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A Review on Numerical Simulation of the Selective Laser Melting Process: Mechanisms, Parametric Influences, and Future Directions

Chen Liu, Yiru Cheng

Tianjin University of Technology and Education, Tianjin 300222, China

ABSTRACT

Selective Laser Melting (SLM) is a leading additive manufacturing technology capable of producing complex metallic components with high precision. However, the intricate physical phenomena involved, such as rapid melting and solidification, lead to challenges in process control and quality assurance, often resulting in defects like porosity and residual stress. Experimental optimization is costly and time-consuming. Consequently, numerical simulation has become an indispensable tool for understanding the underlying mechanisms and optimizing process parameters. This review synthesizes recent research on the numerical simulation of the SLM process. It summarizes key findings on the modeling of melt pool dynamics, heat transfer, and fluid flow, highlighting the influence of primary process parameters—laser power, scanning speed, and hatch spacing—on the thermal behavior and resulting part quality. The paper discusses various modeling approaches, from continuum-based Finite Element Methods (FEM) to particle-level Discrete Element Methods (DEM), and the application of different heat source models. Key challenges, including multi-scale/multi-physics coupling, computational expense, and model accuracy, are identified. Finally, future research directions are proposed, emphasizing the potential of hybrid physics-based and data-driven models, and the integration of simulation with in-situ monitoring for real-time process control and defect prediction.

KEYWORDS

Selective Laser Melting (SLM); Numerical Simulation; Melt Pool Dynamics; Process Parameters; Defect Formation; Heat Transfer.

1. INTRODUCTION

Selective Laser Melting (SLM), a powder bed fusion (PBF) additive manufacturing technique, has revolutionized the production of complex, high-performance metallic parts for industries such as aerospace, medical, and automotive[1]. The process involves using a high-energy laser to selectively melt and fuse metallic powder layer by layer, based on a 3D digital model. This layer-wise approach enables the fabrication of intricate geometries, internal channels, and lightweight lattice structures that are difficult or impossible to produce with conventional manufacturing methods.

Despite its advantages, the SLM process is governed by complex and highly dynamic physical phenomena. The rapid localized heating from the laser and subsequent fast cooling rates result in extreme thermal gradients and complex fluid dynamics within the molten pool. These conditions profoundly influence the material's microstructure, the formation of defects (such as porosity, lack of fusion, and balling), and the generation of residual stresses, all of which directly impact the final component's mechanical properties and dimensional accuracy. Optimizing the vast parameter space of SLM (including laser power, scanning speed, hatch spacing, and layer thickness) through purely experimental "trial-and-error" approaches is prohibitively expensive and time-consuming.

Numerical simulation has emerged as a powerful and cost-effective alternative for gaining fundamental insights into the SLM process[2]. By modeling the coupled thermal, fluidic, and mechanical behaviors, simulations can predict the temperature field, melt pool morphology, fluid flow, and defect formation under various process conditions. This predictive capability allows for systematic process optimization, reduction of experimental efforts, and a deeper understanding of the process-structure-property relationships.

This paper provides a comprehensive review of the recent literature on the numerical simulation of the SLM process[3]. It aims to synthesize the current state of understanding regarding the modeling of key physical mechanisms and to summarize the simulated effects of process parameters on melt pool characteristics and defect formation. The review will also identify the principal challenges in the field and suggest promising future research directions.

2. LITERATURE REVIEW: MODELING THE SLM PROCESS

The numerical simulation of SLM typically involves modeling heat transfer, fluid dynamics within the melt pool, and the resulting thermo-mechanical effects. Research in this area can be broadly categorized by the physical phenomena being modeled and the computational methods employed.

2.1. Heat Transfer and Melt Pool Dynamics

The core of any SLM simulation is the accurate prediction of the temperature field and the resulting melt pool morphology. Researchers have consistently shown that process parameters have a direct and significant impact on these characteristics.

