

Simulation-Driven Distortion, Thermal-Strain, Scan-Strategy, Melt-Pool and Porosity Analysis of a Generatively Designed AlSi10Mg Fastener Component Using ANSYS Additive

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ABSTRACT

Metal additive manufacturing (AM) processes, such as L-PBF, are highly sensitive to the thermal history induced by the process. This results in objects containing residual stresses, distortions, and porosity, which can severely impact the dimensions of the printed object as well as its mechanical properties. To combat these issues, designers engage in simulation-driven process planning. This allows designers to design for additive manufacturing (DFAM) by predicting and avoiding defects in the design before it is physically printed. This paper presents a multi-parametric, simulation-based case study to design and optimize a fastener component, Exercise-80, made of AlSi10Mg. The generatively designed part is analysed using the ANSYS Additive suite of simulation tools. A range of five different studies were performed on the same generatively optimized part, and the results are discussed in detail. The five different studies were: (i) an assumed (uniform) strain distortion study; (ii) a thermal-strain-

based distortion study; (iii) an anisotropic scan-strategy-based distortion study; (iv) a single-bead parametric melt-pool study based on a 3×3 DOE of laser power and scan speed; and (v) a full-factorial porosity study with 3⁵ (243 runs) for laser power, scan speed, layer thickness, hatch spacing, and slicing stripe width. For each of the five studies, the relevant physics, input, and AM process qualification are presented and compared with current literature (2021–2025) on inherent-strain modelling, scan-strategy effects, melt-pool prediction, and generative design for porosity. A structured, multi-fidelity, simulation-iteration approach is provided that enables the designer to move from a generatively optimized design to a build-ready, defect-aware process plan, all without using up physical build material.

Keywords: Additive Manufacturing; ANSYS Additive; Distortion Prediction; Assumed/Inherent Strain; Thermal Strain; Scan Pattern; Melt-Pool Simulation; Porosity Prediction; AlSi10Mg; Generative Design; Design for Additive Manufacturing (DFAM)

1. INTRODUCTION

Metal additive manufacturing (AM), in particular laser powder bed fusion (L-PBF), has moved from a rapid-prototyping technology to a qualified production technology for aerospace, automotive, tooling and medical parts. Metal AM in general, and L-PBF in particular, is a form of manufacturing in which a part is built up layer by layer, by first melting and then solidifying metal powder that has been spread as a layer on a base, with a focused laser beam, guided by a scan path. This building up of layers of metal, by a process of re-heating solidified metal and then re-solidifying molten metal, results in steep thermal gradients within each layer of metal that are converted into inherent (eigen) strains, or built-in stresses. These strains, in turn, are then added, layer by layer, resulting in a part with residual stresses and the potential for out-of-plane distortion, and in certain situations, porosity and lack-of-fusion defects. For certain mechanical parts, for example, threaded fasteners, flanged bolts and precision-fit parts, even small amounts of distortion (down to a few mm) and porosity (a few %) could lead to parts being unusable, due to, for example, assembly interference, reduced fatigue life, etc.

Because of the high costs and long printing times for trial-and-error printing of physical parts, process simulation for additive manufacturing has become the first line of defence against possible failures. With commercial simulation tools, such as ANSYS Additive, which are based on the ANSYS Workbench and the solver ANSYS Mechanical APDL, a designer can, for example, virtually “pre-print” a component before it is actually printed, thus predicting possible distortions, compensating for them, checking the possible effects of scan strategies and testing process parameters for melt-pool stability and possible porosity. In Design for Additive Manufacturing (DFAM), designers first create a digital design and then optimize the design together with the chosen material and printing

process. This is done by simulating the printing process before any physical printing takes place, such as by testing different scan strategies, varying process parameters, and predicting possible distortions.

This paper presents and discusses a structured, multi-parametric simulation study that was performed on a generatively designed mechanical fastener part “Exercise-80” (a hexagonal-socket, flanged bolt-type part) made of the aluminium–silicon–magnesium alloy AlSi10Mg. The simulations were conducted using the multi-physics simulation environment ANSYS Additive. The same generatively optimized part geometry was used for all five different simulation studies, which were conducted in a sequential manner. The five different types of simulation studies that were performed as part of this work are assumed (uniform) strain simulation for fast distortion checking, thermal-strain simulation for prediction of distortion and residual stresses, anisotropic scan-pattern simulation, single-bead parametric simulation for laser-power/scan-speed design of experiments (DOE) to set up melt-pool geometry, and full-factorial porosity parametric simulation for the five different process factors to define the process window for pore-minimized builds.

This work has two objectives. Firstly, a description is provided of the individual simulations and their goals. This description is linked to the Additive Manufacturing process and to ANSYS Additive workflow. Secondly, a review is provided of the recent literature, which has been published in the last 5 years (2021–2025) and which deals with inherent-strain modelling, scan-strategy design, melt-pool modelling, porosity formation and generative design. This review will enable the results of the case-studies to be compared with the current state of the art. The paper is organized as follows. In the first section, a review is provided of the literature which has been published in the last 5 years (2021–2025) and which is relevant to the individual

simulations. In the second section, the component, material and simulation methodology are described in detail. In the third section, the results of the individual case-studies are presented and discussed. In the final section, the implications of the results for simulation-driven AM process planning are outlined.

