Predictive Iterative Learning Control with Data-Driven Model for Optimal Laser Power in Selective Laser Sintering

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Abstract

Building high quality parts is still a key challenge for Selective Laser Sintering machines today due to a lack of sufficient process control. In order to improve process control, we propose a Predictive Iterative Learning Control (PILC) controller that minimizes the deviation of the post-sintering temperature profile of a newly scanned part from a desired temperature. The controller does this by finding an optimal laser power profile and applying it to the plant in a feedforward manner. The PILC controller leverages machine learning models that accurately capture the process' temperature dynamics based on in-situ measurement data while still guaranteeing low computational cost. We demonstrate the controller's performance in regards to the control objective with heat transfer simulations by comparing the PILC-controlled laser power profiles to constant laser power profiles.

Keywords: Additive Manufacturing, Iterative Learning Control, Machine Learning, Intelligent Control, Artificial Intelligence

Introduction

Selective Laser Sintering (SLS) is part of the powder bed fusion (PBF) family of Additive Manufacturing processes. PBF processes utilize high-powered energy sources like laser or electron beam to build solid parts in a powder bed by fusing 2D geometries layer-by-layer. For each new layer, a roller spreads powder across the build surface, so the laser can scan the new powder based on a 2D cross-section of a 3D CAD model. The scanned powder melts and connects with adjacent powder both laterally and in depth. During cooldown the molten powder will solidify as a solid part. Because of high similarities between PBF processes, the findings presented in this paper will be applicable to related PBF processes.

SLS parts are increasingly being used for safety-critical systems, such as aircraft and medical devices, and therefore, are often required to meet strict customer specifications [1]. However, building high quality parts and doing so repeatably is still a key challenge for the SLS process today [1] [2]. Low part accuracy and residual stresses are just a few of the symptoms that are caused by limited process control in SLS machines [1]. Modern machines are equipped with a rising number of sensors, but for a lot of SLS machines process parameters are still run in an open-loop fashion [2]. Parameters like laser power, laser speed, layer thickness etc. are usually set to constant values before the build starts and remain unchanged throughout the build [2]. This leaves any variations or disturbances within the build process unaccounted for by the machine. The machines that do exhibit some control over their process parameters usually rely on conventional feedback controllers, such as PID control, which track simple control objectives and do not possess any predictive capabilities [3] [4] [5]. Advanced control techniques like model-based control suffer from the lack of physics-based models that can capture the complex physical nature of the SLS process while avoiding high computational complexity [1] [2]. Therefore, improving process control is one of the main drivers to enable SLS processes to build high quality parts and serves as the overarching goal for this paper when designing an adequate controller [1] [5].

The quality of an SLS part is affected by a variety of factors. Due to the thermal nature of the SLS process, the thermal profile of the part has a significant impact on the final part quality [5]. Wroe et al. [6] and Taylor et al. [7] identified that for quality purposes the post-sintering temperatures of the newly sintered 2D geometries need to be above a specific post-sintering threshold temperature, which is unique for the employed powder material. In addition, Phillips et al. [8] found that varying temperatures across the powder bed can cause a non-uniform thermal profile in the newly sintered part, which can also lead to subpar mechanical and geometrical properties and immediate process faults, such as curling. This leads to the conclusion that minimizing the deviation of the maximum post-sintering temperature profile of a newly scanned 2D geometry from a desired temperature will significantly increase part quality and thus, is the control objective for the proposed controller.

In order to achieve the above-stated control objective, a feedforward controller was designed that will find an optimal laser power profile for every new layer based on infrared (IR) camera measurements. Optimality here is with respect to the approximations of a data-driven model. Recent research in process control by Phillips et al. [8] [9] has demonstrated the effectiveness of feedforward control of the laser power profile to achieve the proposed control objective for simple part geometries. The proposed controller in this paper will build on these findings. In addition, the controller will utilize an Iterative Learning Control (ILC) approach originally proposed by Spector et al. [10]. The controller extends the original model-free ILC controller with a data-driven model, for the remainder of the paper referred to as Black Box Model (BBM), that is based on historical I/O data from the machine. This gives the PILC controller its predictive capabilities to account for the negative impact of complex geometries, layer-to-layer disturbances, as well as other influences on the control objective. Because of the PILC format, the BBM can leverage state of the art machine learning models such as deep neural networks. These models are capable of handling the data-rich environment of modern SLS machines. The PILC framework is also easily extendable to incorporate optimal and multivariate control approaches, such as multiple control objectives, which will be further explored in a later journal paper. The PILC controller will be introduced in the following section.

