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Achieving dimensional tolerances in metal additive manufacturing via numerical model based process optimization

Sankhya Mohanty, Ömer Can Kücükyildiz, Sònia del Rio Serrat, Milos Nikolas Todorovic, Maximilian Felix Roman Zwicker, Jesper Hattel

Department Of Mechanical Engineering, Technical University of Denmark

samoh@mek.dtu.dk

Abstract
The acquisition of metal additive manufacturing companies by large corporations such as GE and Siemens clearly indicated the central role that additive manufacturing is going to play in developing products of the future as well as reimagining existing designs. On an openly available knowledge level, though, the metal additive manufacturing process still suffers from challenges, such as dross-formation and residual stress driven warpage. This has resulted in significant resource allocation towards hit-n-trial based process optimization for products to meet dimensional accuracy requirements. In this paper, numerical model based process optimization strategies are discussed to address aforementioned challenges and ensure a shortened time from design to accurate manufacturing. The paper first summarizes existing challenges associated with the process and provides a review of the state-of-the-art for process simulation. The different categories of process simulation are discussed and there potential application for process optimization is enumerated. The paper then highlights prior activities dedicated towards this goal, and subsequently documents a case study optimizing the manufacturing process of a designed part. Numerical process models simulating the thermo-mechanical phenomena during additive manufacturing, developed by combining commercial software with in-house codes, are discussed and typical results are demonstrated. Thereafter, the optimization of additive manufacturing machine parameters as well as processing strategies is carried out, and results show how model-based process optimization can reduce the geometrical irregularities and ensure dimensional tolerances. The paper also discusses and demonstrates numerical model based uncertainty quantification which is developed to be complementary to measurement-based uncertainty quantification. Apart from process optimization of the additive manufacturing process itself, other avenues of ensuring dimensional conformity of parts are also discussed- most prominently, post-production heat treatment. The usage of commercial software to address heat treatment, and its benefits on process-planning of metal additive manufacturing form the final part of this article.

Keywords: Selective laser melting, Residual Stress, Optimization, Simulation-based Uncertainty Quantification, Geometrical Irregularities

1. Addressing process challenges using simulations

Selective laser melting (SLM) is currently maturing into an industrial manufacturing process, but there are certain aspects of the process and the geometries it can address that prevent it from becoming an accessible manufacturing method. Quality control of complex parts is complicated for free-form surfaces and a number of advanced metrological equipment/techniques are being investigated for the same [1] [2]. Additionally, there are coordinated efforts, such as the AM-BENCH [3] by NIST, dedicated towards providing a workflow for combining experimental and modelling/simulation studies to understand, characterize and improve the associated manufacturing processes.

Metal AM processes have been reviewed in [4] [5] [6] [7] [8] [9] [10] [11] [12] [13] [14] from experimental and modeling perspective, including current practices and future challenges regarding raw materials, processing and post-processing. For metal AM processes, the main challenges include pore formation, delamination, uncontrolled melt flow behavior, internal stresses, high surface roughness, and low dimensional and geometrical accuracy. Further, AM metal components are known to develop a highly anisotropic internal structure with a higher probability of near surface defects such as voids, leading to reduced fatigue strength. Modelling approaches for metal additive manufacturing have targeted these challenges and achieved moderate degree of predictive capability.

In this paper, we address two of these challenges, namely the internal stress-driven deformations and the irregularities emerging from uncontrolled melt flow behavior. The first challenge is more pertinent for bulk components, while the latter is more influential when producing thin-walled structures and overhanging structures.

2. Tackling stresses and deformations in bulk components

Among the various challenges being faced in using selective laser melting, the generation of large residual stresses during manufacturing and the resultant deformations upon removal of support structures forms the primary goal of various research activities around the globe. A promising method being investigated is varying the processing parameters (e.g. laser power, speed, beam spot size, etc.) during production, based on on-line monitoring/inspections or off-line process planning. A well-discussed alternative approach is controlling the scanning strategy involved in the manufacturing of each layer [15] [16] [17] [18] [19] [20] [21] [22] [23]. Researchers have tested several scan patterns and observed their effect for select group of materials and processing parameters. Apart from using new scan patterns in each layer, simply rotating the scanning patterns from the previous layer by set angles has also shown improvement in residual stresses in SLM parts.

