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In-situ proces control strategies for selective laser melting

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Abstract: Selective Laser Melting (SLM) is an additive manufacturing process that has been attracting the attention of researchers and developers in academia and industry over the last two decades. The SLM manufacturing process is capable of producing sophisticated industrial tools and geometrically complex parts in fewer steps (near net-shape), thus saving resources compared to subtractive manufacturing processes. However, the current industry-scale platforms for manufacturing metal parts via SLM do not sufficiently exploit online feedback control strategies. There is still significant potential for advanced process control which can enhance the overall performance of the system, as well as enable sophisticated manufacture, for example via active control of microstructure to enhance part performance in geometrically complex parts. This paper presents a comparison between the performance of three well-known industrial control strategies, to illustrate strengths and weaknesses in addition to addressing the key challenges and identifying some research opportunities in the field.

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Keywords: Metallic additive manufacturing, selective laser melting, powder bed fusion, feedback control, fuzzy logic, PID, feed-forward.

1 Introduction

With the recent global requirements (sustainability, durability, and environmental-friendly) for most industrial applications, the need for advanced manufacturing techniques is increasing. During the last three decades, the world witnessed an increasing focus on using additive manufacturing (AM) technologies for metals (Al-Saadi et al. (2021)). AM is a manufacturing process for building 3D objects directly from the digital design using a layer-by-layer approach (Seifi et al. (2017)) without the need for traditional manufacturing steps (e.g. subtractive manufacturing). The technology offers many advantages such as a reduction in the number of manufacturing steps, better utilisation of the manufacturing material, and fewer design limitations (Tapia and Elwany (2014)).

AM constitutes several different manufacturing techniques that can handle a wide range of materials and it is used in different industrial sectors such as aerospace, energy, medical, and many more (Guo and Leu (2013)). Among these technologies this paper focuses on the selective laser melting process (SLM), which is classified under the laser powder bed fusion (L-PBF) AM methods. SLM is used to manufacture metallic parts by fusing the powder particles selectively to build the required objects (Duda and Raghavan (2016)). The technique provides a substantial solution to design and fabrication of complex metallic parts requiring a lightweight and solid structure, and specific mechanical features (Vasileska et al. (2020)).

The SLM process generally consists of five main units, that can be described as follows:

(1) The laser unit: the unit responsible for generating the laser beam and controlling its movement over the powder.
(2) Powder delivery unit: this part is responsible for adding new layers. It adds and compresses the material powder uniformly as a layer.
(3) Building platform: the unit presents the working space where the part is printed. After completing each layer, the unit shifts down and allows the powder delivery unit to add a new layer.
(4) Collector unit: a unit to collect the extra powder.
(5) Enclosed chamber: a closed space to control the ambient conditions.

In addition to these units, a monitoring unit could also exist in an industrial machine to monitor the ambient temperature, machine performance and manufactured part. Figure (1) illustrates the basic structure of the SLM process.

The production process of a 3D part goes through a set of steps (Gunasekaran et al. (2021)). It begins with converting the 3D CAD model into cross-sectional layers and saving it in a suitable format (e.g. an .STL file). The machine parameters will be configured which make the process ready to start. The process fabricates one layer after another untill the part is completed. Lastly, the part is removed and cleaned manually or with the help of another machine.

There are still challenges and limitations to fully meet the industrial requirements in metal AM (Mercado Rivera and Rojas Arciniegas (2020)). The process has numerous

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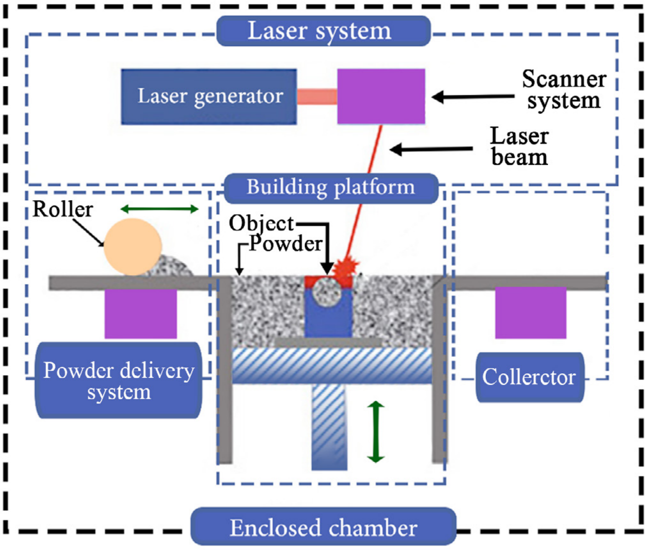