Controller Design

The proposed PILC controller is laid out in Figure 1. At the beginning of each layer, after the new powder has been spread by the roller, one or multiple pre-scan IR images of the powder bed are selected from the IR camera live stream. The IR image(s) will be sent to the BBM along with a pre-defined laser power profile p_{init}. The laser power profile defines the laser power for each point on the laser path, which is segmented into scanlines that make up the soon-to-be sintered 2D geometry. The BBM will then predict the maximum post-sintering temperature profile along the temporal laser scan path for the soon-to-be sintered 2D geometry. This vector of temperature values T_{pred} is compared to a pre-defined desired temperature $T_{desired}$ and an error vector e_k is calculated by computing the difference. If the maximum norm of the error is too high, the laser will enter an offline training cycle where the laser power is updated according to $p_{k+1} = p_k + L * e_k$ based on the ILC update law by Spector et al. [10]. p_k is the laser power that was just used as input for the BBM, L is a gain that can be tuned and e_k is the calculated error. The new laser power profile is sent back to the BBM along with the initial pre-scan IR image(s). The BBM will recalculate the predicted maximum post-sintering temperature profile based on the new laser power profile, which will result in an updated error vector. If the maximum norm of the error vector is too high again, the laser power profile will be trained with another offline training cycle.

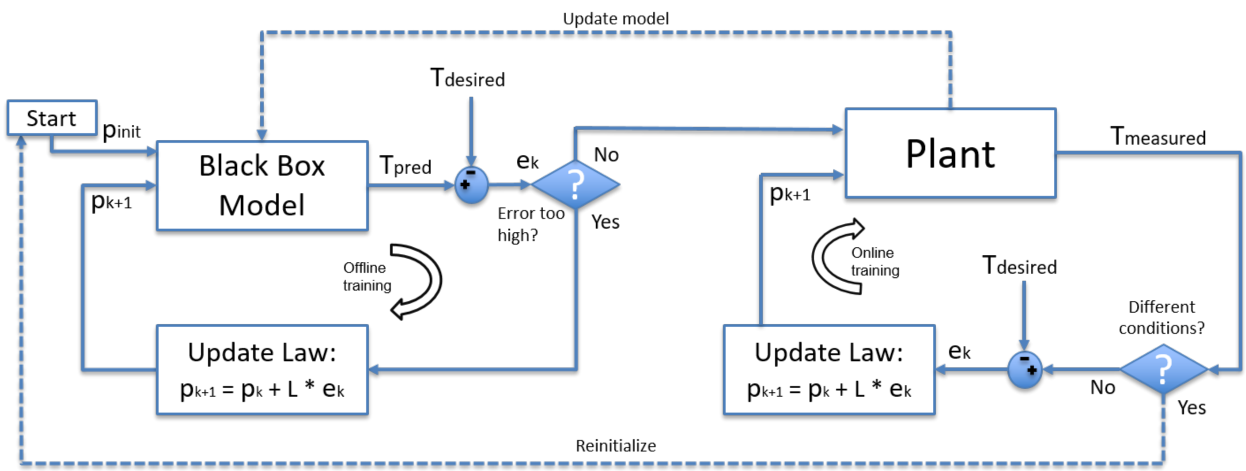
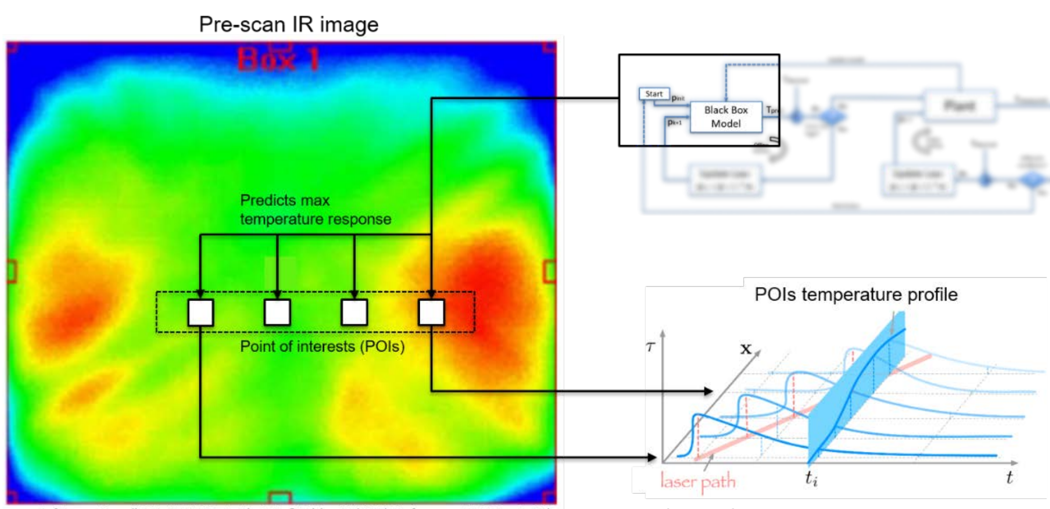


