Optimisation of selective laser sintering and melting process (SLS/SLM) based on numerical simulation and machine learning

PhD Thesis

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Abstract

This research aims to develop an optimization framework for the process of Selective Laser Sintering and Melting (SLS/SLM) by leveraging the extreme efficiency of data-driven models. SLS/SLM is a main representative of Additive Manufacturing processes, which are instrumental to the realization of Industry 4.0. Its principle of operation is based on using heat from a moving laser beam to selectively consolidate pre-deposited powder layers into successive slices of the final part. Model-based optimization is critical for the maturation of SLS/SLM, which is thus far driven by generally sub-optimal setups determined by trial-end-error on actual machines. After decades of research, it still poses extreme challenges mainly stemming from the large discrepancy of scales involved in the process. Emergent computational barriers are somewhat alleviated by the practice of multiscale modeling, which aims to gradually increase the scope of simulations by transferring knowledge between various levels of abstraction.

SLS/SLM is a thermal process, and the temperature history of a given layer, which in part depends on the topology of the trajectory, greatly affects the characteristics of the final part. Discrete particle models struggle to process a single millimeter of laser track. Low resolution models which handle entire parts cannot maintain connection to the thermal history imposed by a specific scanning strategy. At both of these extremes, the critical effects of the laser trajectory are not taken into account. The intermediate scale of a single powder layer, macroscopically considered as a continuous medium, is generally regarded as the most suitable to focus on for optimization related research. The trend is to attempt to optimize for quantities which have strong correlation to the overall quality of the process, peak temperature along the laser path being a typical choice.

Physics models have been successfully employed for predictive simulations at the lower end of the layer scale (~mm). An actual layer, however, typically requires much larger laser tracks ($\sim 10^2$ m). At this scale, physics-based simulations are too costly or even unfeasible. In addition to that, optimization requires multiple simulations for achieving a given objective. Physics agnostic data-driven models exhibit the necessary computational efficiency both for achieving sizeable simulations and also facilitating optimization endeavors. Thus far they have been employed mostly for trivial scanning strategies and/or small geometries. Model-based optimization of process parameters along an arbitrary laser trajectory of significant length is an open problem.

Three modeling platforms of progressively increasing scope are developed in this thesis: The Parent Model, the Surrogate Model and the Power Model. The Parent Model is a macroscopic thermal FEA modeling platform optimized for efficiency in relatively short track simulations (~mm). It implements thermal shell elements, automatic domain creation with progressive mesh coarsening, and solution accelerating techniques. It also employs virtual materials to represent various stages of consolidation, from initial loose powder to fully dense material. Its purpose is to efficiently produce large sets of training data that will support the machine learning platforms developed next.

The Surrogate Model is a data-driven modeling platform based on Artificial Neural Networks (ANNs), built to perform rapid simulations on very large arbitrary trajectories (>10^2 m). It implements the paradigm of a moving black-box model which follows the laser beam and predicts peak temperature and mean density evolution along the laser path. Dynamic regression along a path of arbitrary shape is facilitated by an original trajectory decomposition method which drastically reduces the infinite dimensionality of the topological input. This is achieved by extracting a descriptor which monitors the shape of the trajectory as well as its history within varying memory lengths. The initial machine learning paradigm has a sequential character and thus does not leverage the ability of the ANNs to process sets of input vectors in parallel. This bottleneck is compounded by the fact that temperature feedback proves necessary for increased performance. To remedy this issue, a recursive scheme is implemented which allows the Surrogate Model to process entire trajectories in parallel, by using an initial estimation of the temperature feedback vector, and subsequently refeeding and refining its own results. The final optimized Surrogate Model achieves simulation times of the order of real-time, which constitutes a major efficiency breakthrough.

The Power Model extends the Surrogate Model by incorporating variable laser power in the input vector, thus exposing an independent variable for temperature regulation. The aim is to identify an optimized power profile that counteracts the thermal accumulation effects caused by the topology of the laser path. A one-step-ahead algorithm is initially conceptualized to serve as an efficiency benchmark. Then, an improved adaptive control law is implemented which can be applied to the entire power profile in parallel. It has a recursive character and can achieve a smooth temperature profile given a few iterations. The proposed framework successfully leverages the extreme efficiency of the developed data-driven model to provide an innovative solution for dynamic process optimization.

The Parent Model, which represents the basis of the machine learning chain, was successfully validated against similar models and experiments from the literature, exhibiting less than 10% relative deviation, for the worst cases amongst all comparison scenarios. The surrogate models achieve mean relative errors in the order of 1% for single simulations and less than 2% for the final optimized temperature profile, compared to the Parent Model. Future access to experiments can directly verify and/or help to further increase the accuracy of the developed framework. Regardless, this research mainly aspires to provide a methodological roadmap for innovative application of machine learning to the largely unexplored area of SLS/SLM optimization.