Optimization of 3D printed objects

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Introduction

In traditional manufacturing, complexity is expensive. The cost of complexity takes the form of work-in-progress, tooling, and time to prototype. These costs can be hard to estimate because they depend on many factors.(Gorguluarslan et al. 2017) In contrast, in three dimentional printing, complexity is free. There is a clear trade off between the strength of an object and the amount of material used to print the object. In this project, we aim to show a method for simultaneously optimizing a 3D printable object for both strength and cost. three-dimensional printing is ready to become a viable alternative to conventional manufacturing. (Chen and Gabriel 2016)

Blender is an open-sourced design tool that can output .STL files. STL files specify the surface of a three-dimensional object in terms of triangles on the surface of the object. A consequence of triangular faces is that they require significantly less computational time because neither projection of the polyhedron faces onto the appropriate coordinate planes nor reduction using Green's Theorem are necessary. (Eberly 2002)

Slic3r is an open-sourced tool to convert a model into printing instructions. It creates horizontal slices (layers) and generates tool-paths needed to fill them. It can also calculate the amount of filament to be extruded.

The goal of this project is to create an end-to-end flow from STL file to optimal G-Code file. In order to do that we have to design an experiment, slicing the STL file in many different ways. Focusing the infill parameters, we collect the metadata from the g-code output and enrich with some previously collected tensile strength data. Then we can model both the strength of the object and the amount of filament used to print the object. With those models in hand, we define a cost function that is proportional to filament used minus strength. Using a differential evolution algorithm to find the minimum cost.

Tang et al. (2017) propoesd a lattice design.

Lattice structures can improve stiffness. (Tang et al. 2017)

Von-Mises stress and displacement can be reduced without increasing the volume.(Tang et al. 2017)

manufacturability can be ensured by use of experimentation and artificial neural networks.(Tang et al. 2017)

The lower bound of cross-sectional should be the smallest value that can possible. [gorguluarslan2017improved]

> "additive manufacturing is one of the most promising technologies in the field of manufacturing." - Majeed, Lv, and Peng (2018)

Majeed, Lv, and Peng (2018) has demonstrated the use of big data optimization for additive manufacturing.

the convergence of the genetic algorithm could be further improved.(Gorguluarslan et al. 2017)

For example, a heuristic search could be implemented in order to generate better initial populations, or a quick local search could be done after each crossover and mutation, in order to obtain better child chromosomes.(Gorguluarslan et al. 2017)

In the first phase, the lattice structure is generated using the mesh information of the structure geometry.(Gorguluarslan et al. 2017)

If the manufacturing constraint is directly used in the ground structure optimization process, the unnecessary elements cannot be removed from the structure and therefore the performance is worse than the obtained one when the proposed method is used, as shown in Gorguluarslan et al. (2017).(Gorguluarslan et al. 2017)

It is also shown that the optimized structure has better performance compared to alternative existing methods.(Gorguluarslan et al. 2017)

The second example is used to investigate the minimum diameter value that can be fabricated using the SLS process that will be used for the fabrication of the optimized lattice-based pillar structure.(Gorguluarslan et al. 2017)

The third example was a real-world application of the lattice structure optimization for a seat-bottom frame with a larger number of design variables when compared to the previous examples.(Gorguluarslan et al. 2017)

Moreover, it is shown in the second and third examples that the two-phase optimization framework can successfully find an optimized structure that can be fabricated once the minimum value is known for the specific additive manufacturing machine. (Gorguluarslan et al. 2017)

Molecular dynamics model, discrete element, and finite element model were developed to understand sintering, powder flow, residual stress and cracking in the components.(J. Zhang et al. 2018)

The diffusion of atoms is higher on particle surface than the particle core.(J. Zhang et al. 2018)

tensile test simulations of sintered material show that sintered nickel particles have lower mechanical strengths than the bulk nickel. (J. Zhang et al. 2018)

Higher heating rate leads to a higher mechanical strength because of accelerated sintering rates. (J. Zhang et al. 2018)

The effect of laser power on the temperature distribution of the powder bed was studied using the DEM. (J. Zhang et al. 2018)

The average temperature in the powder bed increases with higher laser power. (J. Zhang et al. 2018)

Garechana et al. (2019) describes our approach for the detection of core technological solutions—which we call "technology fronts" underlying certain device or broad development (three-dimensional printing has been the choice, as explained in the introduction) and the characterization of their dynamics of change across time.(Garechana et al. 2019)

These terms were crossed with patents to build term-document matrices corresponding to a set of time intervals that span from year 1985 to 2017.(Garechana et al. 2019)

We found that some of these fronts are in part coincident with the main taxonomies of typical devices in the three-dimensional printing industry, while others describe "hot points" where engineering efforts are put into practice to improve critical aspect of the devices.(Garechana et al. 2019)

Fortunately, with the wide use of smart sensing devices, real-time and multi-source data can now be collected. (Majeed, Lv, and Peng 2018)

