Physically informed machine learning algorithms for the mastering of additive manufacturing processes

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Architectured materials have emerged as a key avenue for achieving specific properties while maintaining lightweight characteristics. This is particularly crucial in industries such as the aerospatial, where weight reduction is paramount. Additive manufacturing (AM) plays a pivotal role in this pursuit, offering the ability to create intricate structures with precise control over geometry and material distribution. [1], [2] Among the various AM techniques, laser-powder bed fusion (L-PBF) and laser-direct energy deposition (L-DED) stand out for its capability to fabricate complex components with high accuracy. However, achieving optimal results in L-PBF/L-DED necessitates meticulous control of process parameters to minimize defects and ensure desired outcomes. [3] This need for precision is even more accentuated for thin walls (< 400 µm), where such as warping, porosity and dimensional inaccuracies defects can readily appear (c.f. **Figure 1**). Our primary focus revolves around investigating the impact of AM process parameters (the laser power – P and the scanning speed – v) onto the thickness (t) of AlSi7Mg06 thin walls.

This problem can be tackled by the use of multiphysical simulations which, albeit informative, are slow and challenging to scale. Analytical physical models overcome these issues, [4] (c.f. **Figure 2**) but their ouput is more qualitative than quantitative. Besides, any type of simulation involves hidden parameters that are hard to estimate, hindering the simulation process in mimicking the experimental results. On the other hand, the experimental procedure and subsequent measurements present limitations in data acquisition, constraining the feasibility of leveraging data-driven approaches like data science or artificial intelligence. In this study, we aim to overcome these obstacles by the use of physically-informed data-driven approaches.

We have explored the process window by systematically varying parameters and analyzing their effects on wall thicknesses. Utilizing clustering k-nearest neighbors algorithms (c.f. **Figure 3**), we have been able to discern distinct clusters within the (P, v) space solely based on the thicknesses and their standard variations, devoid of any additional input. Each cluster can be attributed to different physical phenomena occurring during the melting process, shedding light on the underlying mechanisms at play. Dimensional analyses have been carried out to unveil relationships between thickness and process parameters. [5] This analysis' relationship has been shown to be valid in one of the found clusters, for whose thicknesses we can make accurate predictions (c.f. **Figure 4**).

Physically-informed Gaussian process algorithms have been employed to elucidate the explored t(P, v) space (c.f. **Figure 5**). By imposing the trend predicted by physical dimensional analysis as the mean in the Gaussian process model, we have effectively integrated theoretical insights with machine learning techniques. This approach has allowed us to map the intricate relationships within the parameter space and to identify critical points through analysis of maximum sigma values. These maxima can guide a strategic design of experiments for exploring new trial points, optimizing the efficiency of our investigations. Furthermore, by integrating theoretical models as mean inputs for the Gaussian processes, we not only succeeded in predicting wall thickness but also in extracting physical parameters that are challenging to measure directly. In addition to this approach, we have developed an iterative algorithm based on artificial neural networks to estimate the "elusive" process parameters, with the ultimate goal of improving the performance of our simulations and enhancing our understanding of the melting process.

In conclusion, the synergistic integration of machine learning approaches with theoretical models has proven successful in elucidating how process parameters influence the thicknesses of laser beam melted walls. This represents a crucial step towards obtaining deeper insights into additive manufacturing processes and advancing the optimization of component fabrication.

References

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Figures

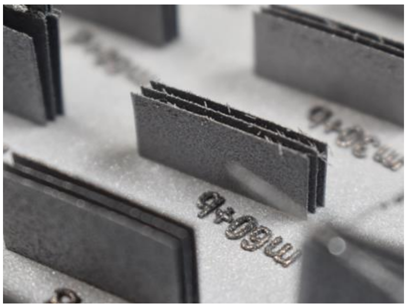

Figure 1. Single-bead thin walls made of AlSi7Mg06 alloy

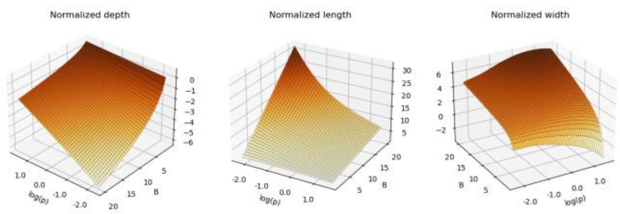

Figure 2. Calculated dimensions as a function of physical parameters which are directly related to the process window parameters

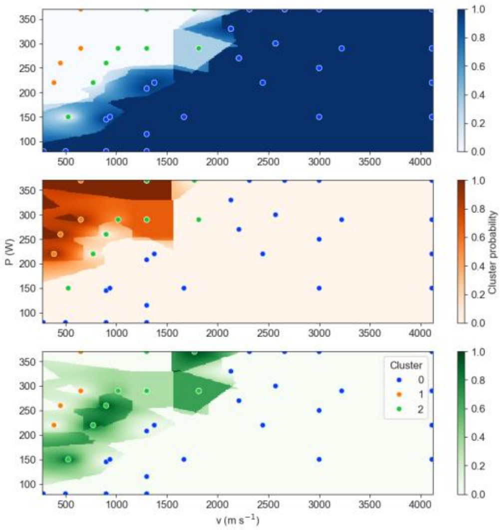

Figure 3. Cluster distribution and probability of cluster appurtenance.

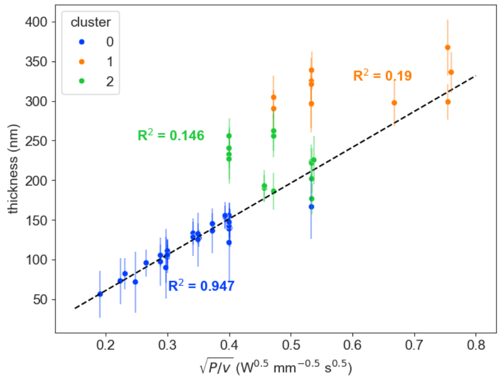

Figure 4. Thickness prediction as a function of the relationship found by the dimensional analysis, for each of the clusters.

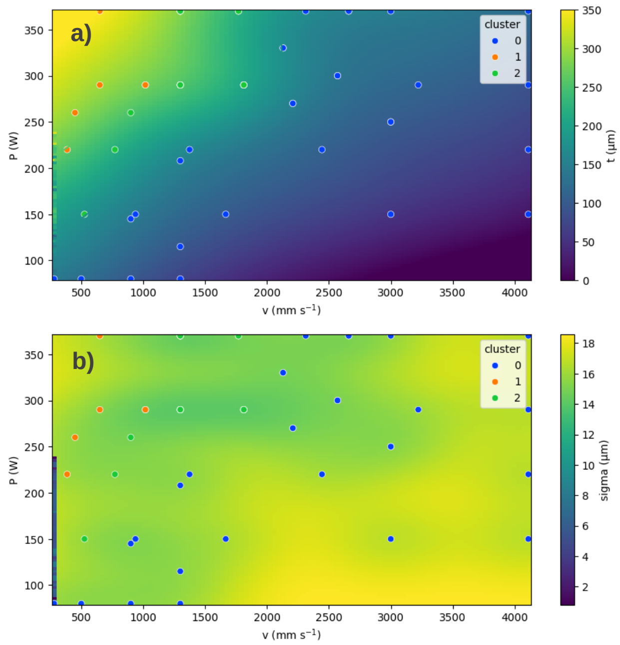

Figure 5. a) Mapping of the t(P, v) space and **b)** sigma obtained through a physically-informed Gaussian process.