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Control of selective laser melting processes: existing efforts, challenges, and future opportunities

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***Abstract*— Additive Manufacturing (AM) or widely known as 3D printing is a technology for producing parts directly from the computer without the need for traditional tools. The technology provides fast production for complex shapes with higher properties. Selective Laser Melting (SLM) is one of AM technologies that is used to produce metallic parts. For the last twenty years, the technique attracted the attention of both industry and academia. The complexity of the underlying physics and the fast dynamics during the process degraded the quality of the produced parts and hampered widespread adoption of the technology. A significant emphasis on the importance of on-line control systems to achieve higher levels of quality and repeatability can be found in the literature. In this review paper, we fill an important gap in the literature represented by the absence of one single source that describes what has been accomplished and gives an insight into what still needs to be achieved in the field of process control for metal-based AM processes. The article ends by discussing future opportunities in the associated on-line control system development.**

I. INTRODUCTION

A new industrial era has been motivated by the development of manufacturing processes. The advanced techniques facilitate the response to the world's requirements in a faster and more effective manner. Additive Manufacturing (AM) is a process that provides rapid manufacturing with optimised use of energy, labour, and materials. The process fabricates parts layer-by-layer directly from the computer. The diversity of materials that can be processed by the different types of AM processes expand the range of applications. The applications involve tool making, aerospace engineering, energy technologies, automotive manufacturing, and medical engineering [1]. AM is classified into seven categories, five of them apply to process metals which are powder bed fusion (PBF), directed energy deposition (DED), binder jetting, material jetting, and sheet lamination processes [2]. This paper focuses on a Selective Laser Melting (SLM) process, which is a specific PBF method, which uses a high power-density laser to melt and fuse metallic powders to fabricate parts. The technology does not only provide prototypes but also produces products ready to be used in different fields [3-6]. SLM offers a design process with fewer limitations, leading to a revolutionary design in different fields. It allows production of complex geometries, lightweight structures, and internal channels to improve product performance and to meet the industrial specifications [7]. Unfortunately, with all advantages offered by SLM and other AM processes, the quality and repeatability of metal parts still hamper significantly their widespread adoption as viable manufacturing processes [6]. The process contains complex underlying physical phenomena and transformations occurring during the process in a short time [8] and [9]. In particular for complex materials, just as titanium alloys used in the aerospace sector. Over 150 parameters affect the SLM process [10]. The facts above mean the optimisation problem is exceptionally challenging and becomes more complex as the complexity of the designed part increases. There are extensive research efforts over the world in the last two decades in modelling and control of AM processes [5],[8], and [11]. The investigations emphasise the importance of control systems to enhance product quality. Figure 1 presents the number of published papers in the area of control and modelling over the last twenty years. In this review paper, we focus on the existing efforts applied in SLM and promising algorithms that show encouraging results on other AM types. In addition to the gaps and future opportunities in the field of the on-line control system. After this section, the paper is organised as follows: section II considers the SLM process description, section III discusses the control effort in SLM, section IV introduces a promising algorithm, section V discusses gaps and future opportunities for improvement and the paper finishes in section VI with some conclusions.

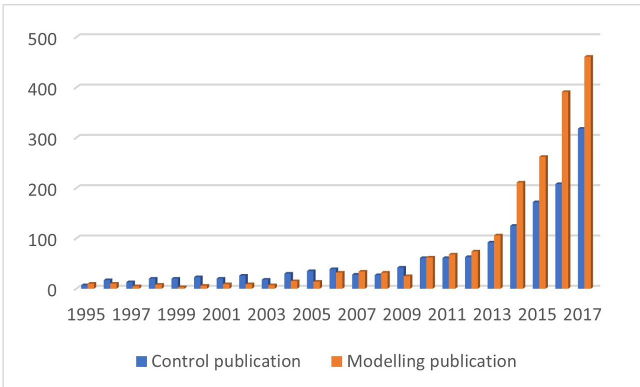

Fig. 1: The published papers in control and modelling over the last twenty years[12]

II. SELECTIVE LASER MELTING PROCESS OVERVIEW

A good understanding of the process is required for better utilisation and optimisation of the process inputs to ensure

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product quality. The fundamental elements of the SLM process are shown in figure 2. The parts can be described as follows [13]:

1) The laser source is considered as the primary source of the heat in the process. The laser power, type, spot size, and other parameters related to laser source have a significant impact on system performance.
2) The scanning motion device is the part that controls the scanning speed, hatching distance and the scanning strategy of the laser source over the powder.
3) The powder feeder and roller/reactor are responsible for adding the new layer after the previous layer is fabricated. The performance of the roller will affect the powder distribution in the newly added layer, thus the quality of the layer.
4) The elevator to lower down the scanned layer to allow the feeder to add the new layer.
5) The enclosed chamber provides a specific feature for the ambient to ensure the quality of the end-product.