In Majeed, Lv, and Peng (2018), a framework for big data-driven manufacturing process optimization for additive manufacturing has been proposed. (Majeed, Lv, and Peng 2018)

The second contribution is the big data acquisition and integration method was developed. (Majeed, Lv, and Peng 2018)

It can be used to collect the multi-source data for additive manufacturing, and then process and exchange the big data between heterogeneous enterprise information systems. (Majeed, Lv, and Peng 2018)

The third contribution is the big data mining and optimization of additive manufacturing. (Majeed, Lv, and Peng 2018)

The data mining method can be used to reveal the relationship between the production performance and process parameters, and the process parameters can be optimized to improve the production performance. (Majeed, Lv, and Peng 2018)

The real-time data can be acquired and transmitted to the enterprise database. (Majeed, Lv, and Peng 2018)

With the help of big data and analysis of variance (ANOVA), the process parameters of additive manufacturing have been optimized to minimize the energy consumption, improve the product quality, and improve the production efficiency by minimizing process time. (Majeed, Lv, and Peng 2018)

Future research works will be carried out on the application of Majeed, Lv, and Peng (2018)'s framework and development of the algorithm to optimize the parameters of the additive manufacturing for different materials and processes. (Majeed, Lv, and Peng 2018)

Workflow

In Gorguluarslan et al. (2017), we present Falcon, a new system that follows a visual analytics approach to improve knowledge discovery in long and complex time series data with practical applications to the field of additive manufacturing.(Gorguluarslan et al. 2017) The calculated activation energy of nickel particle diffusion is 6.10 kJ/mole in the particle core, and 6.24 kJ/mole on the particle surface, which are reasonably in agreement with experimental data 7.89 kJ/mole. (J. Zhang et al. 2018)

In order to study the behavior of these technology fronts, and considering the data features of transversal developments, we opted for a subsetting strategy based on the gamma values returned by the topic modeling solution for each patent, so we could build sub-data sets containing the patents in which claims were clearly focused on the topics identified by our approach.(Garechana et al. 2019) During additive manufacturing processes, a huge amount of real-time big data is generated. (Majeed, Lv, and Peng 2018)

Falcon provides linked visualizations from both temporal and statistical orientations with automated analytics to highlight interesting features. From our informal evaluations of the applied use of Falcon in additive manufacturing, we have learned that non-visualization experts can be vital members of interdisciplinary design teams as they help design new capabilities that respond to their actual needs, and they quickly employ new visual analytics techniques in creative ways to solve problems.(Gorguluarslan et al. 2017) The parallels between the analytical goals in additive manufacturing and other domains suggest that these capabilities are broadly applicable to many domains as they help users develop and refine a more complete mental model of complicated and large-scale time series data. (Steed et al. 2017) These matrices were analyzed using a topic modeling technique, which has shed light on the technology fronts being developed under the broad field of three-dimensional printing.(Garechana et al. 2019) Metrics built on patent data were used to characterize the rate of change of technology fronts, analyzing each of these on a relative basis with respect to the values produced by the rest of the fronts. (Garechana et al. 2019) Majeed, Lv, and Peng (2018) provides a good basis for the application of big data analytics in the additive manufacturing process. (Majeed, Lv, and Peng 2018) Majeed, Lv, and Peng (2018) brings three contributions to successfully implement the big data analytics in the area of additive manufacturing. (Majeed, Lv, and Peng 2018) The first contribution is the architecture of big data-based analytics and its key components in additive manufacturing. (Majeed, Lv, and Peng 2018)