2. LITERATURE REVIEW

2.1 Generative Design for Additive Manufacturing

Generative design tools can create numerous topology-optimized geometries for Additive Manufacturing (AM) using a design environment such as the generative-design environment in Autodesk Fusion 360 used in this study. In such environments, the 'geometric freedom' of AM is exploited by creating multiple candidate geometries, which are 'optimized' (i.e., designed) for a given set of 'loads', 'constraints', 'manufacturing methods', and 'materials'. Recent work has noted, however, that whilst the performance of a generatively designed part may be optimized by the optimization algorithm, the as-built structural performance can vary substantially for given design intents. Peckham et al. [13] reported experimentally for AM parts designed within a generative-design tool, that identical design intents input to the generative-design tool could result in as-built parts with substantially differing structural performance (e.g., over 590% variation in structural performance measure). In such cases, generative-design part designs must be paired with process-simulation studies, such as those for distortion, thermal, scan-pattern, and porosity in this study, to ascertain the as-built part's actual structural performance, as simply treating the generative-design output as 'ready for manufacture' in isolation would not be sufficient.

2.2 Assumed/Inherent Strain Methods for Distortion Prediction

The most commonly used approach for computationally efficient prediction of distortion in metal AM parts, the assumed

(or inherent) strain method, as applied in ANSYS Additive, first applies a pre-calibrated strain tensor to represent the net effect of each layer's thermal cycle and then applies this strain tensor to predict the distortion of the layer. This approach, while still able to apply within a few percent of actual distortion values (depending on part geometry and how the build is set up), does have its limitations as it does not actually solve the full transient thermal problem for every layer. A more consistent approach has been presented by Bellet [1] in a critical reassessment of the inherent strain method. In this work a new variant of the method that improves the physical consistency of the approach is introduced. Other researchers, Taufek et al. [2] for example, have combined a thermomechanical model with an inherent-strain formulation and Nelder–Mead optimization to model the distortion in an additively manufactured cylindrical component. The results obtained with this hybrid approach show that it is possible to obtain substantial improvement in the prediction of part distortion over that obtained with an inherent-strain model, and that the approach is computationally efficient enough to be used within an iterative design process. More recently Dong et al. [3] extended the inherent-strain concept to a temperature-dependent formulation for wire-arc directed energy deposition of Ti6Al4V. The key point of note here for the assumed-strain versus thermal-strain simulation pair considered in this paper is that the inherent-strain tensor is treated as a function of local thermal history - rather than as a single constant that has been pre-calibrated for a particular process and part geometry. This approach is also considered in the work of Gordon et al. [4] who specifically target rapid, production-oriented distortion modelling for L-PBF. In this work a fast inherent-strain-based workflow for rapid prediction of part distortion is introduced and validated against measured part distortion for a range of different parts. The inherent-strain-based distortion modelling approach considered in

this work is, therefore, best understood as a calibrated, low-fidelity screening tool for build-orientation and support-structure design. Its accuracy is, therefore, bounded by the validity of its underlying assumptions regarding the strain field and the process.

2.3 Thermal Strain and

Thermomechanical modelling

More sophisticated models for prediction of distortion are based on the thermal-strain (or thermomechanical) simulation, i.e. the layer-by-layer input of the heat, the conduction and the resulting transient thermal-stress field, typically performed at much higher computational cost than the corresponding assumed-strain models. Giubilini et al. [5] benchmarked several commercial software for AM distortion-simulation using physical printed and measured Ti6Al4V specimens in the form of cantilevers. The maximum deviation between the measured and the corresponding simulated values of distortion was found to be approximately 14% with the corresponding values of pre-compensated STL file (obtained by simulation) resulting in more than 70% reduction in part distortion after printing, i.e. when used for pre-deformation of nominal part geometry. De Leon et al. [6] provided a comprehensive review of the modeling, simulation and process qualification of L-PBF metal parts. In particular, assumed-strain models, thermal-strain models, and full thermomechanical models were placed on a fidelity-versus-cost scale, and it was argued that a multi-fidelity approach (i.e. cheap models for design-space screening, and expensive models for final validation) is by now the standard approach in industrial AM process qualification. The assumed-strain → thermal-strain → scan-pattern workflow used in Section 3 of the present paper is in line with this practice.

2.4 Scan-Pattern and Scan-Strategy

Effects

The laser scan-vector direction and its rotation between subsequent layers of a part affects the local direction of thermal

gradients. This means that scan strategy affects residual-stress anisotropy and distortion, independently of the bulk thermal input. Yang et al. [7] have optimized build orientation and laser scanning strategy for topology-optimized automotive components. The results obtained for the optimized build orientation and scanning strategy, compared with the non-optimized build orientation and scanning strategy, showed that thermal residual stress could be reduced by means of the scan strategy and orientation, without increasing the part's geometry and by means of the bulk process parameters. Hassila et al. [8] have carried out combined modelling and experimental work on Alloy 718 parts obtained by means of different scanning strategies. The results confirmed that the choice of scan strategy affects the magnitude and distribution of residual stress. These results support the anisotropic-strain-coefficient formulation that is used in the ANSYS Additive "Scan Pattern" solver. In this solver, the distortion is scaled differently, depending on whether it is parallel to, perpendicular to, or normal to the scan vector, local to the element being considered. This is because a single, isotropic strain assumption is not sufficient to capture the scan-direction-dependent effects that are observable in experiments.

