on the CE3 FFF printer. The simulated deflection fitness F_D of the support-free truss structures corresponded proportionally to the tested deflection on the load-testing rig in the conducted tests, cf. Figure 10.

The results in Table I presents the measurements that were conducted for the 3D printed truss structures. Table I presents measured force resistance conducted on the load-testing rig (*Res*), cf. Figure 6. F_D and F_B constitute the calculated fitness values from the finite element analyses of the tested truss structures. The force resistance, *Res*, was measured on the test rig, cf. Figure 6 with Voltage-output from the FC23 load-cell. The Voltage-output from the test-rig was subsequently translated to kilonewtons (kN) cf. Table I. We note that a higher *Res*-value constitutes favorable test-performance, whereas lower F_D and F_B constitute favourable simulation performances. The print time, T_{print}, was read from the timer on the CE3 FFF 3D printer after terminated 3D print. The support-free 3D prints measured between 11g to 40g in *Mass*. The gray row in Table I marks the 3D printed half-octahedron concept-seed, cf. Figure 2a, as a baseline for the performances of the remaining 3D prints. The *Name*-column in Table I identifies the different truss structures in Figure 10.

Table I displays that the generated truss structures' deflection performances outperform the baseline half-octahedron concept-seed regarding the fitness objectives F_D and F_B as well as tested force resistance *Res*. The experiments in Figure 9



(a) F_D fitness spread (b) F_B fitness spread

Fig. 8: Examples of MSAA executions on a truss candidate after NSGA-II

show the proposed generative optimization algorithm's capacity to produce a variety of trusses given the fitness objectives F_D and F_B. Furthermore, the MSAA experiments in Figure 8 show that the proposed generative optimization algorithm can optimize truss shapes after truss topology synthesis with the NSGA-II.

Lastly, we observe a significant reduction in the severity of defects from the baseline seed to an optimized truss structure (Evo 3) in Figure 7.

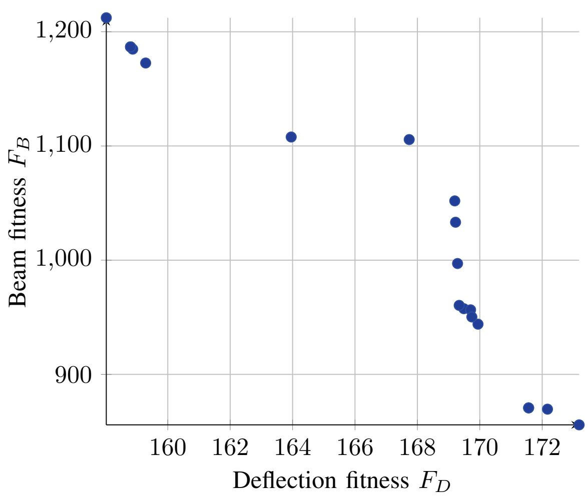


Fig. 9: Pareto front fitness spread among generated trusses after one NSGA-II experiment

V. Discussion

We deduce robustness in the consistency between simulation and reality in the proposed generative optimization algorithm from the results presented in Table I and Figure 10. We observe that the proposed generative optimization algorithm produces local minima for each run, with varying fitness results. Furthermore, there does not seem to be a consistency in how much the fitness objectives F_D and F_B are improved by the MSAA given a synthesized truss topology.

We indicate a connection between calculated deflection fitness F_D and tested real-world force resistance in Figure 10. There seems to be a reduction of defects on 3D prints given optimized trusses compared to the concept-seed in Figure 7.

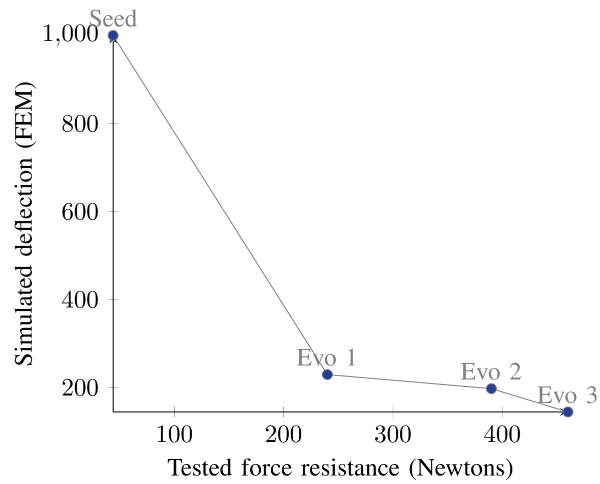


Fig. 10: Comparing simulated and real-world performances

The consistency in Figure 10 validates the evaluation by the proposed FEM, and indicates the utility of optimizing truss structures with the proposed generative optimization algorithm.

VI. Conclusion

This paper presents a generative optimization algorithm for optimizing the topology and shape of 3D rigid-joint trusses, given a multi-objective optimization task for the constrained simulation space of support-free FFF. The results show the capacity to generate and optimize support-free rigid-jointed truss structures. The experiments and results demonstrate a promising consistency between software and hardware. The optimized structures are 3D printed and tested in the real world, and the test results are shown to be consistent with simulations.

The proposed generative optimization algorithm reduces 3D printing defects while maximizing mechanical strength. It facilitates material- and time efficiency in production on both micro-, and macro-scale production, a key in future generative manufacturing.

VII. Future Work

We aim to further test and optimize the proposed generative optimization algorithm, given the multi-objective optimization task. We plan to produce a set of truss structures that do not consider the overhang-constraint as a comparable measure for further research. A comparable data set might be acquired by synthesizing and optimizing truss structures without the overhang constraint or even enforcing a generative optimization algorithm to break the overhang-constraint. A comparable set of truss structures might yield a metric on the time-, material- and optimization efficiency of a support-free truss optimization algorithm. Furthermore, using an anisotropic model of the structure might yield a more accurate representation of the layered physical object.

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