Process development in additive manufacturing of highly reactive alloys aided by machine learning and control theory

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Background

Additive manufacturing (AM) is a disruptive digital manufacturing technology capable of fabricating intricate components with complex geometries and designs, unique microstructures and properties, as well as reduced lead time and cost. However, its broad adoption in industry is still hindered by numerous factors including a limited materials library, various processing defects and inconsistent product quality. In this regard, AI methods such as machine learning (ML) and control engineering could be a way to overcome these challenges and provide a possibility for achieving additively manufactured materials of controlled microstructure and properties.

ML approaches have been successfully applied to AM in various states including pre-manufacturing phases (i.e., material design and topology design), modelling of the manufacturing process, and automated monitoring of the process in real-time[1,2]. In regards to process parameter optimization for AM, ML is a viable approach for replacing traditional cost-, time- and material-consuming trial and error experiments. Accordingly, a substantial amount of ML work in AM is devoted to modelling the relationship between the controllable input parameters (e.g., laser power, scanning speed, layer thickness, beam size) and the desired properties of the manufactured components (e.g., surface roughness, porosity)[3]. A large range of ML methods, including Neural Networks, Gaussian processes, and support vector machines have been utilised, incorporating both simulated and experimental data[3,4]. Since labour, time, and material costs attributed to AM encourage researchers to work with relatively limited data, sample efficient ML approaches, such as Gaussian processes, transfer learning, and model-based reinforcement learning (RL) are promising for scaling the ML efforts in AM[4].

Control engineering methods can also be beneficial for use in AM (laser-powder bed fusion, L-PBF; or selective laser melting, SLM), whereby the application of control engineering has the potential to achieve high-quality builds with guaranteed properties, with a high degree of repeatability and reduced material waste. However, the inherent multiscale complexity of the L-PBF process and its fast dynamics make its modelling a difficult exercise. Despite this, various modelling and control methodologies have been developed in the last two decades[5], with focus on control of laser power, scan speed and strategy, as well as the performance of the powder feeder and roller/reactor. Traditionally, the optimal choices of these parameters are obtained by trial and error and kept fixed during the fabrication process, which may result in heat accumulation leading to undesired characteristics of the melt pool, thermal distortion and cracking. There is a need to design on-line control techniques which can adapt these parameters dynamically to achieve a certain build quality. To this end, various simple controllers such as proportional integral controllers, feed-forward controllers[6], and more advanced model-predictive controllers/feedback linearization techniques have been studied. As building an accurate and tractable model of an AM process such as L-PBF can

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[1] J Liu et al. A review of machine learning techniques for process and performance optimization in laser beam powder bed fusion additive manufacturing. Journal of Intelligent Manufacturing, 2022.
[2] C Wang et al. Machine learning in additive manufacturing: State-of-the-art and perspectives, Additive Manufacturing, 2020, 36.
[3] Kamath. Int J Adv Manuf Technol, 2016, 86. ; Kamath et al. Knowl. Inf. Syst. 2018. 57.; Mondal et al. Metals, 2020, 10.
[4] Zhu et al. CIRP Annals - Manufacturing Technology, 2018.
[5] Al-Saadi, et al, Proc. 29th Mediterranean Conference on Control and Automation, 2021; Wang et al. Add Manufact 31, 2020.
[6] Rivera et al. Int J Adv Manufact Techn, 2020, 109.

be difficult, recent approaches have tended to use model-free techniques, such as iterative learning control and deep reinforcement learning for controlling laser power and scan speed to ensure consistency of the melt pool, albeit with limited success[7].

Magnesium alloys provide a unique opportunity for implementing ML and control engineering, given the distinct challenges associated with AM processing of such alloys. Magnesium is a reactive metal with a narrow range between its melting and boiling temperature and is therefore easily evaporated during AM (e.g., L-PBF) processing. This leads to difficulties in controlling final alloy composition and preventing the formation of defects, thereby inhibiting the repeatability among final components. Moreover, determining the link between such issues and the process itself is burdensome given the numerous processing parameters (e.g., laser power, scan speed, scan strategy, etc.; see Fig. 1) associated with L-PBF, the most commonly used AM process for Mg alloys. The traditional design of experiment approach usually involves extensive trial-and-error, which is time-consuming and costly. In this regard, the use of ML and control engineering could aid in reducing the time and effort required for process design as well as contribute to improving the repeatability of the final component properties, thereby advancing the potential of Mg alloys for numerous applications. In the case of biomedical applications, Mg is highly desired given its good biocompatibility, as well as its degradability within the human body which allows for their use as temporary implants. Since such implants degrade as bone healing takes place, they are crucial for eliminating costly secondary revision surgeries associated with traditional permanent implant materials. Fabrication of Mg-based implants using AM is a potential game-changer since it can also allow for production of patient-specific implants with improved fit and reduced patient discomfort. Hence, careful design of process parameters (e.g., laser power, scan speed) and process control are crucial to be able to make full use of AM processing for biomedical Mg alloys.