Fig. 1. The basic structure of SLM process

factors that affect its performance which means the quality and the repeatability of the process can not be guaranteed (Druzgalski et al. (2020)). In most of the existing SLM and other AM processes, the process parameters are kept constant Wang et al. (2020); Tang and Landers (2009); Volker et al. (2018) throughout the 3D printing process. The parameters are predetermined by trial and error or optimised before production via the use of expert knowledge and modelling/simulations . The use of fixed parameters can lead to heat accumulation and cause irregularity in the melting pool morphology, in particular for complex geometries, which leads to many defects (Tang and Landers (2009)).

Over the last twenty years, extensive research work has focused on enhancing part quality. There is a general agreement that using an online control system will improve process performance (Fleming et al. (2020); Druzgalski et al. (2020); Duda and Raghavan (2016)), thus in the literature, there are several attempts to design a control system for the SLM process. To illustrate the strengths and weaknesses of various control approaches in controlling the SLM process, this work evaluates the efforts that are suitable to establish an online control system for the process. In addition this paper provides a comparison between several control strategies and makes proposals.Based on the best of the authors' knowledge, such comparison and analysis about control systems for SLM were not covered before in the literature.

After this section, the paper will be organised as follows: Section 2 provides a brief survey of the online control effort in the SLM process. Sections 3 and 4 address the control problem, and control design, and simulation case studies. Section 5 discusses the simulation results and points to some research opportunities in the field of online control system of the SLM process. Section 6 sums up the investigation conclusions and future work.

2 Efforts in Online Control for SLM

As emphasised in the literature, using an online control system presents a promising solution to overcome the process perturbations and reduce the effect of meltpool abnormalities during the part building process (Fleming et al., 2020; Gupta, 2017). Several control systems were proposed and studied in the literature. In most of the studies, the melt-pool geometry and/or its thermodynamics were considered as an indication of the process quality (Lee et al. (2019); Holder et al. (2020)). Regulating the melt-pool geometry produces a better microstructure and better mechanical properties. Conversely, controlling the melt-pool temperature prevents porosity, deformation and cracking, in addition to many manufacturing phenomena such as a keyhole and swelling.

Regardless of the controlled variable, paths are correlated to the process energy density that can be controlled by manipulating the effective laser power, scanning speed and scanning strategies (Reutzel and Nassar (2015)). The efforts of controlling the SLM process can be classified into two groups: classical approaches and data-driven based. Proportional (P) and Proportional-Integral (PI) controllers were the first classical online system investigated in (Kruth et al. (2007b,a); Craeghs et al. (2010)). The studies present the first control attempts to control the melt-pool geometry by varying laser power. The controllers were designed based on a second-order empirical model. The investigations showed how effective the online control system could be to enhance the process quality.

Many years after, the advantage of new emerging machines and process mechanisms encouraged researchers to address the control problem in the SLM process again. In (Volker et al. (2018); Renken et al. (2019)), the capability of the Field-Programmable Gate Array (FPGA) board was used to implement a combined control system including a P-controller and feedforward (FF) controller. The proposed control structure is designed to control the temperature of the melt pool by adjusting the laser power. The experiments showed a reduction in system temperature error by 73% compared to the open-loop response. Unfortunately, the study was limited to a few well separated multi-tracks.

In the previous works, the control systems are based on observations and experimental trials. In Wang et al. (2020), the FF controller was designed based on a control-oriented model. The investigation showed the designed controller managed to regulate the melt-pool geometry during the process and reduced the error to 23% compared to operation with a fixed laser power. The use of data-driven approaches in the SLM process started with a feasibility study of using model-free control system presented by Latipova and Baitimerov (2018); Kim et al. (2018). Iterative learning control (ILC) concepts were used to maintain the power input within the scanning portion based on the actual reading from the imaging system. In Ahrari et al. (2017), the same concept was applied combined with a data-driven model to predict the system's performance and reduce the effect of temperature history. The deep-learning and machine learning concepts were also used in (Holder et al. (2020)) to anticipate the disturbance during the process in a specified area. The area of interest was defined by a cylinder that captures the surrounding condition of the operating point. The author presented the system as an optimisation problem that can be solved using an ILC algorithm based on the previous and online data. The research illustrated the feasibility of controlling the process using the online data only. However, the repetitive behaviour, which is the base of the suggested algorithm, cannot be applied to geometrically complex parts.