Simulation and Modeling

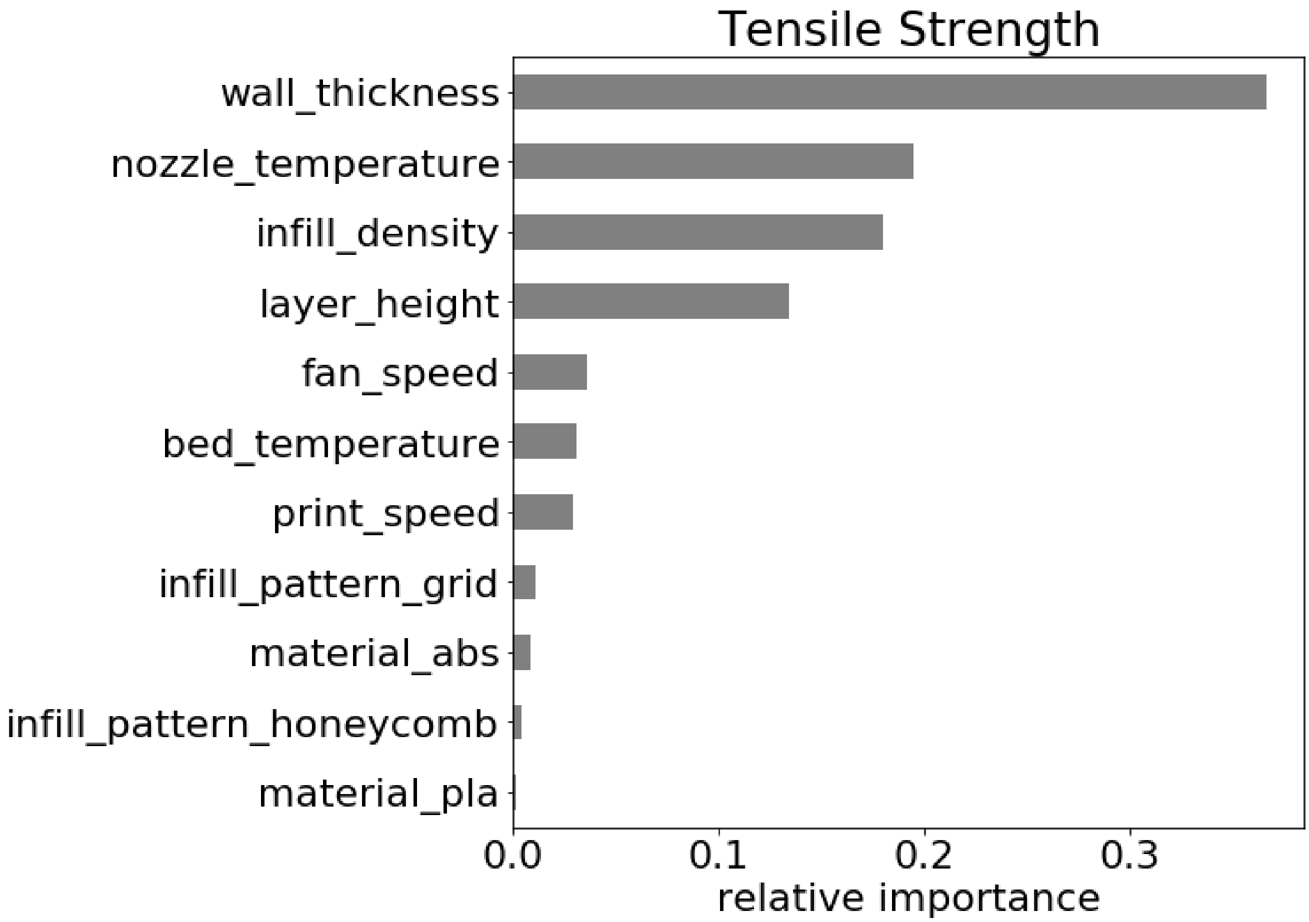
First we model tensile strength. After applying that model to the metadata, we model filament usage as a function of similar inputs.

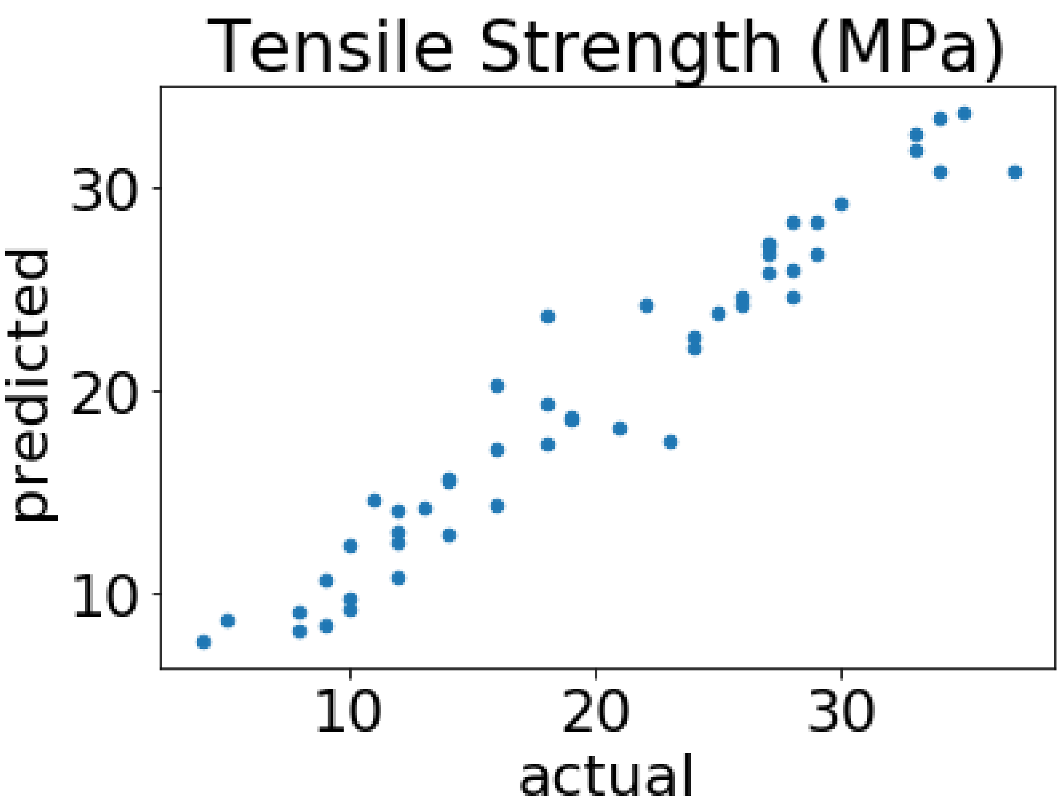
when we modeled strength, we found that the most important parameter was wall thickness. Extrusion temperature, and fill density were also significantly predictive of tensile strength. Every other parameter we looked at was discarded, the top ten features are summarized here.

we used a random Forest to predict tensile strength from these four parameters.