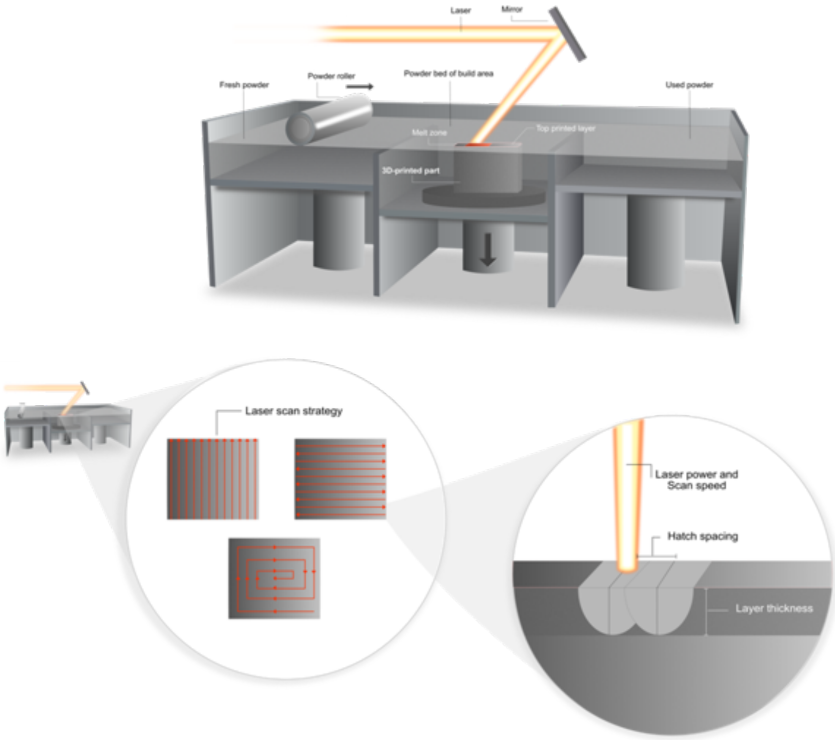

Figure 1. The laser powder bed fusion process.

Project Description and Aims

The research in this project will develop a suite of novel, advanced and complex model-based and data-driven multi-parameter adaptive control methodologies, that can tackle the challenging task of producing structures with arbitrarily complex geometries with guaranteed repeatability.

The key difficulty with implementing model-based system identification techniques, to estimate the AM parameters that can be optimized, is the scarcity of large-scale experimental datasets. To this end, the first task will be to build upon results from ongoing PhD projects and to perform controlled experiments by varying chosen sets of L-PBF parameters (e.g. laser power and scan speed) and obtain measurable outputs that can characterize the build quality. Such outputs will include measurements of porosity and overall density of final components determined using traditional

[7] Ogoke and Farimani. Additive Manufacturing 46, 2021

methods (e.g., Archimedes principle, image analysis). Since data generation is expensive, finite sample-based system identification techniques will be used to identify the input-output relationship to build an accurate dynamical system model of the L-PBF process, which is expected to be time-varying and nonlinear. Robust model-predictive control techniques will then be used to implement real-time control of these parameters that optimize a certain control cost, such as a linear-quadratic cost, while allowing uncertainties in the model. To tackle time-varying systems, such robust control techniques will be made adaptive by adopting parameter estimation techniques that can track parameter changes and by implementing multiple-model adaptive control methods.

Similarly, data-driven or machine learning based L-PBF process parameter optimization techniques heavily rely on availability of data sets with large enough sample sizes. With the help of available experimental data sets, model-free, data-driven control design methods will be developed by using state-of-the-art machine learning techniques such as deep reinforcement learning (based on convolutional neural networks), with an aim to minimizing suitable control costs that optimize the build quality and achieve desired output specifications. In scenarios where only small sample-size data sets are available, Gaussian processes-based Bayesian machine learning techniques will be applied. The key goal will be to develop algorithms that can easily adapt from one AM machine (e.g. 3D printer) to another, which will be achieved by the very nature of such data-driven machine learning techniques.

Interdisciplinarity, Involved Actors and their Roles

The project is interdisciplinary in that it combines ML and control engineering with materials science and biomedical engineering. Cecilia Persson is Professor in Materials Science and the Head of Division of Biomedical Engineering at the Department of Materials Science and will act as main supervisor. She has 20 years of experience in materials research, with a focus on biodegradable materials. She directs a Competence Centre in Additive Manufacturing for the Life Sciences, gathering more than 25 partners from academia, industry and healthcare, for which the results of this type of project would be of very high interest. Indeed, the PhD student would be affiliated to the centre and be able to present within the same and get industrial feedback on the progress. Besides experimental materials science, Prof. Persson also has experience with numerical modelling and a strong interest in statistical analysis, providing a good basis for communication within the project. This project is envisaged to enable the knowledge transfer needed for these multidisciplinary projects including AI to continue to be successful. She is currently the main supervisor of 3 PhD students focussing on AM of Mg alloys, and the student in this project is expected to be able to draw many synergies from their work.

Subhrakanti Dey will act as co-supervisor and given his experience in stochastic and adaptive estimation and control and their applications, as well as his expertise in statistical machine learning, he will drive the design of experiments in generating suitable datasets for model identification, and development of the real-time robust and adaptive control algorithms, as well as data-driven, reinforcement learning based predictive control techniques. He is a Professor of Signal Processing and the Head of Division of Signals and Systems within the Department of Electrical Engineering at Uppsala University and has a broad range of expertise encompassing, signal processing, control, machine learning, and stochastic processes. He has significant experience in applying control and machine learning methodologies to problem solving in other disciplines such as biology and additive manufacturing.

Francesco D'Elia is Senior Researcher in the Division of Biomedical Engineering and will act as co-supervisor. He has over 15 years of experience in design and processing of Mg alloys, including five years in an industrial company. He has designed and commercialized biomedical Mg alloys leading to CE-mark approval for over five orthopedic implants. He has extensive technical experience in L-PBF and will advise the student on process optimization and establishing process-property material relations. He currently co-supervises 3 PhD students working on AM of Mg alloys.

Funding

The remaining 50% of the student's costs will be covered by faculty funding at the 2 participating divisions.