Based on a recent authors' investigation presented in (Al-Saadi et al. (2022)), a fuzzy logic control (FLC) algorithm is presented as a control candidate for the SLM process. A basic FLC was designed to overcome the heat accumulation issue during printing a single layer of metal. The result showed a significant reduction in the error signal. However, the work is limited to theoretical investigations only.

3 Controller Design

3.1 Control problem statement

The objective of the control system is set to manipulate the laser power input Q(t) to regulate the melt-pool cross-sectional area A(t) and reduce the effect of heat accumulation (or lack of heat) during the building process. The heat accumulation causes a variation in the initial temperature (T_{init}) as the layers and tracks change. It is assumed that all the process parameters are constant and independent of the temperature.

Several different control approaches have been proposed to solve the stated control problem. The approaches vary from vary basic structures to the ones which include artificial intelligence (AI) aspects. This paper excludes discussion of AI based controllers because such controllers require a lot of data and are computationally expensive which makes the implementation an unfeasible task with the existing processing capability.

Three control structures are presented in this paper: Proportional Integral Derivative (PID), feed-forward and fuzzy logic. The first two represent the most well-known and used control approaches in the industry, whereas the last has some features of AI but with a fast computational capability. The following sections gives a quick review of the three approaches.

3.2 PID controller design

One of the most commonly used feedback controllers in the industry is the PID controller (Nise (2011)). Despite the fact that it is considered one of the simplest closed-loop controllers, it has a great impact on the system performance and simple tuning method. The design of the PID controller is achieved by selecting three values: proportional gain (k_p), integral gain (k_i), and derivative gain (k_d). The first part increases the system's overall gain, whereas the second and third are used to improve the steady-state error/convergence speed and the transient response respectively. The literature describes numerous alternative algorithms to select the PID gains, however in this work the automatic tuning toolbox in $MATLAB$ will be used for such a purpose as this represents an accepted good practice approach.

3.3 Feedforward controller design

Feedforward control is an effective control scheme to handle measurable or well-known disturbances (Guzmán and Hägglund (2021)) where the impact can be modelled effectively. It is based on an defining an input perturbation linked to the measured disturbance; this input perturbation counteracts the impact of the disturbance on the system's performance. Consequently, the controller performance depends on both the accuracy of the model and the disturbance measuring system. The feed-forward controller is commonly used in conjunction with a feedback controller, the first to give rapid compensation for the disturbance and the second to handle general system behaviour, uncertainty and so forth. Figure (2) presents the basic structure of feed-forward combined with a feedback controller, where the feed-forward controller (C_{ff}) counteracts the dynamic between the disturbance and the output (P_d);d the dynamic between the control signal and the process output is P_u.

