

# A machine learning-based digital twin of the manufacturing process: metal powder-bed fusion case

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(Dated: March 14, 2020)

Additive manufacturing processes are enabling the manufacturing of geometries that were impossible to manufacture before. However, the technology is also facing challenges due to process inconsistencies, such as local overheating which creates large scrap rates. An intelligent process relies on a digital twin [1, 2] to achieve a robust process planning avoiding substantial costs related to trial and error to overcome those obstacles. Such a digital twin of the process hence helps to accomplish a print first-time-right. We build a digital twin of the AM process - including the full print path - using a machine learning algorithm trained on synthetic, physics-based and experimentally validated data. This allows for prediction of overheated regions for a complete workpiece within a reasonable time and the application of improved scan strategies. We outline the general method on an exemplary aerospace part made of In718, successfully predicting overheated regions and correcting it through an alternative exposure strategy.

Keywords: digital twin, machine learning, additive manufacturing

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## I. INTRODUCTION

Additive manufacturing is increasingly used for serial production and holds great promises to revolutionize the traditional manufacturing system by enabling new higher-level performance parts and totally unique business models such as distributed manufacturing. In metal powder bed fusion (PBF), the high scrap rate has a substantial impact on the cost and therefore the adoption of additive manufacturing. Multiple software solutions based on finite element approaches have emerged to address some of these issues. These technologies are aiming at optimizing the build preparation including the support and the part orientation to minimize the distortions. Nonetheless, other challenges leading to scrap cannot be solved on the component level but are a consequence of a sub-optimal vector and process parameters selection. The combination of short scanning vectors and overhang areas can lead to the increase of the melt pool size yielding an accumulation of material that is at the origin of multiple recoating collisions. Further, these overheated zones are usually resulting in inconsistent microstructures and properties due to the different thermal history. To the knowledge of the authors no one has solved this problem for PBF previously. While the thermal history in small excerpts induced by a laser propagating through the part can be simulated using finite element approach, the large spread in spatial and time scales renders it an impossible task to simulate a whole part on the scale of the melt pool dimensions. Leveraging synthetic data obtained from appropriate FEM simulations for a machine learning model can help to overcome this problem [3]. In [4, 5] the authors show how the calculation of the thermal history in a direct energy deposition (DED) process can be applied to a whole part using machine learning.

In section 2, the novel machine learning framework is introduced providing detailed elements on the architecture of the solution. Then, the validation approach of the methodology and specifically how the physics-based synthetic data are verified is outlined. A use case is described based on a complex aerospace geometry made of Inconel 718. Finally, we conclude our results and provide a hint about how such a framework could be extended from its actual process planning usage to a future self-healing use case.

## II. MATERIALS AND METHODS

The intelligent path analyzer approach reported here can be divided into two major parts: the training part and the simulation part (see Fig. 1). Key starting point to perform a thermal