2.5 Single-Bead or Melt-Pool Parametric Simulation

The single-track (single-bead) simulation is widely used as the first step of the L-PBF parameter development to calibrate the melt-pool dimensions as a function of the energy density. The physical interpretation of the melt-pool depth, width and length in terms of the energy density is strongly correlated with the subsequent downstream defects such as lack-of-fusion (when the melt pool is too shallow) and keyholing/porosity (when the melt pool is too deep). Al Amin et al. [9] have developed a heat-source model for quantitative melt-pool prediction in laser AM of IN718 using a physically constrained model to predict the melt-pool dimensions as a function of the energy density. The results of the

simulation for the quantitative prediction of the melt-pool dimensions as a function of the energy density for a given set of parameters (power and scan-speed) are shown for the single-bead parametric study of this paper. The process maps are created for the given set of parameters (power and scan-speed) of the single-bead DOE study in order to create a “process map” that defines the process window for a given set of parameters (power and scan-speed) for the full-part builds.

2.6 Porosity Prediction and Process-Window Mapping

This problem, like the ones above, arises from the complex interaction between several parameters such as laser power, scan speed, layer thickness, hatch spacing and scan strategy. For that reason, many studies have resorted to using full-factorial DOE or even machine-learning-assisted approaches to study the porosity. The work by Stwora et al. [10] is an example of a theoretically and experimentally validated approach to model the relationship between several L-PBF process variables and porosity in stainless steel 316L parts. Other authors, such as Staszewska et al. [11], have used machine-learning classification and regression to study porosity in L-PBF parts. The authors reported high cross-validation accuracy (over 90%) for pore-morphology classification, and created process maps, which can be used as a data-driven alternative to physically based porosity

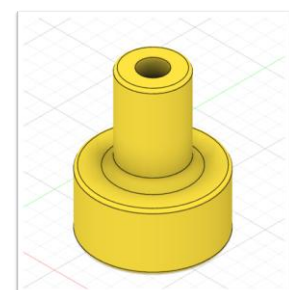
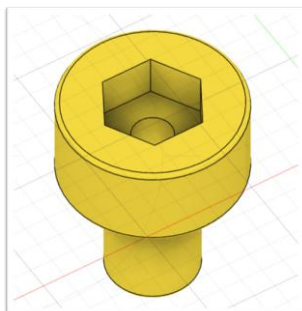
simulation to create process maps. In the present work, a five-factor, 243-run full-factorial DOE for porosity (Section 3.8) was performed, which, in agreement with the high computational cost to create such a process map (as mentioned in the above works), is shown in Section 4.3 to be a computationally expensive but very complete method to define a process window.

2.7 AlSi10Mg Process Property Relationships

AlSi10Mg is one of the qualified L-PBF aluminium alloys, having a favourable strength-to-weight ratio, thermal conductivity and printability. Liu and Shi [12] performed response-surface-methodology-based multi-objective optimization for L-PBF AlSi10Mg and found that the three key parameters (laser power, scan speed, and hatch spacing) influence three object functions (density, surface roughness, and mechanical properties) jointly, and found that near-default “generic-machine” parameter settings (such as baseplate temperature, laser power, and scan-speed) define a useful process window for this alloy. The resulting property–parameter relationships for this alloy form the background for the melt-pool and porosity simulation results of Section 4.

MATERIALS & METHODS

3.1 AlSi10Mg Process Property Relationships



A hexagonal-socket, flanged bolt-type mechanical fastener was chosen case-study component for the above studies as depicted in the figure above. A reference envelope

for the component is specified as a head of Ø40 mm diameter A/F20 (20 mm across-flats) internal hexagonal-socket flanged bolt of Ø9 mm diameter through-hole with a

stepped cylindrical shank of Ø20 mm diameter and total component length of approximately 50 mm (20 mm head height plus 30 mm long shank) including $1 \times 45^\circ / 0.6 \times 45^\circ$ chamfers as per the reference drawing shown above for reference only. Rather than simply making the part from the conventional drawing to check for fit as would be the case for a machined part, an alternative and generatively optimized geometry was created and optimized within the generative-design environment in Autodesk Fusion 360. The design utilized the original reference envelope, hex-socket drive feature and through-hole features as Manufacturing/Functional Constraints and allowed the solver to freely generate and optimize the non-functional volume of the part. Generative design of this nature is typically used to generate a mass- or

material-optimized version of a functionally equivalent part to a machined fastener part, hence L-PBF is typically not used as a direct drop-in part to a machined fastener part and instead is designed and manufactured within Fusion 360's generative-design environment and then output as an STL file for subsequent simulation studies (i.e. optimized .stl file for all subsequent work in this report).