More information about the process and its parameters can be found in [14]–[16].

III. Efforts in on-line control for SLM process

Most of the existing SLM and other AM processes are based on constant parameters [17]–[19]. These parameters are determined by trial and error at the beginning and fixed during the fabrication process. Research investigations showed that maintaining the parameters unchanged increases the heat affect zone [19]. Consequently, the heat accumulation produces irregular morphology of the melting pool, excessive dilution, thermal distortion and cracking. Other process uncertainties also add to the complexity of optimising the process, for example, powder batch-to-batch variability and recoater degradation, which further complicate the control requirements. Therefore, the properties of the produced parts cannot be guaranteed. The predetermination of an optimal processing set of parameters for specific mechanical properties is a commonly used method to enhance product quality or printability [20] and [21]. However, such an approach is neither economical nor robust enough to deal with perturbations.

On the contrary, using an on-line control system can compensate for the disturbances and improve the quality of the produced parts. Different control algorithms have been implemented and investigated, varying from classical to advanced controller techniques. Significantly, most of the researchers used the thermodynamic and/or the melt-pool geometry as a key to define the product quality during the fabrication [9] and [22]. The first term can introduce different kinds of defects (porosity, deformation, and cracking) and phenomena (keyhole, rippling, swelling), whereas, the second is related to microstructure evolution and thermo-mechanical properties. Irrespective of the used term, both are related to energy density which can be controlled by varying laser power, scanning speed, and scanning strategies [23]. The following content summarises the previous efforts in on-line control approaches for the SLM process.

Proportional (P) and Proportional-Integral (PI) controllers were used in the first attempts to investigate the controllability of the melt pool size by manipulating the laser power [24]–[26]. In these attempts, the designed controller was based on a second-order model which was identified using experimental data collected from a high-speed CMOS camera and photodiode. The studies presented the effectiveness and importance of the on-line control algorithm. An illustration of the effect of the applied algorithm is presented in figure 3.

With the development of measurement and processing equipment, more developed algorithms were investigated. In [18] and [27], a combined control system consisting of a feed-forward control and a P-controller was proposed. The temperature of the melt pool was controlled by changing the input laser power. The strategy showed a fast response to the change in the temperature and promising results for practical implementation with a reduction of 73% in the temperature deviation compared to the open-loop system. Despite that, the experimental implementation was limited to multi-track. In this work, the advantage of parallel processing was utilised using FPGA.

Some of the research efforts investigated a particular phenomenon. In [17], a feed-forward (FF) controller was applied to overcome the issue of over melting and keyhole formation. The approach was used successfully for DED processes. The controller was based on an analytical control-oriented model that considers the temperature history of the previous track. The experimental result of multi-track-single-layer printing showed a reduction on the over melting and disappearances of the keyhole. Additionally, a reduction in the average error rate by 23% was recorded compared to the fabrication with fixed laser power.

Whereas all of the previous works focus on controlling the

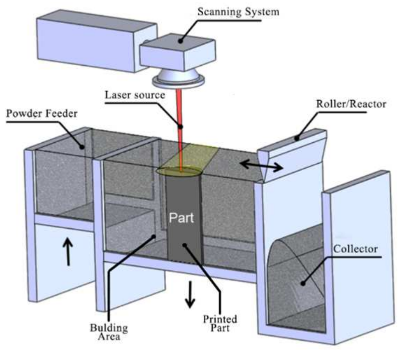

Fig. 2: The basic structure of the SLM process [15].

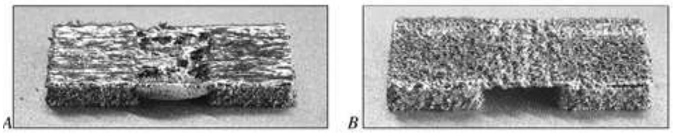

Fig. 3: Printing attempts with fixed laser power (A) and with a feedback controller (B) [25].

melt pool parameters within the scanning vector, a layer-wise control approach was introduced in [7]. In such a method, the information of the previous layer is gathered and analysed then used in the following layer to correct the deviation from the desired performance. The authors measured the melt pool area using a metal-oxide-semiconductor camera. Based on the information provided from the feedback, the energy density was changed in the new layer. The study showed the effectiveness of the approach to overcome heat accumulation and reduce the effect of the swelling phenomenon.