Predictors of tensile strength

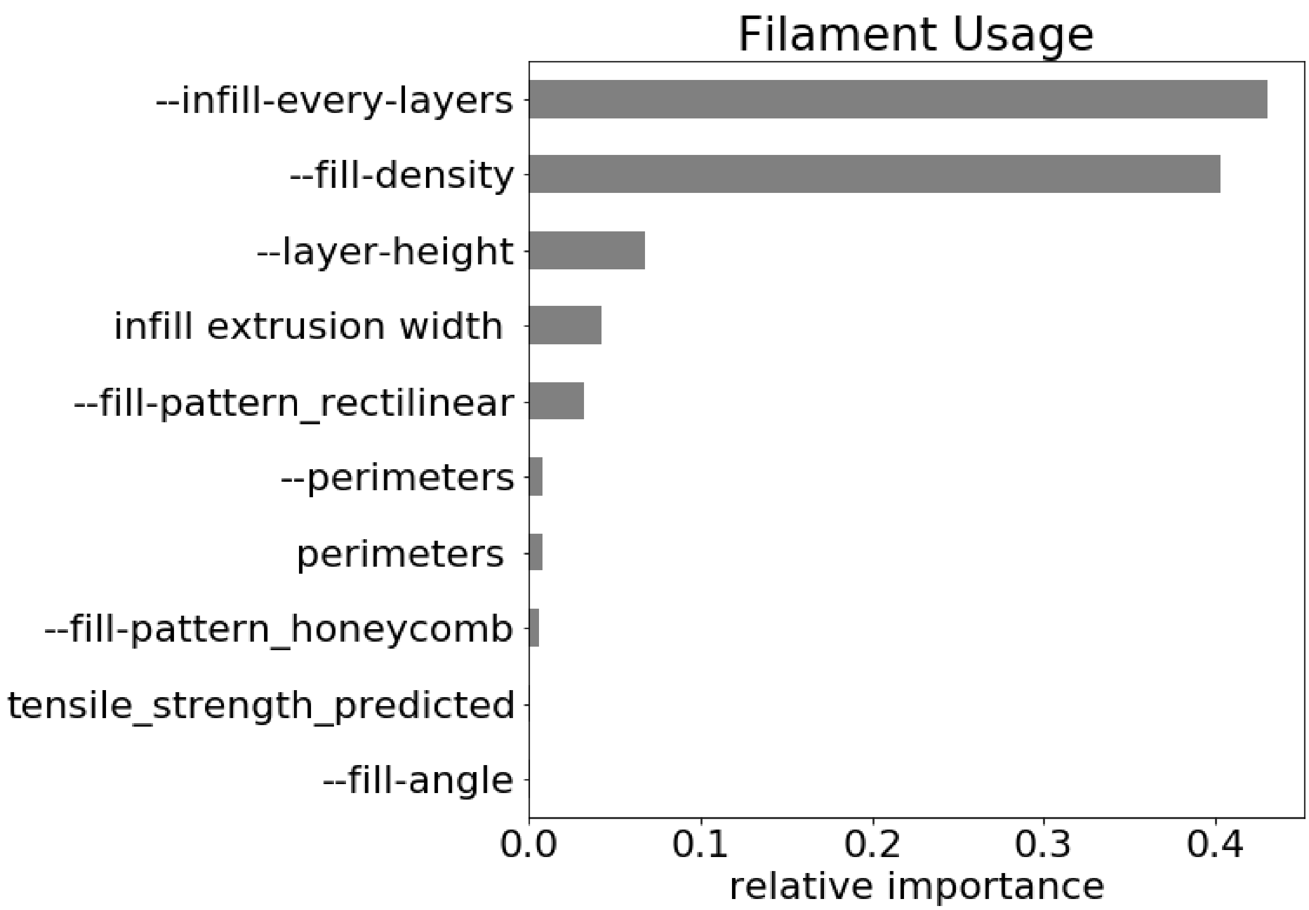
column	description	units
wall thickness	Number of solid layers on surface	# of layers
nozzle temperature	Extrusion temperature	°C
infill density	percent of volume to fill with pattern	%
layer height	height of each layer	mm
fan speed	speed of cooling fan	% of max
bed temperature	temperature of platform	°C
print speed	speed of robot arm	mm/s
infill pattern	pattern of non-solid layers	Rectilinear or Honeycomb
material	material	ABS or PLA