Figure 1: Predictive Iterative Learning Control

Once the maximum norm of the error vector is low enough, the trained laser power profile will be applied to the plant in a feedforward manner. After the laser has scanned the 2D geometry and new powder has been spread, the controller will restart the process of finding a laser power profile for the next layer or continue learning with the previous laser power profile. This depends on whether the initial conditions of the next layer are similar to the previous two. If the 2D geometry for the next layer differs from the previous two 2D geometries or if the temperature on the powder bed has changed significantly, the process will be reinitialized. If not, the laser power profile will enter an online training cycle in which the previous laser power profile will be updated based on the in-situ IR measurements from the newly sintered powder bed, similar to the original ILC controller by Spector et al. [10]. The reason the condition depends on the previous two layers is that the BBM takes into consideration whether the previous layer was sintered or not.

The offline training cycle gives the controller the predictive capability that allows it to account for varying 2D geometries like overhangs, layer-to-layer disturbances and non-uniform powder bed temperatures. If the maximum norm of the error is not minimized, but only reduced to an arbitrarily low value, the laser power profile is obviously only near-optimal. The online training cycle will guarantee that for a repeating 2D geometry the controller will, given sufficient iterations, converge to an optimal laser power profile with respect to the plant. Furthermore, the BBM will continue being updated throughout the build and from one build to the next, so that any approximation errors that might exist in the beginning should be significantly reduced over time. Furthermore, the offline training cycle enables easy plug-in of different BBMs that are trained on I/O of the machine as well as possible Grey Box Models (GBM) that combine complex heat transfer simulations with I/O data. Since the BBM is an integral part of the PILC, the next paragraph will detail how the BBM predicts maximum post-sintering temperature profiles for the 2D geometries.

For any given layer, the pre-defined laser scan path is split into equally spaced points of interest (POIs). The BBM will predict the maximum post-sintering temperature for each individual POI in order to build an interpolated maximum post-sintering temperature profile over the entire scan path. This is illustrated by Figure 2 for one enlarged scanline. The profile in blue in the bottom right graph shows an exemplary interpolated profile. The profile usually follows the red line, but is rotated for visualization purposes. Before the BBM can make any predictions during runtime, it is trained on historical data from either the machine or simulations. 80% of the data is used for training of the BBM while the remaining 20% is used for validation. One data point in the dataset consists of a feature vector and a target value. The target value represents the maximum post-sintering temperature for the corresponding POI. The feature vector is made up of different elements, such as laser power with which the laser will scan the corresponding POI. It also includes the initial temperature value of the POI from the pre-scan IR image(s) and the initial temperature values from pixels surrounding the POI. The size of the POI is currently set to correspond to the size of a pixel in the IR camera. Other information, for example whether a previous layer was sintered, is also included in the feature vector. During runtime the BBM will receive a set of feature vectors as input, where the number of elements is equal to the number of POIs selected for the laser path. The BBM will make a prediction for each feature vector and will build the interpolated maximum post-sintering temperature profile for the entire laser path.



Left image: Bourell, D. L., Watt, T. J., Leigh, D. K., & Fulcher, B. (2014). Performance Limitations in Polymer Laser Sintering. *Physics Procedia*, 147-156.
Bottom right graph: By Yuxin Chen (CalTech)

Figure 2: BBM predicts max post-sintering temperature for each POI

Different models were trained and validated, including linear regression, polynomial regression, support vector regression, k-nearest neighbors (KNN) and deep neural networks. For this paper, KNN and polynomial regression were used predominantly. KNN is an instance-based learning approach that uses a similarity measure to compare the queried data point with the dataset to make predictions. Polynomial regression is a model-based approach that builds a mathematical model from the training dataset which is then used for predictions during runtime.