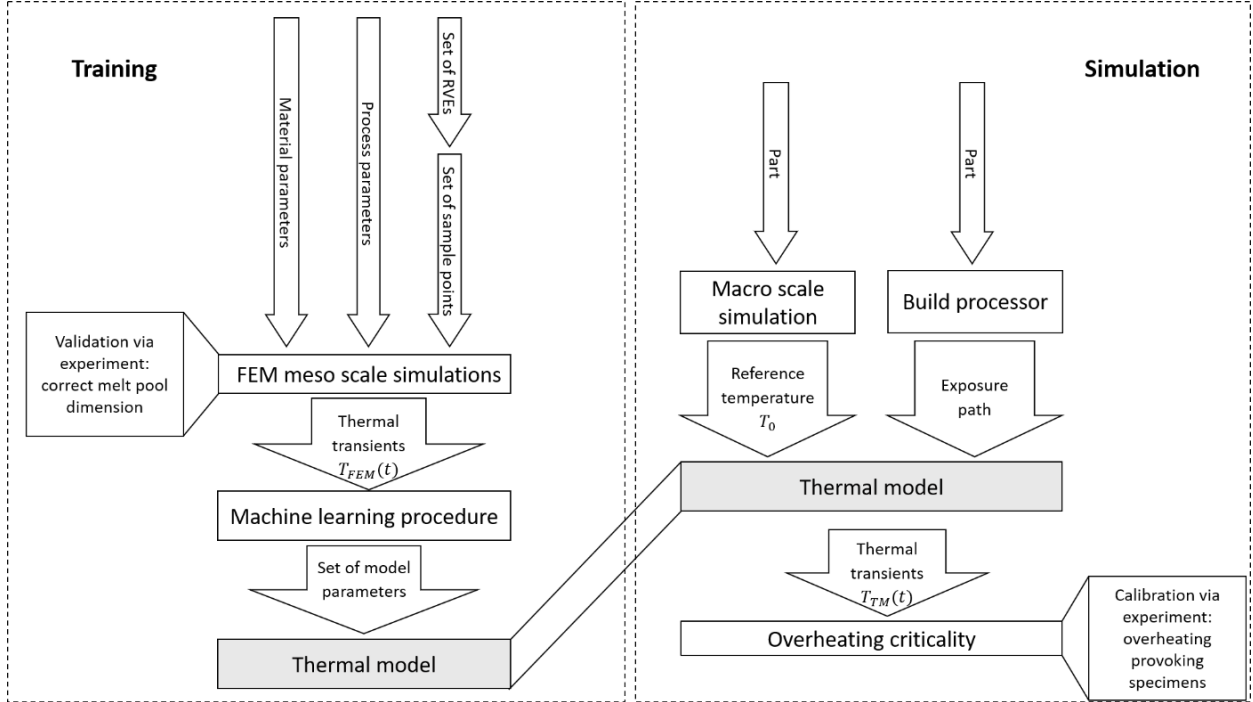


FIG. 1. Intelligent path analyzer approach: Left: Workflow to teach the machine learning model with the synthetic data. Right: Workflow for local overheating simulation of the complete exposure path.

simulation of the full powder bed fusion process to print a part - including the exact and complete exposure path - is to overcome the well-known problem of the spread of spatial and times scales when applying a finite - element based method (FEM). A common approach is to separate thermal simulations according to its scales as follows [6]:

$$T(t) = T_0(t) + T_{\text{fast}}(t) \quad (1)$$

Here, the reference temperature  $T_0$  is obtained from a macro-scale simulation of the complete workpiece as the long-time temperature, averaged over a layer after the exposure [7]. The fast-changing part  $T_{\text{fast}}$  is the short time behavior induced by the local propagation of the laser following the set exposure path. Combined, they provide the full thermal transient. The macro scale simulation can be applied to a whole part to print and is the starting point of the simulation procedure (see right-hand side of Fig. 1). However, a thermal model needs to be set up to obtain the fast changing part based on the concrete exposure path provided by the build processor. This renders a training procedure necessary to obtain the thermal model (see left-hand side of Fig. 1). The training starts with the supply of meaningful synthetic training data to learn from. This can be obtained from a meso-scaled thermal FEM simulation on a spatial scale fine enough to represent the dimensions of the melt pool. It solves the heat equation including a Gaussian