A direct and pragmatic approach towards solving the challenges of residual stresses-driven deformations would be to pre-stress or pre-bend the component accordingly so that the desired geometry is achieved after deformations. This would involve characterizing the 3D distribution of stresses in the component (via numerical simulations of the entire manufacturing process chain) and then running optimization procedures upon the geometry. The challenge lies in the extensive computational requirements for such an approach. Running a full multi-scale, multi-physics simulation of the additive manufacturing of a component is computationally prohibitive at the current technology level.

2.1. Reduced Order Thermo-mechanical Modelling

One of the solutions to the aforementioned problem of large computational requirements is to use reduced order models. In reduced order models, the actual multiscale multiphysics problem is simplified to reach an approximate solution within acceptable computational times. For instance, Figure 1 shows how the thermo-mechanical phenomena during additive manufacturing can be divided into multiple length scales. Here, the additive manufacturing process is divided into two hierarchical processes, i.e. the task of selectively changing (melting/consolidating) material is handled separately from the task of adding multiple layers. First, the manufacturing of a single layer is simulated thermally by successive addition and melting/consolidating of unit cells in given processing sequence (Figure 1 left). The result of such thermal simulations is passed on to the next hierarchy of simulations i.e. of adding multiple layers. Here, a thermo-mechanical simulation is performed wherein layers are added at appropriate time intervals with a prescribed initial temperature coming from the previous single-layer simulations. The resulting computational time for the thermo-mechanical simulations is considerably low compared to the case when the entire geometry is modelled thermo-mechanically one unit cell at a time

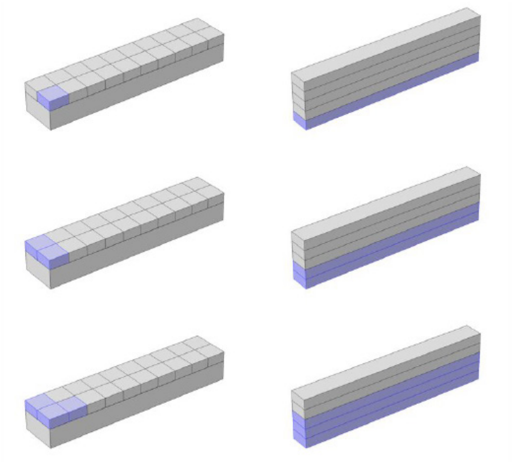

Figure 1. Building a layer using unit cells (left), and adding multiple layers (right) during selective laser melting. Grey regions indicate inactivated domains

2.2. Thermal Models & θ criteria

While reduced order models are a smart approach towards determining the stress state in components being additively manufactured, the task of reducing deformations can be handled to a large extent through thermal models only. Case in point is the usage of θ-criteria [18] [19] [24] [25] to relatively assess the quality of different scanning strategies. The θ-criteria combines indicators for thermal homogeneity along with indicators for degree of consolidation (final component density) and indicators for process defects arising out of overheating (such as vaporization-induced pores, balling effects, etc.). Other such criteria can also be found in Ahrari & Mohanty et al [26] wherein indicators for residual stresses and distortions are discussed.

2.3. Process optimization using simulations

As a case study, 19 Ti-6Al-4V samples were manufactured using a combination of optimized and non-optimized scanning strategies. Two geometries were investigated in this study, rectangular pieces of 10x100 mm and square pieces of 30x30mm. The optimization procedure can be found in [24] and [25]. Figure 2 shows a CAD image of the build-plate for this study.

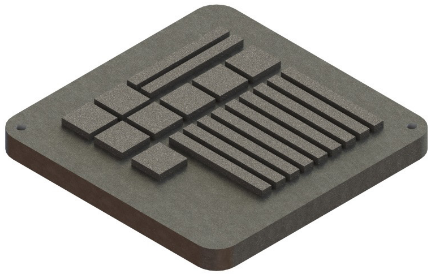

Figure 2. Ti6Al4V components made using different scanning strategies on a steel baseplate

As a generic rule, the differing scanning strategy and the orientation of the sample will lead to different thermal conditions during manufacturing and consequently different stress concentration and deformation upon removal of support structures. The state of residual stresses can often be high enough to cause cracking and/or delamination in the component. For instance, Figure 3 shows one of the samples that cracked during removal of the support structures.