3.2 Material Properties

The AlSi10Mg component was modelled using the powder properties for AlSi10Mg as defined in ANSYS Additive, in a linear-elastic stress model. The properties were held constant for all 5 simulations and are summarized in Table 1. The values were based on as-built L-PBF properties for AlSi10Mg and were obtained from literature [12].

Table 1 shows AlSi10Mg properties applied across all five ANSYS Additive Simulation Studies

Property	Value	Unit
Material	AlSi10Mg	-
Stress mode	Linear Elastic	-
Yield Strength	273	Mpa
Elastic (Young's) Modulus	66.1	Gpa
Poisson's Ratio	0.33	-

3.3 Simulation Platform and General Workflow

To provide a basis for comparison of the five different simulations, a common workflow has been established for all of them within the framework of ANSYS Additive, the cloud-based simulation environment. ANSYS Additive links voxel-based geometric pre-processing with the mechanical/thermal solver ANSYS Mechanical APDL (MAPDL). This pipeline consists of the following seven steps, which can be observed in the activity logs for each of the simulations: voxelization of the input part's STL file with a given voxel size and sample rate, slicing of the resulting voxel model with a given layer thickness and layer/scan-rotation angles, automatic support structure generation on the basis of overhang angles, wall thicknesses, and safety factors, mechanical/thermal solver

execution (where applicable: a dedicated MAPDL cutoff-displacement solve), support-structure optimization, and, finally, distortion compensation by means of pre-deformation of the nominal part geometry on the basis of the solution's displacement field in order to allow it to return to its intended shape. Distortion compensation is followed by conversion of the voxel-based results into a visualization format (VTK to AVZ).

3.4 Study 1 – Assumed Strain Simulation Purpose:

This assumed-strain (uniform/inherent-strain) simulation uses a single pre-calibrated strain tensor that is applied to every voxel in every layer. Thus, instead of a full transient thermal solution being produced for every voxel in every layer, a

simple solution is produced for every voxel in every layer.

Configuration: For this simulation (Simulation ID 5323), 6 strain zones were used. The layer thickness was set to 50 μm . The starting layer angle and layer-rotation angle were set to 67°. The voxel size was set to 3.0 mm. The voxel sample rate was set to 5. The strain scaling factor was set to 1. Support generation was set to automatic. The minimum overhang angle was set to 45°. The support factor-of-safety coefficient was set to 1. The support-to-part yield-strength ratio was set to 0.4375. The maximum wall distance was set to 1000 μm . The minimum support height was set to 5 mm. The wall-thickness bounds were set to 100–1000 μm . Support generation was set to automatic.

Why It Is Done/Importance of AM: The assumed-strain simulation (the assumed uniform or inherent-strain) solves the simulation in a fraction of the time it takes to solve a thermal or scan-pattern simulation. Therefore, it is the most appropriate first screening tool for a new design. It can identify the high-distortion regions and check whether the chosen build orientation and support layout are suitable. This simulation can also generate an initial distortion-compensated STL, which can be used for further studies, such as the thermal-strain and scan-pattern studies, which are described in the subsequent sections.

3.5 Study 2 – Thermal Strain Simulation

Purpose:

The thermal-strain simulation represents the thermal cycle layer by layer, i.e. first the heat is generated by the moving laser, then it is conducted to the already solidified material (including the baseplate) and finally it is cooled down. This simulated thermal history is then used to calculate the resulting strain field instead of using a single pre-calibrated tensor for the assumed-strain simulation.

Configuration: The run was performed with the following setup of parameters (Simulation ID 5325): voxel size = 0.5 mm,

mesh-resolution factor = 6, number of solver cores = 9. The machine parameters were set as follows: baseplate temperature = 80 °C, laser power = 250 W, scan speed = 750 mm/s, laser beam diameter = 80 μm , layer thickness = 50 μm , starting layer angle = 57°, layer-rotation angle = 67°, hatch spacing = 100 μm , and slicing stripe width = 10 mm.

Why It Is Done/Importance of AM:

Because of the layer-by-layer resolution of the thermal history of the layers, gradient-dependent effects are resolved, i.e. heat accumulation in thick areas and reduced heat dissipation in overhanging features. The results of this thermal-strain simulation form a physically founded second opinion for the assumed-strain simulation and, in the end, the basis for the final, high-confidence distortion compensation. The fastener under investigation is a stepped, partially hollow fastener with highly varying thermal mass throughout the build height of the fastener.

3.6 Study 3 – Scan Pattern Simulation

Purpose:

The purpose of the scan-pattern simulation is to introduce direction-dependent (anisotropic) strain coefficients to the model to represent the fact that distortion caused by scan strategy is not uniform in all directions.

Configuration: For this simulation (Simulation ID 5324) the anisotropic strain coefficients have been set to 1.5 for the local scan direction, 0.0 for the scan direction perpendicular to the scan direction and 1.0 for the build (Z) direction. In addition, same settings for the layer thickness (50 μm), the starting angle (57°) of the layer and the layer-rotation angle (67°) as for Study 2 (thermal-strain) have been selected. The option for excluding contour scan directions has been left unchecked.