Results

In the preceding section, a PILC controller was introduced that will significantly improve process control to build high quality parts. The controller was designed to minimize the deviation of the maximum post-sintering temperature of a newly scanned 2D geometry from a desired temperature. In order to demonstrate the performance of the PILC controller, different heat transfer simulations were conducted that compared the PILC-controlled laser power to no laser power control. The simulations were performed with a C++ heat transfer simulation designed by Zhang et al. [11]. Before running the test simulations, different trial simulations were conducted to collect enough data to train the BBM. The collected dataset had 2500 data points. The trial simulations were designed to closely imitate the historical data from the SLS testbed at the University of Texas at Austin that is equipped with a variety of sensors like IR cameras.

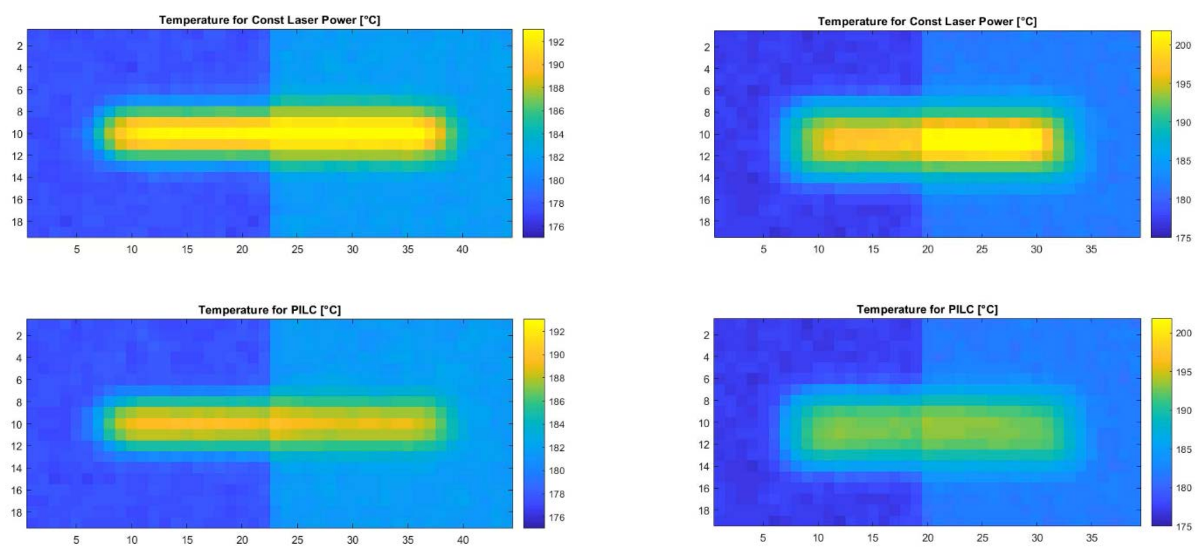


Figure 3: Two different simulation cases: (left) 1 scanline; (right) 2 overlapping scanlines

For brevity, two simulation cases were selected that are presented in Figure 3. For both cases, two powder beds were set to the same initial conditions where one side of the powder bed is 5°C hotter than the other. For the left simulation case in Figure 3, one scanline is sintered from left to right on each powder bed. The top heat map features the temperature response of the sintered scanline for a constant laser power profile of 7.5 W, while the bottom one shows the temperature response for the PILC-controlled laser power profile. The desired post-sintering temperature for the scanlines is 188°C. As indicated by the two heat maps, the post-sintering temperature of the scanline for the PILC case tracks the desired target temperature of 188°C closely and exhibits a uniform post-sintering temperature across the part. In contrast, the temperature response for the constant laser power profile is overshooting the desired post-sintering temperature and exhibits a non-uniform distribution across the part due to the initial temperature difference on the powder bed.

Figure 4 features the above described findings in graph form. The left image of Figure 4 shows different laser power profiles over time, where each time instance corresponds to a specific location on the laser path. The top laser power profile was used for the constant laser power case and as the initial training profile for the PILC. The PILC trained for several iterations and converged to the bottom profile. When applied to the plant, the maximum post-sintering temperature response of the scanline is recorded on the right. In line with Figure 3, the maximum post-sintering temperature response of the PILC-controlled laser power is able to significantly improve the control objective. The border areas of the right graph are greyed out, since the control objective is difficult to meet at the corresponding powder bed locations just by controlling the laser power. This is due to the laser starting and ending at those regions, which means no heat has propagated from adjacent sintered regions yet. It would require unreasonably high laser powers to instantly achieve the desired post-sintering temperature.