Effect of Process Parameters: A general consensus in the literature is that increasing laser power or decreasing scanning speed leads to a higher linear energy density, resulting in a larger and deeper melt pool. Zhang [4]demonstrated through CAE software simulation that at a constant scanning speed, increasing laser power leads to higher peak temperatures, melt width, and melt depth. Conversely, at a constant laser power, increasing the scanning speed reduces the interaction time, leading to a smaller melt pool and lower peak temperatures. This fundamental relationship is a recurring theme across studies on various materials, including 316L stainless steel, Ti6Al4V, and Maraging steel.

Heat Source Models: The choice of the heat source model is critical for the accuracy of the simulation. Common models include the Gaussian surface heat source and volumetric heat sources like the double-ellipsoid or Parabolic Optical Penetration Depth (POPD) models. Yang et al. [5]compared the traditional Gaussian surface model with a POPD volumetric model, finding that while the surface model was more accurate for predicting melt pool width, the volumetric model was superior for predicting depth, especially at medium to high energy densities. Li et al.[6] (2021) also found that the double-ellipsoid heat source model yielded more accurate results compared to experimental data for 18Ni300 steel than the Gaussian surface model, as it better accounts for energy penetration into the powder bed.

Melt Pool Fluid Flow: The fluid flow within the melt pool is driven primarily by Marangoni convection (surface tension gradients), recoil pressure from metal evaporation, and buoyancy. Numerical simulations have been crucial in visualizing and understanding these complex flows. Chen et al. [7] established a multiphysics model showing that the melt pool shape evolves from circular to elliptical, with the central part remaining stable while the solidification front progresses. Shao et al. [8]highlighted that strong Marangoni convection is the dominant heat transfer mechanism within the melt pool, becoming more pronounced at higher laser powers. At high energy densities, the recoil pressure from evaporation can become significant, depressing the melt pool surface and potentially leading to keyhole formation.

2.2. Simulation of Defect Formation

A key application of SLM simulation is the prediction and mechanistic understanding of defect formation.

Porosity and Lack of Fusion: Lack-of-fusion porosity typically occurs at low energy densities, where there is insufficient energy to completely melt the powder particles or fuse adjacent tracks. In contrast, keyhole-induced porosity occurs at high energy densities, where a deep, vapor-filled cavity (keyhole) becomes unstable and collapses, trapping gas bubbles within the solidifying metal. Numerical models have been instrumental in identifying the process windows that avoid these two competing defect mechanisms.

Surface Defects and Morphology: Defects such as "balling" and "humping" are related to melt pool instabilities. Balling, where the molten metal forms spheres instead of a continuous track, is often attributed to poor wettability and the Plateau-Rayleigh instability, prevalent at low energy densities. Humping is a periodic surface wave phenomenon observed at high scanning speeds, which Qiu et al. [9] attribute to the accumulation of molten metal at the rear of an elongated melt pool. Simulations help to elucidate the fluid dynamic conditions that lead to these surface irregularities.

Residual Stress and Deformation: The intense, localized thermal cycles in SLM generate significant residual stresses, which can cause part distortion, warping, and cracking. Thermo-mechanical FEM models are widely used to predict these stresses. Fan et al.[10] utilized FEM to generate a dataset for training a Genetic Algorithm-Backpropagation (GA-BP) neural network, which successfully predicted residual stress in Al-Mg-Sc-Zr alloy parts and identified optimal process parameters to minimize it. This highlights a powerful synergy between physics-based simulation and data-driven methods.

2.3. Advanced Modeling Approaches

To improve accuracy and capture more complex phenomena, researchers are developing increasingly sophisticated models.

Multi-Scale and Multi-Physics Modeling: Some studies combine different modeling techniques to capture phenomena across scales. Chen et al. [11]used the Discrete Element Method (DEM) to simulate the random packing of the powder bed, providing a more realistic initial condition for a subsequent Finite Volume Method (FVM) simulation of the melt pool. Song[12] (2024) proposed a multi-scale framework combining DEM for the powder bed, FVM for melt pool dynamics, and a Cellular Automata (CA) model to simulate the resulting microstructure evolution.