Why It Is Done/Importance of AM: As stated previously, real L-PBF scan strategies, such as used here, alternate scan-vector directions between layers of build, typically by 67° or so, to distribute thermal

gradients, and resulting stress, between different directions. Thus an isotropic strain model would not be able to capture scan-pattern-induced components of the part's total distortion. The anisotropic coefficients above allow a simulation of this type to decompose the part's total distortion into a component caused by the scan-pattern of the L-PBF process and a component caused by

the part's bulk thermal history (as captured in Study 2). The process engineer can then tell whether more reduction in part distortion is to be had by varying the part's scan strategy (a relatively easy, reversible process change) versus varying the part's supports or part geometry (likely to be much more difficult).

Table 2. Comparative solver configuration for the three distortion-prediction studies

Parameter	Assumed Strain	Thermal Strain	Scan Pattern
Simulation ID	5233	5325	5324
Strain Model	Uniform (6 Zones)	Layer-wise thermal history	Anisotropic ((1.5 / ⊥ 0.0 / Z 1.0))
Voxel Size	3.0 mm	5.0 mm	-
Layer Thickness	50 μm	50 μm	50 μm
Starting Layer Angle	67°	57°	57°
Layer Rotation Angle	67°	67	67°
Laser Power or Scan Speed	(Not modelled)	250 W / 750 mm/s	(inherits thermal Setup)
Solver Core	-	9	9
Relative Computational Cost	Low	High	High

3.7 Study 4 – Single Bead Parametric Simulation

Purpose: This study uses single laser bead-on-baseplate simulations to investigate the effects of varying the laser power and scan speed when printing with a 100 μm diameter laser beam at 80 °C baseplate temperature. Results for 9 different power/speed combinations (3 power levels x 3 speed levels) are reported (Simulation IDs 5327–5335).

Why It Is Done/Importance of AM: In the above single-track simulation, we computed the melt-pool depth, length, and width. To generate a process map and then compare the results with the calibration values and/or reference values, we performed a 3×3 grid of power and speed in the above simulation. This type of process map is the standard first step to qualify a new material and/or a new machine. It is cheap (9 single-track

simulations in this study) and very diagnostic. In the above study, we diagnosed two major types of defects. Lack-of-fusion type of porosity between layers is caused by insufficient melt-pool depth. The keyhole type of porosity and spatter on the surface are caused by excessive melt-pool depth. We will quantify the above two types of defects in Study 5. The results from this single-track simulation are summarized in Table 3 in Section 4.2.

3.8 Study 5 – Porosity Parametric Simulation

Purpose: The purpose of this study was to evaluate a 3×3×3 mm representative volume element using a full-factorial design of experiments for five process factors each at three different levels (Simulation ID 5336). The five factors were listed in Table 4.

Table 4. porosity parametric simulation: five factor, three level full factorial design (3³ = 243 permutations)

Factor	Level 1	Level 2	Level 3
Laser Power	195 W	250 W	300 W
Scan Speed	800 mm/s	950 mm/s	1000 mm/s
Layer Thickness	40 μm	50 μm	60 μm
Hatch Spacing	Level A	Level B	Level C
Slicing stripe width	10 mm	15 mm	20 mm

Why It Is Done/Importance of AM:

Porosity forms based on a combination of factors, namely the energy density (power and speed) that is required to form a solid bond between layers, inter-layer bonding (layer thickness) and scan-overlap (hatch spacing and stripe width). In order to investigate the interaction between these parameters a full-factorial design of experiments was used, requiring significantly more computation in order to arrive at a process window which indicates the best combination of the five factors to prevent porosity and thus to be used for production printing of structurally loaded fasteners. The results from this study are summarized in Table 5 and depicted in Fig. 8. The output from this study effectively forms a process window, which indicates the best parameter sets to prevent porosity for fasteners.

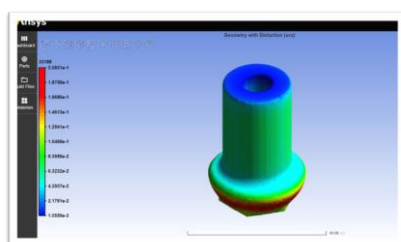
4. RESULT & DISCUSSION

4.1 Distortion Prediction: Assumed Strain, Thermal Strain & Scan Pattern

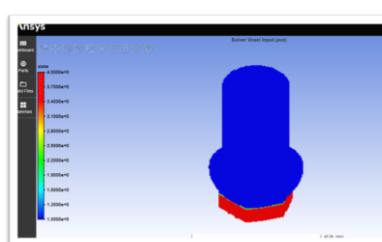
Figures 2–4 above display the results of the three different studies carried out for the part shown in Figure 1 to investigate its distortion: assumed-strain (AS), thermal-strain (TS) and scan-pattern (SP). The distortion is displayed in terms of geometry with distortion (GWD), solver voxel input (SVI), after-cutoff displacement (ACD), on-plate stress/displacement (OPSD) and support stress/displacement (SSD) plots. The distortion, shown for all three studies, reveals a particular distribution corresponding to the part's geometry. Highest displacement values are found at the rim of the hex-socket cavity and at the flanged base of the part. The highest values of stress are found in the on-plate

stress/displacement (OPSD) plots, forming a ring around the support-cutoff plane at the base of the flange, and in the support stress/displacement (SSD) plots the highest values of stress are found at the outer perimeter of the support lattice directly beneath the flange. These high values of stress correspond to classic distortion/residual-stress concentration sites in LPBF: thin-walled overhanging features and cross-sections with large changes in cross-sectional area (e.g. shank vs. flange).