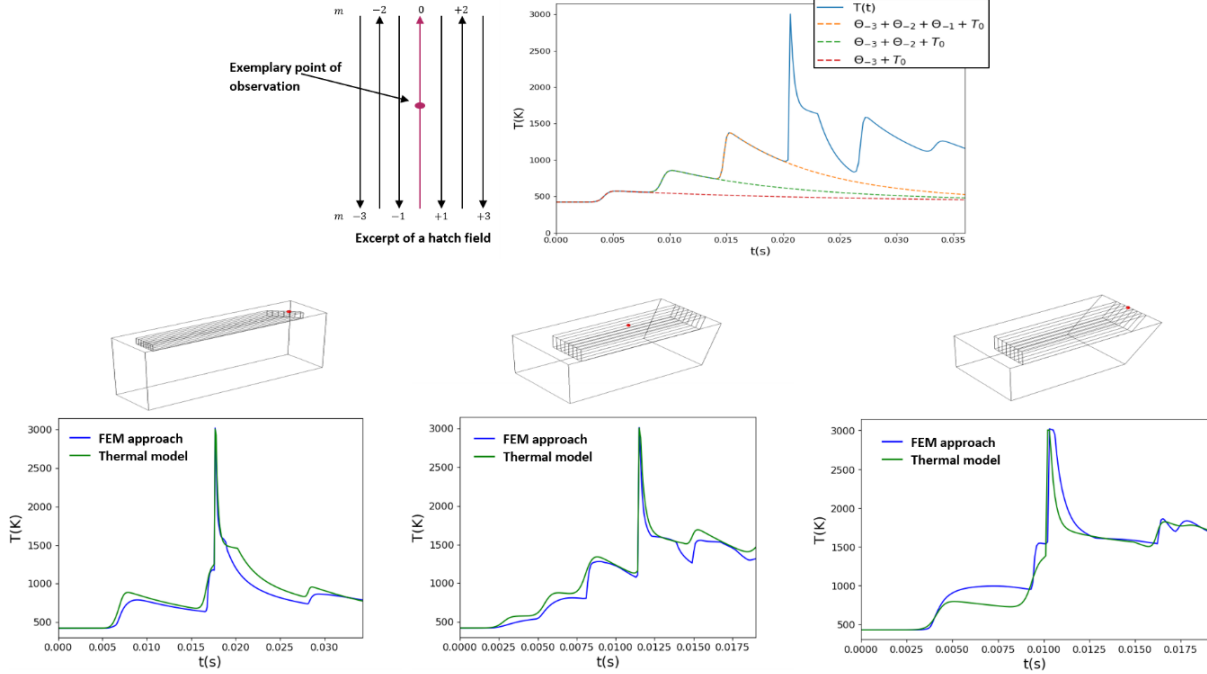


FIG. 2. Visualization of the applied ansatz for the thermal model and examples of the used RVE including a comparison of FEM data (FEM) and the Machine Learning-based thermal model (TM)

heat input representing the moving laser and heat loss via conduction and radiation as well as a Dirichlet boundary condition set to the reference temperature  $T_0$ . A calibration process ensures that the simulation reproduces the dimension of the melt pool in bulk material correctly. These simulations are then computed on so-called representative volume elements (RVEs), representing different possible excerpts from a build process. From these, the short time, thermal information for specified sampling points are extracted (see Fig. 2) providing the training data.

For a concise assessment of the thermal history in any point on the exposure tracks the complete path needs to be considered. However, depending on the thermal properties of the material only a finite number of prior and posterior vectors needs to be included for the thermal history of an exposure vector. This justifies the extraction of thermal data from the RVEs and the following ansatz for the thermal model (TM)

$$T_{\text{TM}}(x, y, z, t) = T_0(z) + \sum_m \theta_m(x, y, t) \quad (2)$$

with a *finite*  $m$ . The full thermal transient is hence the sum of the layer - dependent reference temperature  $T_0$  and an in - plane dependency on the surrounding exposure vectors described by  $\theta_m$ , i.e. the contribution of the  $m$ -th prior and posterior vectors (upper part of Fig. 2). The synthetic training data is obtained for a specified material in combination with a determined process and its

parameters. The resulting FEM simulations are realized in a set of RVEs. This set is chosen in a way that the RVEs represent all possible combination of relevant features influencing the thermal history in the sample points, such as surrounding mass and length of vectors. From each RVE thermal transients are extracted on a finite number of sampling points. Additionally, an elasticity study with respect to the process parameters is made in order to ensure that the process parameters can be varied within a reasonable range. The result of this procedure - that only needs to be done once - is a data base containing all the parameters of the specified thermal model for a specific combination of material and process parameters. The thermal transients shown in Fig. 2 indicate that the thermal model can reproduce the very different thermal transients successfully. Once the thermal model is fixed, it allows now a fast calculation of the temperature transient in any sample point on the exposure path in the simulation procedure of any concrete part.

For the full simulation the part is simulated first on a macroscale providing the reference temperature in each layer and the build processor defines a definite exposure path. Next, the thermal model is applied to a finite number of sampling points on each exposure vector of the designated strategy providing the thermal history in each point. Those thermal transients provide us with a vast amount of information usable for different kind of analysis. However, the current goal is the precise prediction of local overheated regions. Local overheating is defined as the consequence of a too wide melt pool resulting from a sub-optimal combination of process parameters, laser path and the geometry to be built. In order to reflect this in a single criterion per sample point, we chose to consider the temperature for the sample point in that point in time when the spatially closest point in the subsequent vector is written. This is a good indicator of a too wide melt pool. In order to calibrate the span of criticality with respect to local overheating, a set of simple specimens provoking a range of overheating are printed and accordingly to those results the relevant thresholds for criticality are set. This is the second part of the calibration procedure ensuring the correctness of the simulation of the intelligent path analyzer.