With the highly complex phenomena and complex physics involved in the SLM process, it is very challenging to get an accurate model that can lead to precise control design. Therefore, model-based control systems have limitations in their performance. Different research groups were interested in studying the feasibility of using a Model-Free Control (MFC) system. In [28] and [29] an Iterative learning control algorithm (ILC) is used to regulate the power profile within the scanning segment based on live measurement from the coaxial camera. In [30], the same concept was applied in addition to a data-driven model to predict the performance of the system and reduce the effect of the complex geometry and temperature history. The machine learning (ML) concepts such as deep-learning (DL) were used in [31] to predict the distortion during the process. An area of interest was defined by cylinder, presenting the information near and below the operating point. The suggested approach presented the system as an optimisation problem and solved for the best input using an ILC algorithm based on the previous and on-line data. Conclusively, the efforts demonstrated the feasibility of deriving process decisions using the on-line data only without the need for a mathematical model. The scope of research was not limited to controlling the laser power or scanning speed. A few groups were interested in studying the effect of scanning path and scanning strategy on the melt pool size and temperature, such as [32] and [33]. The investigations showed that the residual stress and distortion could be minimised. However, all the existing industrial processes come with pre-sited scanning strategies.

In [11] and [34] the focus was directed to monitoring and control of the surface roughness using coherent imaging. The roughness was improved by post-processing using laser pulses and refilling the gaps. In [35], a backstepping control was designed for a nonlinear partial derivative equation model. The model was developed to capture the thermodynamics of the phase change of the melt pool. The investigation was limited to proving the Lyapunov stability of the controller. Table I below summarises the control efforts found in the literature.

IV. Promising Control Methods Used for Other AM Process

Most of the metallic AM systems are based on the same concept and melting requirement. Therefore, many efforts that were investigated or implemented in other AM process can be adequate for the SLM process. An example of such attempts can be found in [17] and [36]–[38]. The following context presents promising techniques that were applied with the DED AM process but not yet investigated with SLM technology. Table II below summarises several different approaches, discussed next, which were investigated to control the different AM process.

A. Simulated feedback

In [36], the implementation of a feed-forward and a model-based simulated output feedback controller was investigated. The method aids to overcome the issue of real measurement. The simulation results demonstrated up to 50% enhancement in the accuracy of the deposition geometry. However, the main challenge for practical implementation is the absence of a high-fidelity model simulator.

B. Model predictive control

With the constraints included in the DED process, model predictive control (MPC) attracted the attention of a few groups. In [39] a generalised model predictive control (GPC) law was proposed to track the temperature of the melt-pool. A higher level of MPC was investigated in [40] and [41]. They applied a multivariable predictive control to control the multi-input-multi-output (MIMO) control-oriented model for the cladding laser aided power deposition process. The approaches try to control the geometry and temperature profile of the melt pool by varying the laser power and scanning speed.

C. Feedback linearisation

In [42], a MIMO reduced-order model was derived and controlled using a feedback linearisation method. The simulation results for a single layer deposition showed the effectiveness of the control technique.

D. Model-free adaptive iterative learning control

The performance of the model-free adaptive iterative learning control (MFAILC) algorithm was investigated to overcome the complicity and uncertainty of the model [43]. The algorithm is used to control the width of the melt pool in wire arc DED AM process by moderating the laser power. The results showed good tracking performance and robustness against disturbance in welding speed and stick-out length.

V. Challenges and Future Opportunities

With all the advantages that SLM processes have, there are several concerns about the repeatability and reproducibility to adapt the technology worldwide [44,45]. Almost all research efforts focused on single-tracks or elementary geometries, such as thin walls and cubes which ignored the ability of AM to produce arbitrarily complex geometries that cannot be produced (or are very difficult to) using traditional manufacturing technologies such as subtractive, casting, forming etc. The in-depth investigation of the performance of the control systems with complex shapes is required to fulfil the practical application of SLM. Besides that, there are few efforts investigating the phenomena that could appear during the building process. From the control perspective,