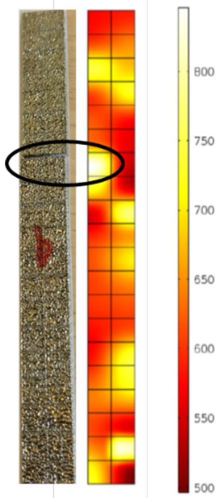

Figure 3. Identifying locations of defects & possible cracks via a temperature distribution map

The large residual stresses (often present in Ti6Al4V samples) cause deformations in bulk components when the support structures clamping them to the base plate are progressively removed. During such removal of a sample containing macro-porosities, the pores act as stress-concentration zones and crack-initiation locations. The same phenomena of stress-concentration and crack-initiation also occurs in regions of hot-tearing which can result from inappropriate scanning strategies. Figure 3 shows the temperature field at end of the production of a layer in the cracked sample. The hotspots during manufacturing can clearly be identified, and provide a good indication of where defects can arise during the manufacturing process.

Using process optimization, it is possible to avoid/minimize such defects and produce parts that are qualitatively better. For instance, Figure 4 shows two samples from the build plate produced using different scanning strategies. Piece 2 was produced using the zig-zag(anti-parallel) scanning path along with the stripes strategy as has resulted in significant deformation upon removal of supports, while Piece 19 shows considerably lower deformations.

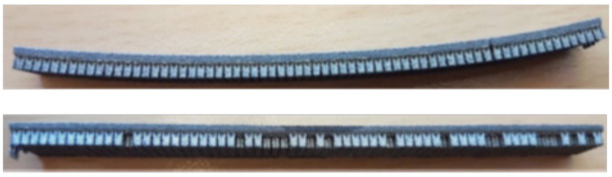

Figure 4. Different scanning strategies resulting in different deformations when removing support structures: Piece 2(top) and Piece 19 (below)

The samples were removed from the base-plate using wire EDM technique and were then measured on a Zeiss OMC 850 CMM machine using special fixtures for positioning and aligning the parts. A fixed group of points was selected to assess the deformation in the samples before and after removal as shown in Figure 5.

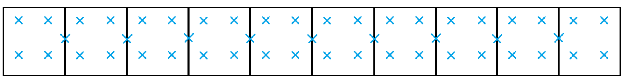

Figure 5. Points for measuring deformation before and after removal of support structures in rectangular samples (Piece 2)

Figure 6 shows the deformation measurements in Piece 2 and Piece 19. As the CMM machine measures heights relative to a reference point, the measurement in case of Piece 19 had to be corrected to ensure the same reference height was selected for measurements before and after removal of support structures. Additionally, the removal of support structures was carried out along a fixed direction as shown in Figure 7, and thus the deformation measurements had to be transformed to evaluate the actual deflections in components. Figure 8 shows the corrected deflection in Piece 2 and Piece 19. It can be observed that Piece 2 deforms by as much as 14 mm while the deformation in Piece 19 is limited to 0.9 mm. This trend in deformations clearly indicate the influence of scanning strategies on the deformations (via residual stresses) and the efficacy of reducing deformations and stresses by optimizing scanning strategies through numerical simulations.