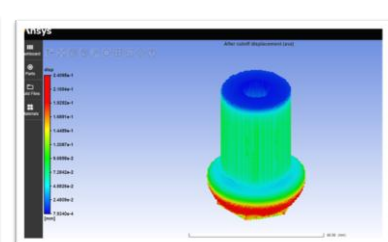
As the analysis progresses from an assumed-strain field to a thermal-strain field and then to a scan-pattern field, the same qualitative results are found. The results are as expected since all studies use the same model, geometry, orientation, and support. Each successive study however includes increasing amounts of physical realism. The thermal-strain study therefore includes the layer-by-layer thermal history rather than assuming a constant amount of strain for each layer. The resulting distortion is therefore as expected. As mentioned previously, Giubilini et al. [5] and De Leon et al. [6] have used a multi-fidelity verification strategy to increase the confidence in the results of early analysis. The resulting predicted distortion can be used for a final check on the resulting distortion-compensated geometry. The results can be used to verify whether changes to the scan-strategy could further reduce the predicted distortion. The increased sensitivity of distortion to scan-strategy as reported by Yang et al. [7] and Hassila et al. [8] supports this approach. The results from the assumed-strain study are used to verify the early stages of the verification process such as checking the orientation and support of the model.



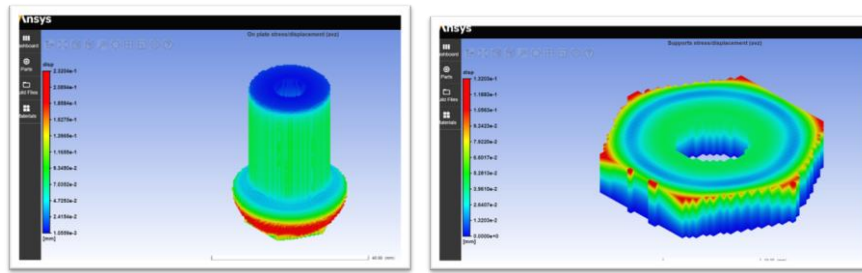
2.1 Geometry with Distortion



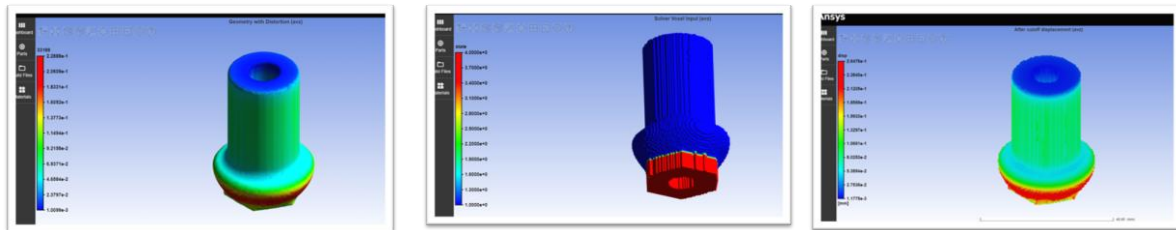
2.2 Solver Voxel Input



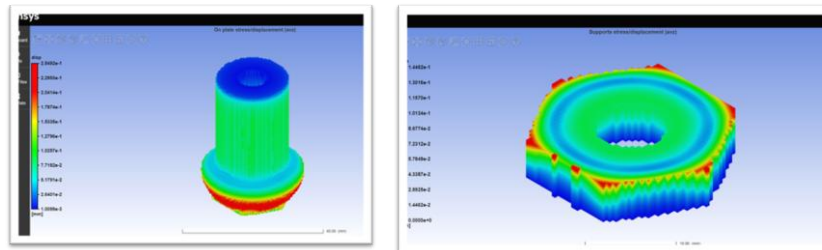
2.3 After Cutoff Displacement



2.4 On plate Stress/Displacement 2.5 Supports Stress/Displacement
Fig (2.1–2.5) Assumed Strain simulation results

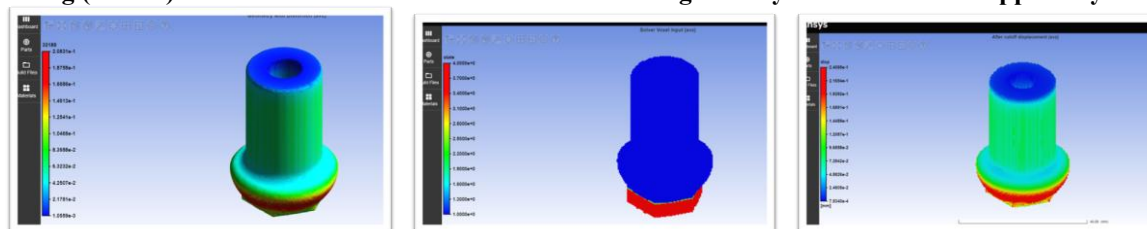


3.1 Geometry with Distortion 3.2 Solver Voxel Input 3.3 After Cutoff Displacement

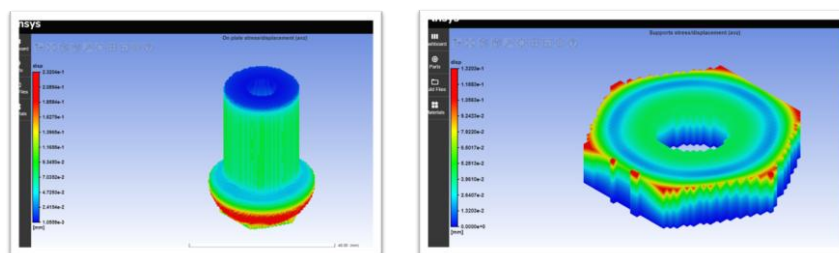


3.4 On plate Stress/Displacement 3.5 Supports Stress/Displacement

Fig (3.1-3.5) Thermal Strain simulation results for same geometry orientation and support layer



4.1 Geometry with Distortion 4.2 Solver Voxel Input 4.3 After Cutoff Displacement



4.4 On plate Stress/Displacement 4.5 Supports Stress/Displacement

Fig (4.1-4.5) Scan Pattern simulation results, incorporating anisotropic (scan vector dependent) strain coefficient

4.2 Distortion Prediction: Assumed Strain, Thermal Strain & Scan Pattern

Table 3 summarizes average values for the nine permutations of power and scan speed of laser beams for a given bead in average

melt-pool depth, length, and width. These values for average melt-pool depth, length, and width are sorted in increasing order of power and scan speed of laser beams. For a given set of permutations of power and scan

speed of laser beams, median values of average values for a given bead in average melt-pool depth, length, and width were reported by the Solver for a given set of input parameters for the 9 permutations of power and scan speed of laser beams for a given set of input parameters for the simulation, and these reported median values for average values for a given bead in