TABLE I: Current Control efforts for SLM processes

Control Objective	Control strategy	Control variable	Process Signal	Ref
To investigate the controllability of the SLM process using feedback	P and PI control	Laser power	Melt-pool geometry	[24]-[25]
To overcome the overheating problem and keyhole formation	FF			[17]
To control melt pool temperature at sufficient time	FF combined with P- controller		Temperature profile	[18],[26]
To avoid heat accumulation	Layer-wise			[7]
To control the temperature profile of the scanning segment	Model-free-ILC			[28]-[30]
To investigate the feasibility of ML control system	ML-ILC			[31]
To improve the surface quality of the product	-		Surface geometry	[11],[34]
To investigate the effect of scanning path strategy	Open-loop control	Scanning path	Melt-pool geometry	[31],[32]
To investigate the Lyapunov stability	Backstepping	Laser power		[35]

TABLE II: Promising techniques applied for other AM process

Method	Objective	Control Variable	Process signal	Achievement	Ref
Simulated feed	To overcome the issue of real measurement	Laser power	Height of the decomposition	Feasibility of the control algorithm	[36]
GPC	To Compensate of the lack of deposition		Melt pool temperature	Good tracking performance and robustness algorithm	[39]
Multi-variable predictive control	To control the geometry and temperature of the melt pool	Laser power and Scanning speed	Melt pool and temperature profile	Prove the feasibility of the control algorithm	[40],[41]
Feedback linearization	To reduce the residual stress			Simulation Investigation about the proposed algorithm	[42]
MFAILC	To regulate the melt pool temperature	Laser power		Good tracking performance	[43]

the following summarises some of the various challenges and opportunities from the literature.

A. Challenges

1) Challenges and limitations regarding the used model: The lack of an adequate process model that can be used to design a practical on-line control algorithm was noted. The previous efforts showed that suitable physics-based control-oriented models barely exist for SLM processes and data-driven models are still underdeveloped. Additionally, since the quality of the data-driven model depends on the amount of available or accessible data, the shortage of real data is a significant obstacle for any implementation.

2) Challenges and limitations regarding control technique and data processing: The unavailability of fast enough control systems to capture the dynamics of the process and respond to any perturbation in an appropriate time was indicated by many researchers. Processing speed is considered as a challenge and a limitation to implement an on-line control system. Apart from that, most of the research studies did not address the stability, uncertainty and robustness in any significant depth. From the level of control (in-layer, layer-wise, and surface quality) point of view, almost all the efforts targeted a specific scenario without investigating the effect of combining them. Although the model-free control algorithm helps to overcome the need for a mathematical model, the technique requires exact repetition from iteration to iteration. However, this is not applied in most of the shapes.

B. Future Opportunities

With the aforementioned challenges and limitation, the following future opportunities can be seen:

1) Opportunities in model development: The existing model needs to be extended to be able to include the behaviour of the process while producing complex shapes. The model improvement can involve the temperature history of the built tracks and layers in addition to the formation phenomena. The following approaches look promising to develop a control-oriented model for selective laser melting processes:

- Using the leverage of similarity between SLM and other AM process, a model can be developed to fit the process.
- Develop a physics-based model that can capture the required specification and be simple enough to design an on-line controller.
- Using ML and data-driven concepts, that can capture different information about phenomena included in the SLM process, in order to design a tailored control approach.

2) Opportunities in control system development: As it was mentioned in section V.A.2, the majority of the proposed methods did not take into consideration the control issues such as stability, robustness, and uncertainty. Therefore, more investigation is required in this area. In terms of an on-line predictive control system, to the best of our knowledge, the implementability of model predictive control (MPC) is not yet investigated for SLM process. Using MPC can compensate for the uncertainty of the derived model. Likewise, a multi-level control system that links the different level of control (in-layer, layer-wise, and surface quality). Such a technique can improve product quality by ensuring the quality of building in different stages. A model-free control concept can play an essential role in overcoming the issue of modelling; however, more investigation is required.

VI. Conclusion:

This work is aimed to gather the previous works on on-line control for Selective Laser Melting (SLM) processes. The investigation emphasised the importance of the control system. The work demonstrates how the control system affects the production time, mechanical properties, microstructure, defects, geometry accuracy, and disturbance compensation, therefore, enhancing the overall performance of the system and the quality of the produced parts. Different efforts were presented besides some other promising algorithms. The challenges and limitations that face the current works were highlighted. Based on that, future opportunities were presented. To ensure the quality of the produced parts from SLM process, further investigation in the on-line control system is indispensable.

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