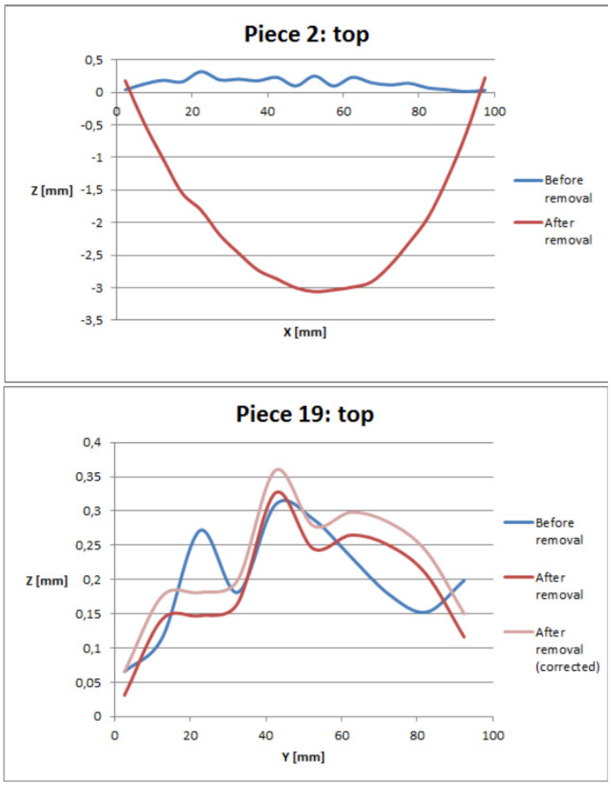

Figure 6. Deformation before and after removal of support structures: Piece 2 (above) and Piece 19 (below)

Figure 7. Directional removal of support structures for rectangular samples (as seen in Piece 2)

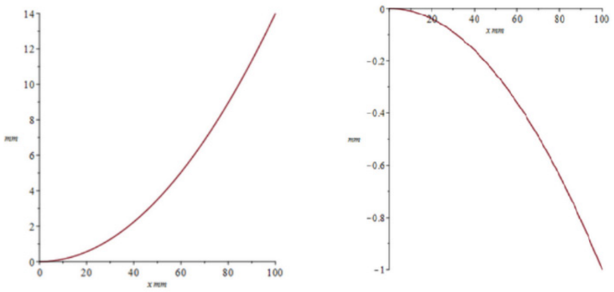

Figure 8. Corrected deformations in Piece 2 (left) and Piece 19 (right). Note the scanning strategy induced internal stresses have resulted in negative deflection in case of Piece 19.

3. Tackling distortions in thin-walled components

A thin-walled component produced with SLM is often constituted of a single or a few tracks stacked up on top of one another. The dimensional characteristics of these parts are thus influenced by the possible irregularities in the single tracks formed during SLM of these components. The thermal conditions during SLM of thin-walled components are also different than those experienced by non-thin walled components, as the heat transfer effectively reduces to a 2D planar case. Similar thermal irregularities also exist during production of overhanging structures, wherein the deep powder bed changes the melt pool conditions.

Apart from the thermal considerations arising out of the component geometry, the production of thin-walled components is also sensitive to the irregularity (stochastic uncertainty) in processing parameters. For instance, the angle of incidence and direction of propagation of laser beam at any location of the powder bed causes an effective elongation in the heat input domain (as shown in Figure 9).

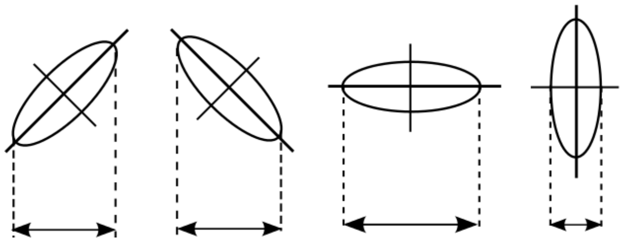

Figure 9. Elongation of effective heat input domain due to movement of laser beam in specific directions [27]

While stochastic simulation methodologies can allow for taking into consideration uncertainties such as those mentioned before, these techniques often rely on accurate measurements for calibrating and validating the models. Figure 10 shows the irregularity of three melt tracks produced using identical processing parameters when manufacturing thin-walls/overhangs. Assessing the correct width of the melt track from such samples is a challenge in itself, and consequently using said measurements in direct stochastic simulations can be inappropriate.

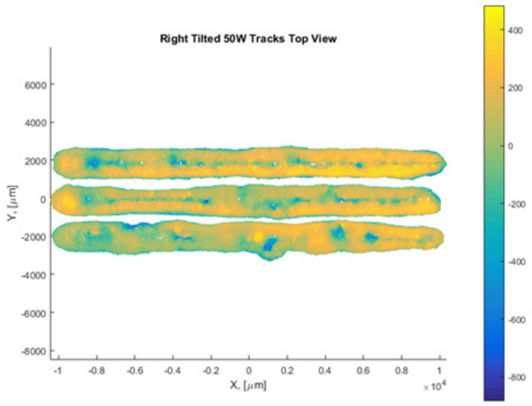

Figure 10. Top view of right tilted tracks produced at 50W.