average melt-pool depth, length, and width of a given set of permutations of power and scan speed of laser beams for a given set of input parameters for the simulation for the 9 permutations of power and scan speed of laser beams for a given set of input parameters for the simulation are, in each case, within about 0.002 mm of the corresponding average value.

Table 3. Single bead parametric simulation results: Avg melt pool depth, length, width for 3(power) * 3(speed) based on plate, AlSi10Mg laser beam diameter 100µm, baseplate temp 80° C

Power (W)	Speed (mm/s)	Sim ID	Avg Depth (mm)	Avg Length (mm)	Avg Width (mm)
195	800	5330	0.053	0.140	0.126
195	900	5333	0.051	0.138	0.122
195	1000	5327	0.090	0.136	0.119
225	800	5331	0.066	0.173	0.150
225	900	5334	0.058	0.155	0.134
225	1000	5328	0.056	0.153	0.130
250	800	5332	0.084	0.221	0.182
250	900	5335	0.075	0.201	0.165
250	1000	5329	0.066	0.181	0.149

From the above average values of the melt-pool geometry for all the 9 permutations, two trends can be easily seen. Both trends are physically consistent and are due to the increase in the volumetric energy density, $E \propto P / (v \cdot d)$, where P is the laser power, v is the scan speed and d is the beam diameter. (i) Increase in the laser power at a fixed scan speed, increases the average values of the melt-pool depth, length and width. For example, at a scan speed of 900 mm/s, the average values of the melt-pool depth are 0.051 mm at a laser power of 195 W, 0.058 mm at a laser power of 225 W and 0.075 mm at a laser power of 250 W. (ii) Increase in the scan speed at a fixed laser power, decreases the average values of the melt-pool depth, length and width. For example, at a laser power of 250 W, the average values of the melt-pool depth are 0.084 mm at a scan speed of 800 mm/s, 0.075 mm at a scan speed of 900 mm/s and 0.066 mm at a scan speed of 1000 mm/s. The largest melt pool in the sweep of single bead studies corresponds to the highest energy-density combination, which would

be the first candidate to check against keyhole-porosity risk in Study 5. On the other hand, the smallest melt pool corresponds to the lowest energy density, which would be the first candidate to check for lack-of-fusion risk. Thus, as described by Al Amin et al. [9], single-bead parametric studies such as those in this study are used as diagnostics to assess potential porosity problems in a full porosity DOE, such as that planned in Study 5. Thus, Study 4 is a prerequisite for Study 5, rather than a parallel study to investigate potential lack-of-fusion problems.

4.3 Porosity Parametric Results and the Cost of Full Factorial DOE

Study 5 involves the porosity parametric simulation that was set up as a full $3^5 = 243$ -permutation factorial DOE for the laser parameters (laser power, scan speed), part parameters (layer thickness, hatch spacing) and slicing parameters (slicing stripe width) on a $3 \times 3 \times 3$ mm representative volume element.