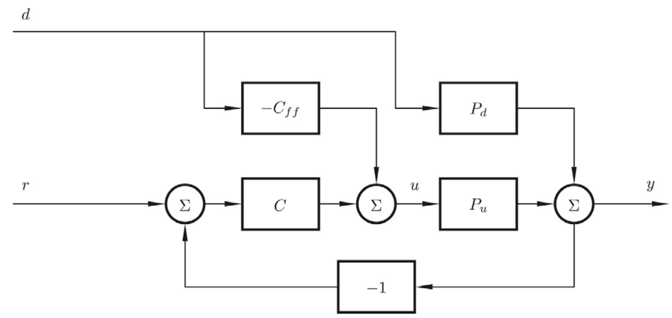

Fig. 2. The basic structure of feed-forward control

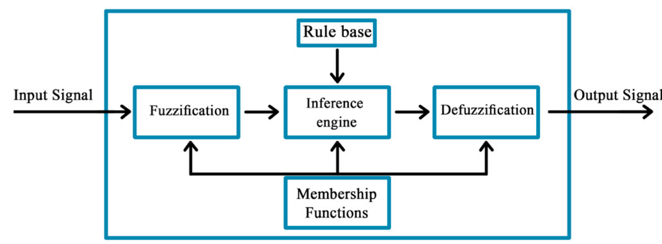

Fig. 3. The basic structure of the FLC system

3.4 Fuzzy logic controller design

Fuzzy logic control (FLC) theory offers a convenient control solution for systems that can not be described accurately (Lhachemi et al. (2019)). The technique exploits human experiences, general knowledge and observation to formulate control frameworks. The controller consists of a fuzzifier, defuzzifer, set of rules, set of membership functions, and inference system. The first two, convert the signal value from crisp to fuzzy and vice versa. The input can be presented by the actual system output, states, or offset signal. The control decision is made by the inference system based on the predefined rules and membership functions.

Figure (3) presents the basic structure of an FLC system. In this work, the input signals are selected to be the error $e(t)$ in the desired cross-sectional area and its derivative $\frac{\mathrm{d}}{\mathrm{d}t}e(t)$. Both signals were divided into five subsets (linguistic variables): high negative (HN), negative (N), zero (Z), positive (P), and high positive (HP). The output of the FLC was selected to present the control signal "the laser power" and it was divided into five linguistic levels: very negative (VN), negative (N), zero (Z), positive (P), and very positive(VP). Table (1) presents the designed fuzzy rules. It is important to note that the design process of

FLC for SLM, including the choice of linguistic variables, membership functions and fuzzy rules is a research area that requires more investigation and is part of future work.

4 Process Model and Simulation Result

Modelling and simulation of the additive manufacturing process are essential research fields. They play an important role in accelerating the design and production time by reducing (eliminating in some cases) the need for the actual trials. Many modelling efforts can be found in the literature. The vast majority of the efforts are related to modelling thermal dynamics in the melt pool. That is because many properties are related to the temperature of the substrate during the process. The model used in this work is an extension of the model presented in Wang et al. (2020). The model combines the heat energy equation and the Rosenthal solution to estimate the cross-sectional area $A(t)$ of the melt-pool with respect to the laser input power $Q(t)$ and the $T_{init}(t)$ initial temperature. The heat equation, the system, model and the initial temperature are given by equations (1) to (3).

$$\frac{d}{dt}(\rho V(t)e(t)) = -\rho A(t)v(t)e_b + P_s(t) \tag{1}$$

$$\frac{dA(t)}{dt} = f(A(t), T_{init}) + g(A(t))Q(t) \tag{2}$$

$$T_{init}(x,y,z) = T_a + \Sigma_{j=1}^{i-1}\frac{q_i}{2\pi k R_j}e^{-v_j(w_j R_j)/2a} \tag{3}$$

where ρ,e_b, $e(t)$, k, a are the material density, the specific energy, the specific internal energy, the thermal conductivity constant, and the thermal diffusivity of the material respectively. $P_s(t)$ and $v(t)$ presents the power delivered and the scanning speed of the laser system. The symbols q_i , R_j and w_j presents the virtual source power 'the power of the end point of the track', the distance between the operation point and the virtual source and the distance in the x-direction between the operation point and the virtual, where i is the number of printed tracks. The derivations of equation (2) and the melt-pool volume $V(t)$ calculations are shown in Wang et al. (2020).

The model presented by equations (2, 3) is used to simulate printing four tracks with length of 1 cm using Ti6Al4V powder parameters. The scanning strategy is illustrated in figure (4). Two simulations cases were conducted, first with an ideal implementation of the Rosenthal solution to compute T_{init} using equation (3) and the second a random variation in the temperature signal is introduced to mimic the actual situation during the process. Figure (5.a) presents the initial temperature before every time step for two simulation cases. The system response is illustrated in figure (5.b).