The alternate approach would be to combine the statistical uncertainties associated with measurements along with the statistical uncertainties in process parameters. This would result in artificially enlarged parameter uncertainties, but would result in predictions that can be directly matched with subsequent measurements following the same technique/machine. Figure 11 shows a multi-parameter sampling produced using Latin Hypercube technique in which real parameter uncertainties have been combined with measurement uncertainties. Figure 12 shows the measured track widths (with associated standard deviations), and the predicted track widths for the corresponding process parameter settings. More details regarding the procedure of the analysis can be found in [28].

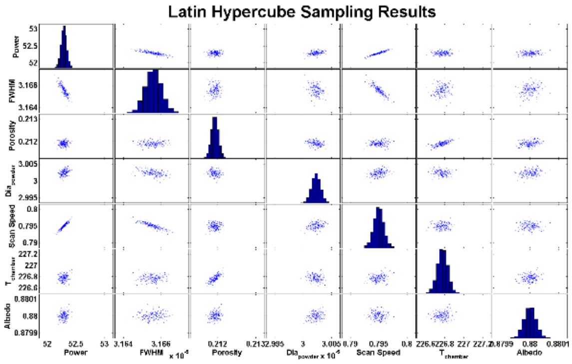

Figure 11. Incorporating real and measurement uncertainties in processing parameters into process simulations

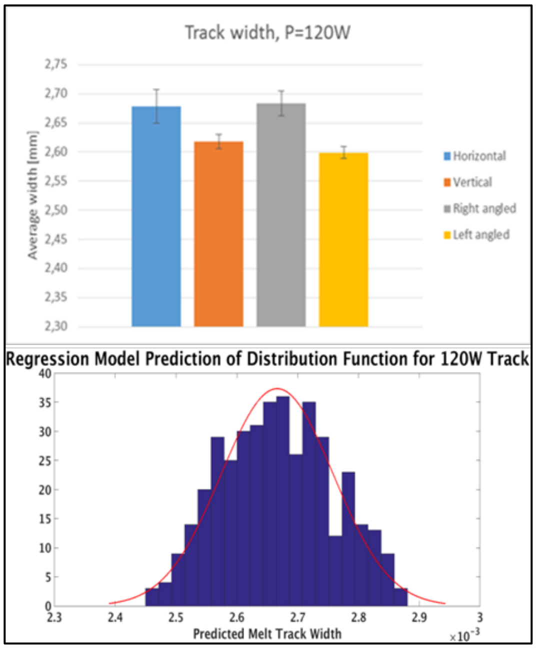

Figure 52. Measured values of track width (top) and predicted value (below) through response surfaces built using simulation-based uncertainty quantification methods [27]

4. Process chain optimization for achieving dimensional requirements

The previous two techniques for achieving dimensional targets are computationally expensive (though much leaner than full multi-scale, multiphysics simulations) for every-day commercial applications, and their usage makes greater sense in critical components and/or expensive materials. For other cases, it has historically been easier to use post-processing techniques to solve process-induced defects. The most common of these techniques is heat-treatment, which is usually carried out to relieve stresses and produce improved microstructures. The usage of simulations in this domain is also quite effective and in practice. Most commercial software dealing with high temperature metal processing, such as MAGMASOFT [29] and SORPAS [30], have developed associated heat treatment modules which are relatively simple (compared to SLM simulations) and easy to optimize. In addition, more generic simulation software packages (such as Simulia, Simufact, Netfabb) have also developed modules combining fast reduced-order process models for SLM with modelling of post-processes such as heat treatment. Thus, seen from a commercial perspective, focus on developing an optimized process chain has a greater return as compared to focusing on solely optimizing the SLM process.

5. Summary

The paper summarizes existing challenges associated with the additive manufacturing process and corresponding process simulation. Two of these challenges, namely the internal stress-driven deformations and the irregularities emerging from uncontrolled melt flow behavior, are addressed and their modelling techniques are discussed. For the case of stresses and deformations in bulk components, a case study optimizing the manufacturing process of a designed part is described and the benefit of reduced order modelling is made clear. The paper also discusses and demonstrates numerical model based uncertainty quantification, which is developed to be complementary to measurement-based uncertainty quantification. In the end, a short note is provided on the usage of commercial software to address additive manufacturing and heat treatment, and its benefits on process-planning of metal additive manufacturing.

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