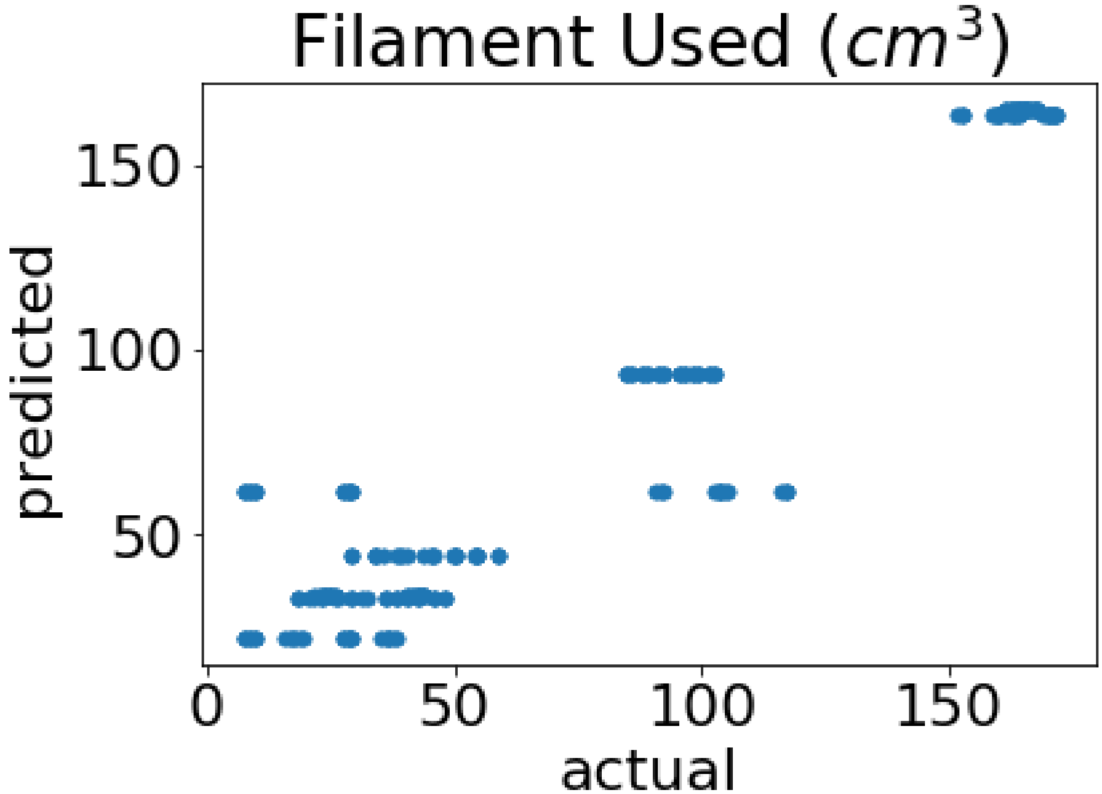

Tensile Strength
wall_thickness
nozzle_temperature
infill_density
layer_height
fan_speed
bed_temperature
print_speed
infill_pattern_grid
material_abs
infill_pattern_honeycomb
material_pla
0.0
0.1
0.2
0.3
relative importance


Tensile Strength (MPa)
predicted
10
20
30
10
20
30
actual

Predictors of Filament usage

column	description	units
infill every layers	Infill every N layers	#
fill density	volume to fill with pattern	%
layer height	height of each layer	mm
infill extrusion width	filament flow width	mm
fill pattern	fill pattern	fill pattern
perimeters	horizontal solid layers	perimeters
fill angle	horizontal infill pattern	degrees





For filming usage, we found that the number of skipped layers, in-fill density and layer height are significantly important. Every other future was discarded. We used a 2nd random Forest to predict filament usage from these three parameters.

Improving the accuracy these models is beyond the scope of this project.

Looking at a plot of strength vs filament usage we see an opportunity for optimization in the top left corner where using less filament results in reasonably strong object.

Chen and Gabriel (2016) found thickness of Fill, Fill Rate, Extruder Speed and Extruder Head Temperature have an effect on tensile strength.(Chen and Gabriel 2016)

Model Limitations

The limitation of Majeed, Lv, and Peng (2018) is that only a framework is proposed, and the algorithm for data analysis, such as association, classification and clustering are not studied in Majeed, Lv, and Peng (2018). (Majeed, Lv, and Peng 2018)

To do so, an initial manufacturable lattice structure is generated under the overhanging areas. (Gorguluarslan et al. 2017)

failure	effect	coutermeasure
overhang	collapse	add support structures
shinkage	deformation at corners	increase fan speed
pillowing	sagging infill	increase fill density
stringing	unintended structure	decrease retraction speed

over-hanging areas with no common support structures (two disjoint subgraphs) could be separated in various clusters, and each cluster could be optimized again with a normal optimization.(Gorguluarslan et al. 2017)

While support structures are outside the scope of this project, Gorguluarslan et al. (2017) provides a framework to optimize support structures for additive manufacturing.