Table 1. Fuzzy logic set of rules

Input Variable		Change in error ($\frac{d}{dt}e(t)$)				
		HP	P	Z	N	HN
Error ($e(t)$)	HP	VP	VP	VP	VP	VP
	P	VP	P	P	P	VP
	Z	VP	Z	Z	Z	VN
	N	VN	N	N	N	VN
	HN	VN	VN	VN	VN	VN

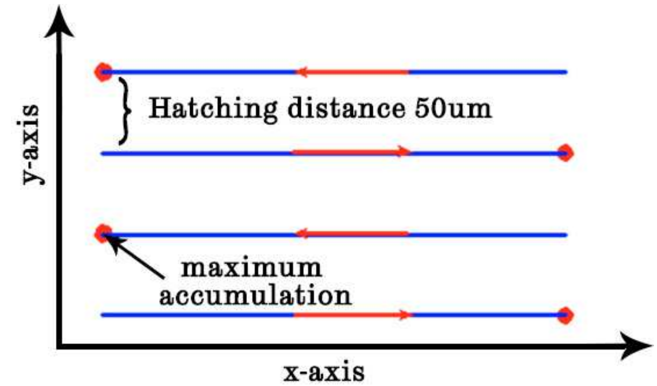

Fig. 4. The scanning pattern used in the investigation, where the arrows present the laser scanning direction.

5 Discussion and Future Opportunities

As can be seen from figure (5.a), the worst case occurred at the return end. The initial temperature which presents the heat accumulation effect the system response as shown in the figure (5.b). The cross-sectional area drifts away from the desired size and the error worsens in every track leading to the aforementioned building defects.

Introducing the control system enhanced the transient and steady-state responses of the system in general as seen in the green/yellow plots in figure (5.a). The PID and the FF controller combined with PID perform almost the same, except at the beginning of each track where the controller with feed-forward acts slightly better due to its capability to anticipate and reject the disturbance before it effect the system. By comparison, the fuzzy logic controller significantly improves the system's behaviour. The PID and the FF control strategies suffer from many limitations due to the non-linearity of the process and the inaccuracy of the model, whereas the FLC is better able to deal with such problems. Table (2) presents the numerical comparison of performance in terms of maximum error, integral absolute error (IAE), and the settling time. The presented values shows the superiority of the fuzzy logic controller over the other two approaches.

In the second simulation case where the random variation in the initial temperature signal was introduced, all the controllers' performances are affected. The settling time in such case is difficult to measure, however the IAE value could illustrate the change in the system performance. Figure (6) presents a comparison of the IAE before and after adding the random variation and again FLC is seen to be the best.

Despite the promising potential shown when using an online control system, the implementation faces some challenges, recommendations and future opportunities.

Table 2. Performance indices of the designed control systems

Performance index/ Control strategy	Settling time 'second'	Maximum error in %	IAE
PID control	0.0027	6.5	3.30E-06
Fuzzy logic control	0.0013	3.7	2.80E-06
Feed-forward control	0.0023	6	3.29E-06