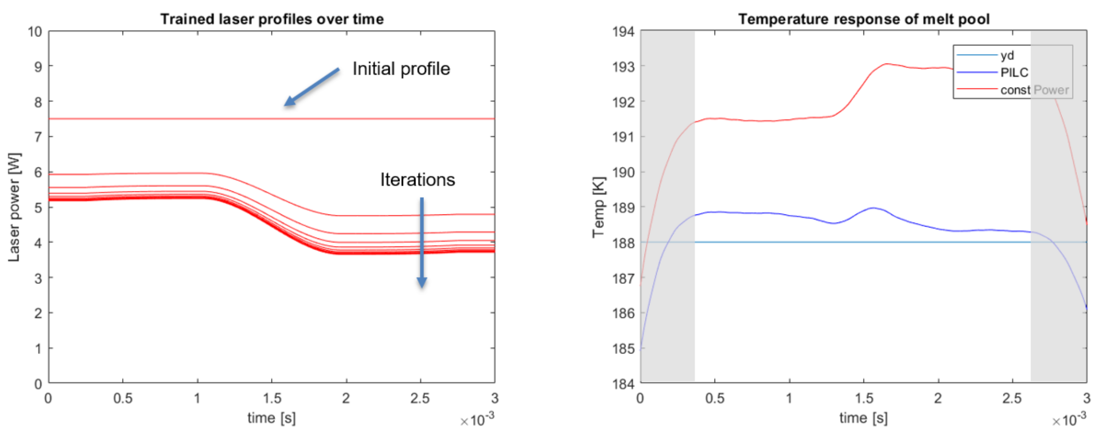


Figure 4: (Left) Trained laser power profiles; (Right) Post-sintering temperature response of scanlines

The second simulation case utilizes the same initial conditions as in the first case, but simulates two overlapping scanlines scanned sequentially, instead of just one scanline. The heat maps on the right of Figure 3 show similar results to the first simulation case. The PILC-controlled post-sintering temperature response (bottom heat map of right simulation case in Figure 3) is able to track a desired temperature of 192°C accurately and has a uniform profile across the two scanlines in contrast to the constant laser power. The same findings are represented in Figure 5.

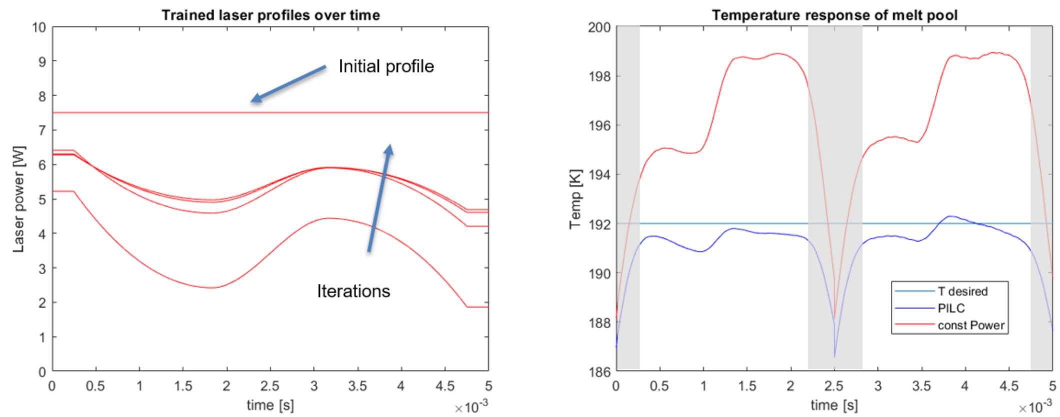


Figure 5: (left) Trained laser power profiles; (right) Post-sintering temperature response of scanlines

Conclusion

In order to significantly improve process control and, in turn, part quality, we designed a PILC controller that minimizes the deviation of the post-sintering temperature profile of a newly scanned 2D geometry from a desired temperature. The controller does this by finding an optimal laser power profile for each new layer during build operations. Due to the controller's predictive capabilities, it successfully anticipates negative effects on the control objective, such as non-uniform powder bed temperatures, complex part geometries and layer-to-layer disturbances. By incorporating data-driven models, we bridged the gap between modern control theory and machine learning. Data-driven models provide accurate predictions with low computational cost and enable the controller to continuously update itself based on new data from the machine. We demonstrated the controller's performance with heat transfer simulations by comparing the PILC-controlled laser power profiles to constant laser power profiles with respect to the effect on the control objective. Further research will experimentally validate the controller and extend the PILC framework to incorporate optimal and multivariate control approaches, such as multiple control objectives.

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