Optimization

In order to find a minimum cost we can ask a genetic algorithm to modulate these five parameters and search the space. Here we've shown how fill density collapses towards an Optimum just under 50% fill density.

looking at a default slicing rectilinear infill pattern and a single wall infill density about 13% I compared it to our Optimum slicing infill about 50% pattern is Honeycomb and four layers but they use about the same amount of material. in order to generate better initial populations. (Gorguluarslan et al. 2017)

The analysis of the results concludes that the process capability indices (Cp and Cpk), can be improved and at the same time optimal parameters can be identified using Six Sigma DMAIC (Define, Measure, Analyze, Improve, and Control) approach which is a win-win situation.(Chen and Gabriel 2016)

A BESO(Bidirectional Evolutionary Structural Optimization)-based optimization process is used to find the optimum struts' thickness distribution.(Tang et al. 2017)

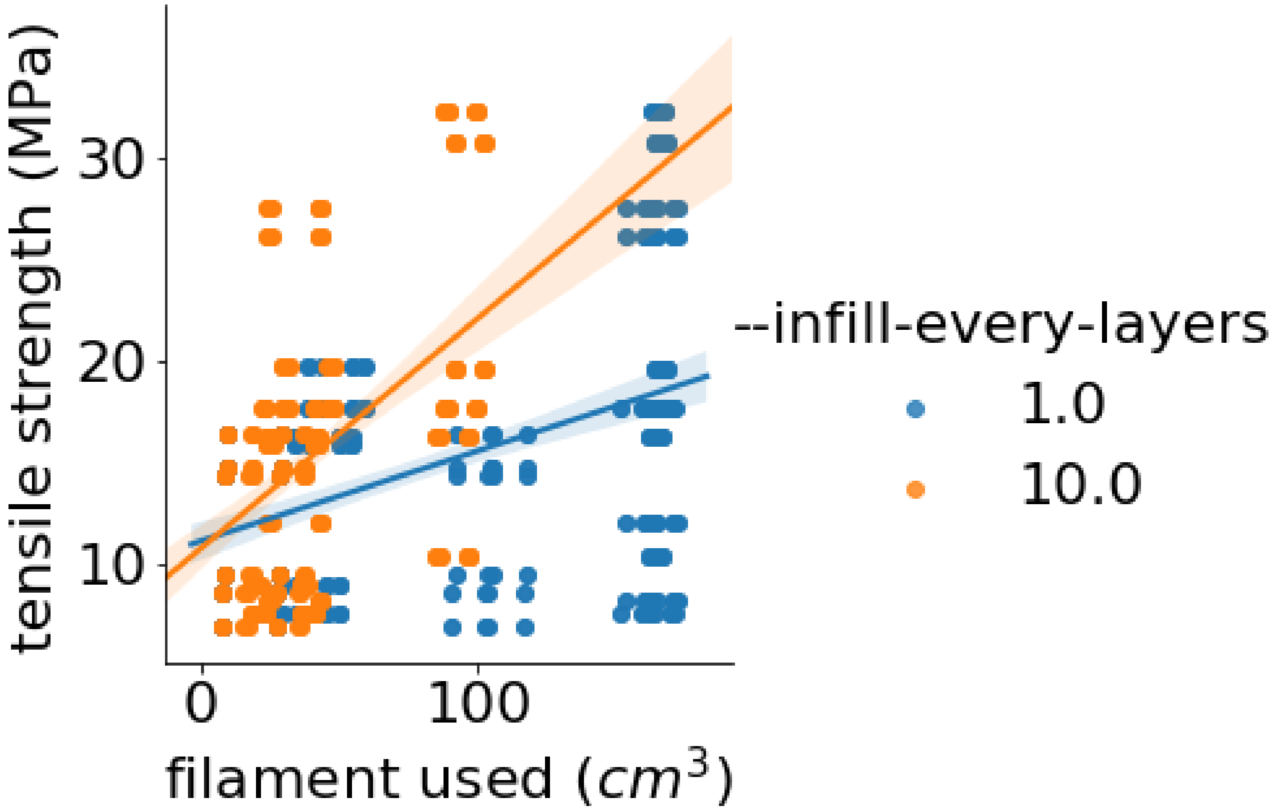
The heterogeneous lattice structure optimized by the proposed method has a better performance compared to the homogenous lattice structure.(Tang et al. 2017) Finally, the process can be optimized to obtain a larger feasible area for design and optimization. (Tang et al. 2017)