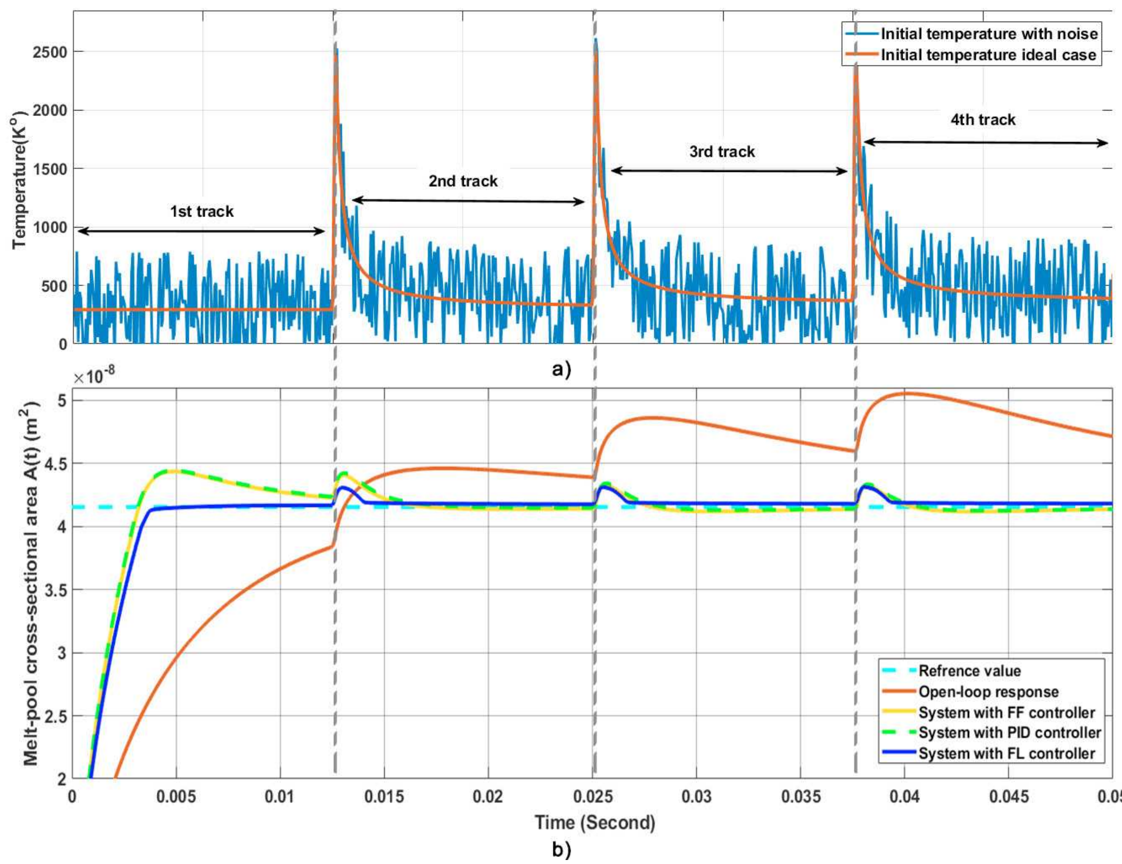

Fig. 5. a) The initial temperature profile in both cases. b) the system responses with different control systems.

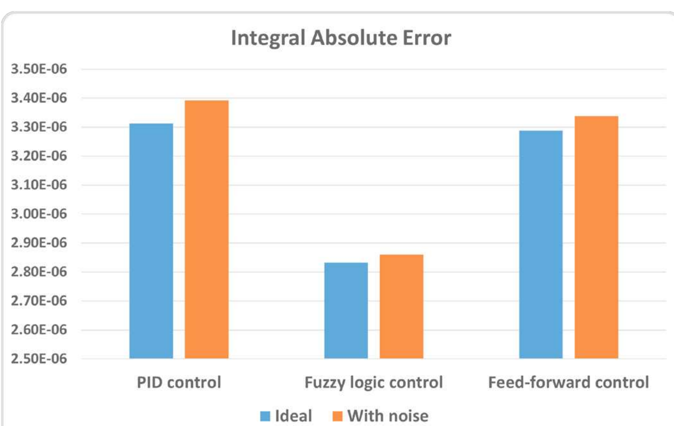

Fig. 6. A comparison between the IAE value for the control systems before and after adding the random variation in the temperature signal.

- A practical validation for the model and control system is outstanding. Using Rosenthal solutions has a limitation in presenting the heat accumulation. The method considers the source of disturbance is the end of each track. Practically the disturbance could occur from the point before, the underneath layer and/or the surrounding environment.
- Most of the existing effort, including this work, tested the control system performance in the process of printing or building simple shapes (identical tracks/layers). In order to show the effectiveness of the control system, a complex building process needs to be included in the investigation and the evaluation.
- The tuning method used in this work are limited to the classical approach. It is worth investigating how modern tuning (adaptive for example) methods could enhance the system performance, especially when the investigation considers complex shapes.
- There are many research investigations about the best control algorithms that can be used in the SLM process. However, in most cases, practical implementations are missing due to manufacturers blocking sensor/actuator access; more accesible equipment is needed to investigate the potential fully.
- There is a research opportunity to study the impact of the control system on the morphological structure of the parts. Will better consistency in the melt pool improve mechanical and structural properties?

6 Conclusion

This research work provides a comparison and evaluation of three common industrial online control strategies applied to a selective laser melting process. The work reiterates the observations of previous investigations about the potential of online control to significantly improve behaviour. This in itself should serve as a motivation for equipment manufacturers to allow better access to the sensor/actuator architecture to allow proper practical investigations. Moreover, the comparison of different control approaches demonstrates an advantage in pursuing intelligent control methods, such as fuzzy logic controllers as compared to more classical control strategies, an observation that is perhaps unsurprising given the number of non-linear and hybrid characteristics that are present. Certainly this merits further investigation and proposals for systematic tuning rules to deal with the more complex shapes which are common in AM. One can also investigate more advanced feedback control methods, using more sophisticated control theory as well as intelligent-based control methods, while balancing the need for simple systems that could be realised in an industrial setting.

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