### III. RESULTS

The described algorithm is seamlessly integrated as AM Path Optimizer in the NX AM build preparation. Once the user has finished the build preparation and a build processor (BP) created the job file, the algorithm systematically predicts local overheating based on the full laser scanning path. Subsequently, a new job file is generated based on the simulation results deploying an enhanced strategy. The results for an impeller structure printed on a TRUMPF TruPrint5000 are

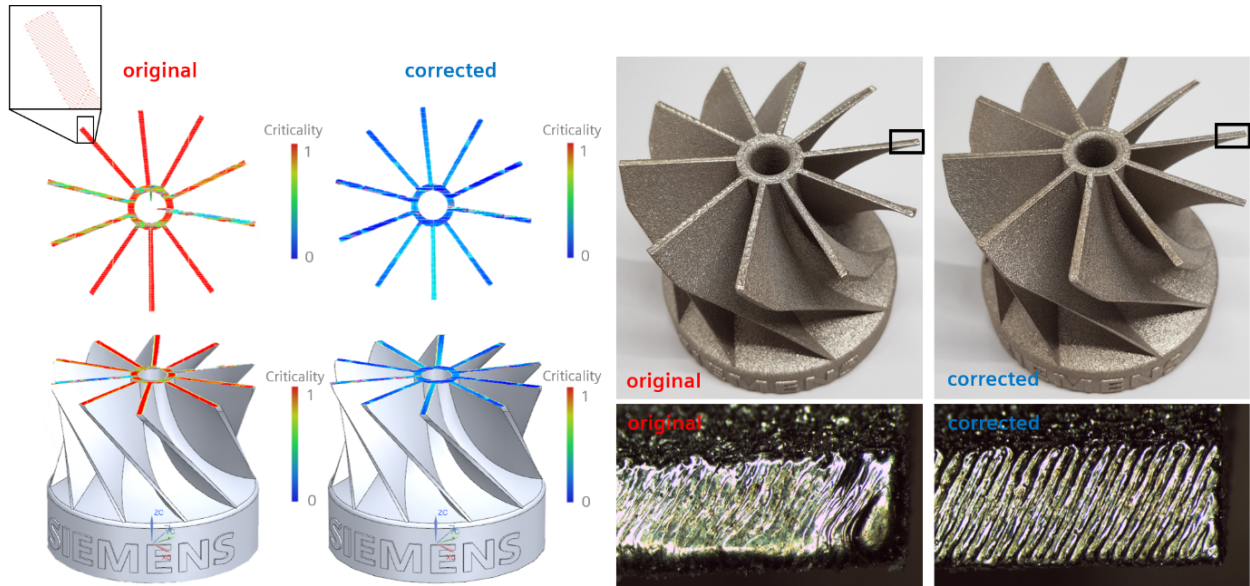


FIG. 3. Demonstration on the impeller specimen exposed by the original and corrected strategy. Left: Simulation results as shown in the NX interface. Right: Microscopic picture of printed results show strong enhancement after correction based on the simulation: parallel and distinguishable welding tracks instead of the initial melt bead.

shown in Fig. 3 with a stripes-based exposure strategy provided by the TRUMPF BP. On the left-hand side, results for an exemplary layer are depicted. First, based on the original exposure strategy overheating is simulated. The resulting color range directly reflects the criticality in each sample point, with the range set by the calibration. Based on this overheating prediction, a corrected alternative strategy is deployed and resimulated, indicating the successful avoidance of this effect. On the right-hand side, the printed specimens are shown and microscopic pictures of the top layer of one wing are compared. The pictures indicate that in the original strategy a large bead has been formed, while after correction clearly distinguishable and parallel welding tracks are observed. This proves the successful avoidance of the overheating effect. Whereas for the results depicted in Fig. 3 delay times have been introduced in order to correct local overheating, the thermal information obtained in the described method allows to implement a much more sophisticated corrective strategy combining an optimization approach with heuristics for the improved design of exposure strategies that SIEMENS have experimented on other use cases.

## IV. DISCUSSION

We have introduced a new digital twin of the manufacturing process for metal powder bed fusion. This digital twin can simulate the transient temperature at each point and thus detect issues such as overheating. The framework is based on a machine learning algorithm trained on experimentally validated, synthetic data obtained from a finite element approach. The algorithm considers the scan strategy, the laser parameters, the materials properties and the part geometry. With this framework we have introduced a first machine learning based digital twin of the powder bed fusion process used as a robust tool to perform predictive and corrective process planning and speed up of the computation compared to finite element approach with a factor of  $10^7$  without parallelization. Future work consists in using a similar framework trained on in-process monitoring data, thus achieving in process, corrective, or self-healing capabilities, where up-front simulation and in-process data stimulate each other.

## ACKNOWLEDGMENTS

The authors would like to thank Dr. Jeroen Risse from TRUMPF for providing the validation testbed on the TruPrint5000. The authors would like to thank Dr. Darya Kastsian, Dr. Tom van't Erve and Dr. Frank Heinrichsdorff for their valuable contribution.

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