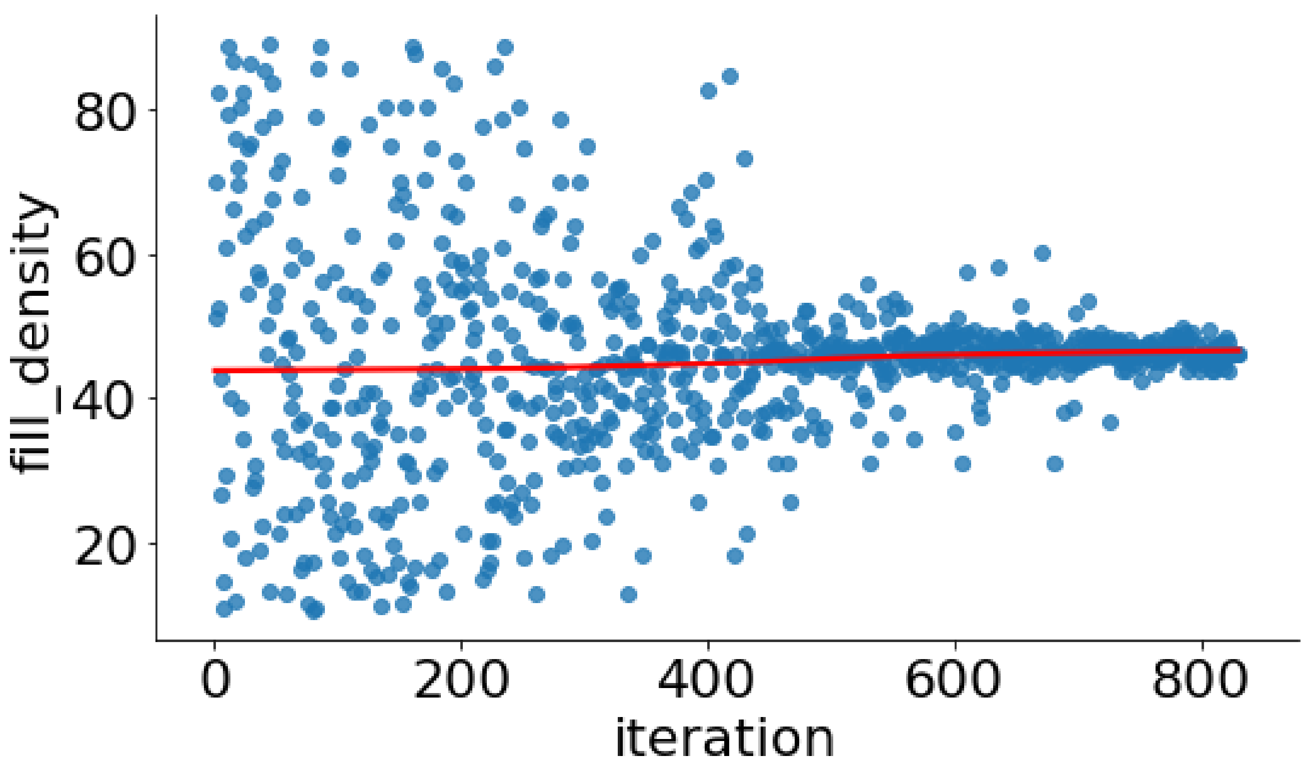
relations between strut dimensions and mechanical properties can provide a feedback to lattice simulation and optimization model with more accurate material properties.(Tang et al. 2017)

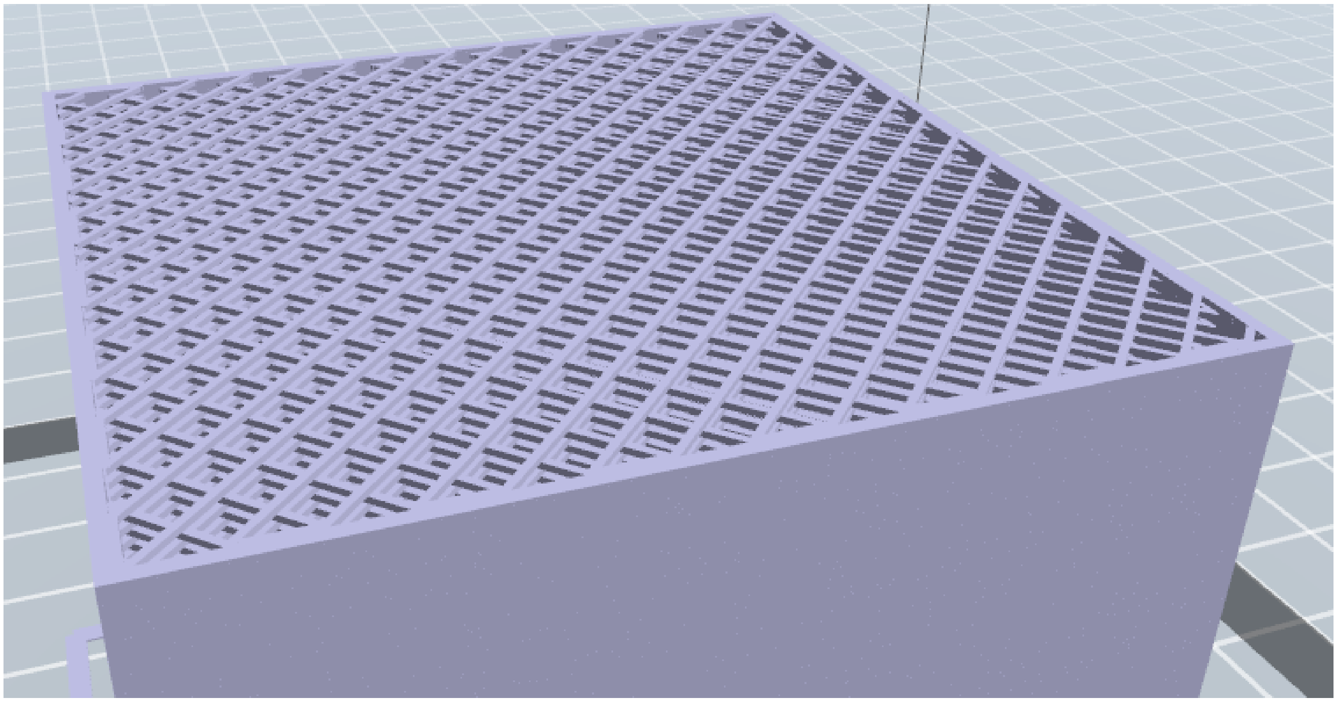
In order to further improve the optimization of the support structures, the objective function (that only includes the material volume) could be extended, by taking into account the support removal and finishing costs.(Gorguluarslan et al. 2017)