Material		Machine	
Material	AlSi10Mg	Name	Generic
Porosity Geometry		Baseplate Temperature	80 °C
Width (X)	3 mm	Laser Power	195, 250, 300 W
Length (Y)	3 mm	Scan Speed	1,000, 950, 800 mm/s
Height (Z)	3 mm	Layer Thickness	50, 40, 60 µm
		Laser Beam Diameter	100 µm
		Starting Layer Angle	57 °
		Layer Rotation Angle	67 °
		Hatch Spacing	0.1, 0.2, 0.5 mm
		Slicing Stripe Width	10, 15, 25 mm

This figure quantifies the computational resources for a porosity parametric study. These results are useful. However, most researchers agree with Stwora et al. [10] and Staszewska et al. [11] that full-factorial physics-based DOE studies are expensive. To reach an actionable process window for a specific application, many researchers now supplement their full-factorial design of experiments with additional resources, e.g. fractional-factorial designs, response-surface methodology [12], or even machine-learning models. Such models can be set up to learn from a subset of the full grid of possible experimental settings. In the case of the fastener component, one natural way to refine Study 5 (if the full 243-run grid proves to be too expensive to repeat for

additional design iterations) would be to use the single-bead results of Study 4 to first select a reduced set of power/speed combinations based on the energy density in the single beads. Then, a smaller factorial design or even a response-surface methodology would be used to search for the optimal process window as a function of the layer thickness and the hatch spacing, i.e. a two-stage screening strategy as already implicitly present in Studies 4 and 5.

4.4 Synthesis Why Five Studies, and Why in this Order

Table 5 outlines the studies, their physical fidelity, cost of the studies and the principal goal of each study.

Table 5. Summary comparison of five ANSYS Additive simulation studies performed in this work

Study	Physical Model	Relative Cost	Key Output	Primary Design Decision Supported
Assumed strain	Uniform/inherent strain per layer	Low	On plate distortion; Compensated STL	Build orientation & Support Screening
Thermal Strain	Layer wise transient thermal	High	Distortion; on plate/support Stress	High Fidelity distortion compensation
Scan Pattern	Anisotropic, Scan vector dependent strain	High	Direction resolved distortion	Scan Strategy turning
Single Bead Parametric	Melt pool geometry vs power/speed	Low - Medium	Melt pool depth/length/width	Energy density calibration
Porosity Parametric	Pore formation risk vs 5 factor DOE (23 runs)	Very High	Process window / porosity risk map	Final parameter set selection

Taken collectively, these 5 simulation studies represented an increasing-fidelity/increasing-cost simulation “loop” (versus just a series of 5 studies), and were meant to be read together as a template to be implemented prior to first physical part for

any generatively designed L-PBF component. Specifically, for the “distortion/supports” screen, an “assumed strain” study (Section 3.4) was conducted first to yield results quickly. Subsequently, a “thermal-strain” study (Section 3.5) and

“scan-pattern” study (Section 3.6) were undertaken in a progressively more physically realistic manner to improve upon the initial distortion prediction, by representing thermal history (and anisotropy) and scan-vector-dependent anisotropy, respectively. Following upon that, the “single-bead” study (Section 3.7) was employed as an independent means for calibrating the “melt-pool/energy-density” relationship. By last, a “porosity” study (Section 3.8) was implemented that in combination with the above simulation studies (together, in increasing order of physical realism) enabled the defining of a process-parameter (in particular, defect-minimized) “process window” (of defect minimized L-PBF parts), via a DOE (design of experiments) on all 5 variables.

5.CONCLUSION

This paper uses five studies of simulation of process planning for generative design of L-PBF components to present a set of process planning studies and a process planning design for generative design. The five simulation studies of the generative design of fasteners, in increasing order of cost and of physical fidelity of the simulation model, were (i) and (ii) an assumed-strain distortion/suppression study and an inherent-strain study to determine distortion of a component, (iii) and (iv) a study of thermal strain and scan-pattern-dependent anisotropy and a study of single-bead melt-pool parametric studies, to establish a basis for the study of (v) the porosity-dependent design of process parameters in a DOE. The findings of the five simulation studies of a generative design for a single fastener of AlSi10Mg, were (i) and (ii) that an assumed-strain study gave the same sort of distortion results as a thermal-strain/scan-pattern study, (iii) that a single-bead melt-pool study gave energy-density results and so could be used for subsequent studies, (iv) that a full-factorial DOE study of the parameters for a study of porosity-dependent design, gave a set of results that indicated that such design studies would be

expensive for design of components by generative design, so that reduced-design-space studies and other surrogate design studies could be useful.

This case study further demonstrates a key insight in the field of AM, that generatively optimized geometries, are not manufacture ready, but rather inputs to a structured multi-fidelity simulation process. Hence, design alone does not guarantee performance in the as-built case [13]. Future work will focus on (a) completing and statistically analyzing the results of the full 243-run porosity DOE, (b) physically building and metrology measuring the compensated design to validate the assumed-strain and thermal-strain predictions of distortion, as recently done by Giubilini et al. [5], and (c) reduced or machine-learning-assisted DOE for porosity screening to make the five-study DFAM workflow practical for typical, iterative DFAM applications.

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