Optimization in Additive Manufacturing

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May 2019

Introduction

Two important points emphasized in Eberly (2002) are the projection of the polyhedron faces onto the appropriate coordinate planes to avoid numerical problems and reduction using Green's Theorem to obtain common subexpressions to avoid redundant calculations. (Eberly 2002)

reduction using Green's Theorem handles polyhedron faces with four or more vertices. (Eberly 2002)

projection of the polyhedron faces is necessary in order to robustly compute what is required by Green's theorm. (Eberly 2002)

When the polyhedron faces are triangles, neither projection of the polyhedron faces onto the appropriate coordinate planes nor reduction using Green's Theorem are necessary. (Eberly 2002)

A consequence of the formulas as derived in Eberly (2002) is that they require significantly less computational time than Mirtich's formulas. (Eberly 2002)

In Chen and Gabriel (2016) the effect of parameters e.g Thickness of Fill, Fill Rate, Extruder Speed and Extruder Head Temperature are investigated in 3D printing process to study their significance on the response variables of tensile strengths of the 3D printing parts.(Chen and Gabriel 2016)

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)

3D printing technology has lot of scope in the coming years to conduct experiments, research projects, and process improvements and implications.(Chen and Gabriel 2016)

Going further, 3D printing is ready to emerge from its niche status and become a viable alternative to conventional manufacturing processes in an increasing number of applications in most businesses and schools. (Chen and Gabriel 2016)

In Tang et al. (2017), a design method of lattice structures under the manufacturability constraints of AM process has been proposed.(Tang et al. 2017)

The meta-model for the selected AM (Additive Manufacturing) process is obtained from experiments and ANN (Artificial Neural Networks). (Tang et al. 2017)

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

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)

The heterogeneous lattice structure optimized by the proposed method has a better performance compared to the homogenous lattice structure.(Tang et al. 2017)

The meta-model obtained from the experiment and ANN has ensured the manufacturability of the lattice structure by certain AM process.(Tang et al. 2017)

If the design domain can be enlarged, smaller strut thickness, performance can be further improved.

relations between strut dimensions and mechanical properties need to be further investigated.(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)

Finally, the process can be optimized to obtain a larger feasible area for design and optimization. (Tang et al. 2017)

In Gorguluarslan et al. (2017), a new framework has been proposed to optimize support structures for additive manufacturing.

The aim of the framework is to sustain all the overhanging areas of a part, leaving aside the deformation and thermo-accumulation issues.

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

Then, a GA (Genetic Algorithm) optimizes an initial manufacturable lattice by removing the maximum number of beams, while ensuring that all the areas to support are still sustained. (Gorguluarslan et al. 2017)

Naturally, working on such tree-like structures also contributes to ease the removal of the external supports during the finishing step. (Gorguluarslan et al. 2017)

The GA control parameters values the most suited for the LS2DO problem have been selected through a DoE (Design of Experiments).(Gorguluarslan et al. 2017)

In Gorguluarslan et al. (2017) the support structures of five cases were generated and manufactured. Their volumes have been compared to the ones of support structures generated by several other state-of-the-art strategies, underlining the interest of the developed algorithm in terms of volume optimization.(Gorguluarslan et al. 2017)

Other approximation or meta-heuristic algorithms could also be used to find an approximate solution to the DST problem and compared to the GA presented in Gorguluarslan et al. (2017). (Gorguluarslan et al. 2017)

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

The computation times have also been compared, and if commercial solutions perform faster but with less optimized volumes, the proposed approach is faster than other academic methods.(Gorguluarslan et al. 2017)

the convergence of the GA 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)

Furthermore, in order to decrease the computation time of the GA, the various overhanging areas could be optimized by stages: once a first quick optimization is completed, the 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)

Because each cluster would contain less overhanging areas and fewer initial beams, their optimization would converge exponentially quicker, resulting in a reduced overall computation time.(Gorguluarslan et al. 2017)

Naturally, such a decomposition strategy could also benefit from an ad-hoc GPU implementation.(Gorguluarslan 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)

However, these costs can be hard to estimate because they depend on many factors (e.g. the tools used, the training of the operator).(Gorguluarslan et al. 2017)

Finally, because the deformation and thermal accumulation problems have been left aside, the proposed framework is only a first block in the wide area of support structure optimization.(Gorguluarslan et al. 2017)

Its coupling with thermo-mechanical optimization algorithms is of interest in the future, in order to generate poly-functional support structures, that can sustain overhangs, rigidify features subject to deformation, and dissipate the thermal accumulation areas of any additively manufactured part. (Vaissier et al. 2019)

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)

Falcon leverages a human-centered design grounded in the visual information seeking strategy [1].(Gorguluarslan et al. 2017)

Falcon provides linked visualizations from both temporal and statistical orientations with automated analytics to highlight interesting features.