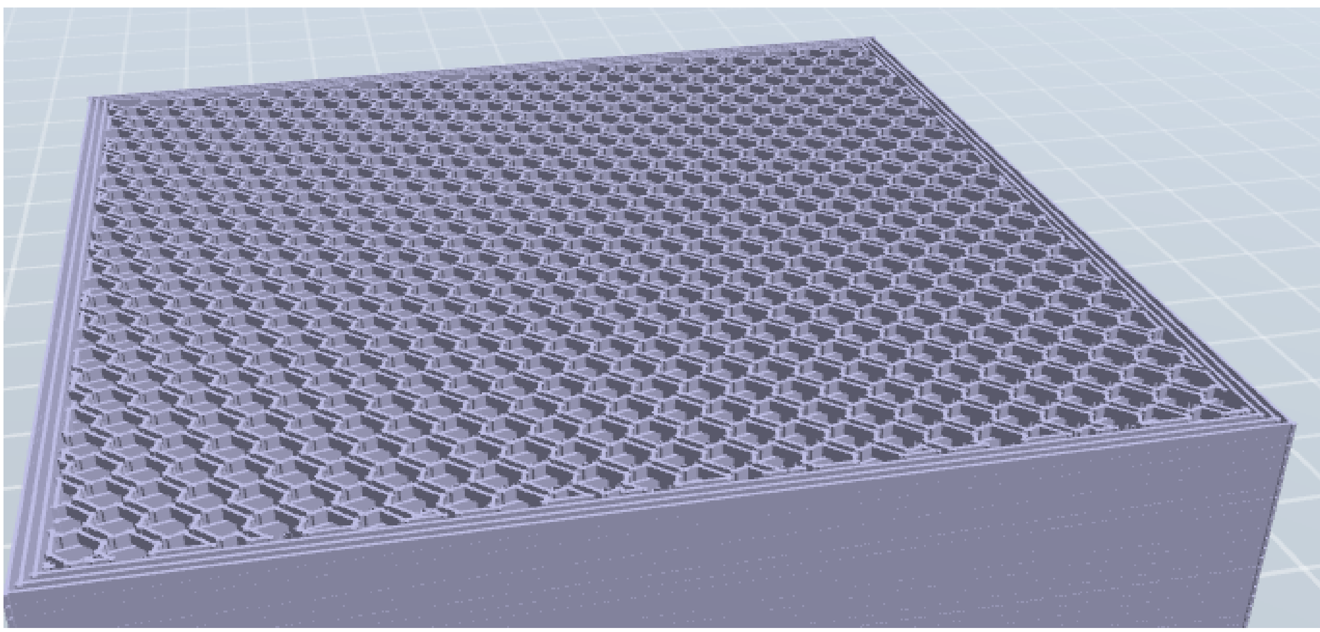
The first example, i.e. the cantilever beam example, is used to show that the proposed framework can produce an optimized structure with minimal computational cost by considering the minimum manufacturing limit.(Gorguluarslan et al. 2017)

Gorguluarslan et al. (2017) has shown that using a genetic algorithm performs better traditional generation strategies.


tensile strength (MPa)
30
20
10
0
100
filament used (cm^3)
--infill-every-layers
1.0
10.0


fill_density
80
60
40
20
0
200
400
600
800
iteration





Summary

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