Data-Driven and Hybrid Models: As the complexity of SLM grows, purely physics-based models can become computationally prohibitive. Hybrid approaches that integrate simulation with machine learning are gaining traction. The work of Hu et al. [13]on residual stress prediction is a prime example. Yan[14] (2025) developed a data-mechanism hybrid model to accurately predict the energy consumption of the SLM process, achieving a prediction accuracy of over 95% by using experimental data to compensate for the errors in a physics-based model.

3. CHALLENGES AND OPEN ISSUES

Despite significant progress, several challenges remain in the numerical simulation of SLM.

- **Model Accuracy and Validation:** Models inherently rely on simplifying assumptions ([15] e.g., treating the powder bed as a continuum, approximating laser absorption) and require accurate, temperature-dependent material properties, which are often unavailable. Rigorous validation against high-quality experimental data remains a critical and challenging step.

- **Computational Expense:** High-fidelity, multi-physics simulations, especially for large components or multi-layer builds, are computationally intensive, often requiring high-performance computing resources and long simulation times.
- **Multi-scale Coupling:** Seamlessly and efficiently coupling models across different length and time scales—from individual powder particles (microns) to melt pool dynamics (microns to millimeters) to part-scale thermo-mechanical behavior (centimeters)—is a major ongoing challenge.
- **Defect Prediction Complexity:** While models can predict well-understood defects like keyhole porosity, the formation of stochastic defects, such as those arising from powder spatter or atmospheric inconsistencies, remains difficult to capture deterministically.

4. FUTURE DIRECTIONS

Building upon the current state of the art and the existing challenges, several future research directions can be identified:

- **Hybrid Physics-Informed Machine Learning:** The integration of machine learning with physics-based simulations holds immense promise. Machine learning can be used to create surrogate models that accelerate computations, optimize parameters based on simulation data, and even discover new process-structure relationships from complex datasets.
- **Integration with In-situ Monitoring:** A major goal is to use simulations to build robust models for real-time, closed-loop process control. This involves creating "digital twins" that can interpret data from in-situ sensors ([16] e.g., thermal imaging, acoustic sensors) to predict impending defects and automatically adjust process parameters to mitigate them.
- **Advanced Multi-Scale Frameworks:** Further development of computationally efficient frameworks that link micro-scale phenomena ([17] e.g., powder spreading, microstructure evolution) to meso-scale melt pool behavior and macro-scale part properties will provide a more holistic understanding of the process.
- **Energy Consumption and Sustainability Modeling:** As SLM moves towards industrial-scale production, modeling and optimizing for energy efficiency and overall sustainability, as demonstrated by Yan [18] (2025), will become increasingly important. This involves not just the melting process but the entire system's energy footprint.

5. CONCLUSION

Numerical simulation has proven to be an essential tool for advancing the science and technology of Selective Laser Melting. As reviewed in this paper, simulations have provided profound insights into the complex interplay of heat transfer, fluid flow, and solidification dynamics that govern the SLM process. They have elucidated the fundamental effects of key process parameters on melt pool dimensions and thermal history, and have helped to uncover the mechanisms behind common defect formations like porosity, balling, and residual stress.

Despite the successes, challenges related to computational cost, model accuracy, and multi-scale integration persist. The future of SLM simulation lies in the development of hybrid data-driven and physics-based models, the integration of simulation with in-situ process monitoring to enable real-time control, and the creation of comprehensive multi-scale frameworks. Addressing these challenges will accelerate the optimization of SLM processes, improve part quality and reliability, and further solidify SLM's role as a transformative manufacturing technology.

CONFLICTS OF INTEREST

The authors declare that they have no conflict of interest.

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