In addition, Falcon offers intuitive mechanisms to access multiple levels-of-detail as necessary.(Gorguluarslan et al. 2017)

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)

An improved two-phase lattice structure design optimization framework that effectively considers the minimum cross-sectional parameter values that can be fabricated using AM machines is developed in Gorguluarslan et al. (2017).(Gorguluarslan et al. 2017) An efficient optimization algorithm, namely, the MFD algorithm, is also integrated into the optimization process to considerably reduce the computational cost of the ground structure optimization.(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) Then, a conventional ground structure optimization process is performed by setting the lower bound of the cross-sectional parameters to near zero with the MFD algorithm. In the second phase, the elements with diameters smaller than a pre-determined threshold value are removed from the lattice configuration.(Gorguluarslan et al. 2017) Then, a second optimization procedure is conducted by setting the lower bound of the cross-sectional parameters to the minimum value that can be fabricated using a specific AM machine.(Gorguluarslan et al. 2017) Although the second optimization process might increase the computational cost, the MFD algorithm finds the solution very quickly, making the computational time spent for optimization trivial.(Gorguluarslan et al. 2017) Three different examples are used to show the effectiveness of the optimization framework with the MFD algorithm.(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) 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) It is shown that an A-pillar with comparable performance to that of the existing design can be achieved based on the linear FEA results.(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) Gorguluarslan et al. (2017) showed that the MFD algorithm can find the optimal solution much faster than the SQP algorithm.(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 AM machine. (Gorguluarslan et al. 2017)

In J. Zhang et al. (2018), a multi-scale multi-physics modeling framework for the L-PBF process is presented.(J. Zhang et al. 2018)

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)

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)

Atomistic tensile test simulations of sintered material show that sintered nickel particles have lower mechanical strengths than the bulk nickel crystal because of their porous structures. (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)

The predicted distortion of the L-PBF printed component is in good agreement with experiment. (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 (3D printing has been the choice, as explained in the introduction) and the characterization of their dynamics of change across time.(Garechana et al. 2019)

After retrieving a dataset containing 3D printing patents from database Patseer, we designed a text-mining procedure that allowed us to identify the most relevant concepts these patents dealt with, according to the statements contained in their claims.(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)

These matrices were analyzed using a topic modeling technique, which has shed light on the technology fronts being developed under the broad field of 3D printing.(Garechana et al. 2019)

We found that some of these fronts are in part coincident with the main taxonomies of typical devices in the 3d 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)

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-datasets containing the patents in which claims were clearly focused on the topics identified by our approach.(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)

AM is one of the most promising technologies in the field of manufacturing. (Majeed, Lv, and Peng 2018)

The AM technology has a great potential to change the very essence of design and manufacturing. (Majeed, Lv, and Peng 2018)

During AM processes, a huge amount of real-time big data is generated. (Majeed, Lv, and Peng 2018)

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

Majeed, Lv, and Peng (2018) provides a good basis for the application of BDA in the AM process. (Majeed, Lv, and Peng 2018)

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

Majeed, Lv, and Peng (2018) brings three contributions to successfully implement the BDA in the area of AM. (Majeed, Lv, and Peng 2018)

The first contribution is the architecture of big data-based analytics and its key components in AM. (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 AM, and then process and exchange the big data between heterogeneous EIS. (Majeed, Lv, and Peng 2018)

The third contribution is the big data mining and optimization of AM. (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 proposed big data-based MP optimization framework for additive manufacturing (BDMP-AM) has been demonstrated in a case study of the application scenario. (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 ANOVA, the process parameters of AM 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)

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)

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 AM for different materials and processes. (Majeed, Lv, and Peng 2018)

Data Quality

Workflow

Feature Importance

Simulation

Model Limitations

Regression Analysis

column	description	units
variable1	description1	units1
variable2	description2	units2

Preprocessing

column	description	units
enrichment1	calculation1	lbs/ft
enrichment2	calculation2	gal/ft
enrichment3	calculation3	lbs/gal

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Modelling

Reduced Model

Residual Analysis

Summary

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