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<th>Title</th>
<th>Review of machine learning applications in powder bed fusion technology for part production</th>
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ABSTRACT: Additive manufacturing (AM) has become a viable option for production of industrial parts to meet the growing demands for customized components with complex geometry within a short lead time. Powder bed fusion (PBF) technology is often favored for its superior geometrical resolution and system stability. In the perspective of PBF machine users, the part production cycle can be broadly divided to three stages: the preparation stage, the printing stage and the postprocessing stage. The complexity in each stage gives rise to a challenging task for process control and quality assurance. The rising of machine learning in recent years sheds light on tackling this multi-factorial challenge in order to improve the overall performance of AM for part production. This article provides a review of machine learning techniques that are applied in or relevant to the part production cycle in PBF systems. The studies to date have showed segmented applications of machine learning techniques in different processes related to AM. To gain insight into the system behavior of PBF machines, more efforts could be put into constructing effective data representations and performing holistic analyses for the entire production cycle.

KEYWORDS: Machine Learning, Additive Manufacturing, Powder Bed Fusion, Review

INTRODUCTION

Part production cycle in PBF systems

PBF encompasses technology that uses either laser or electron beam as the heat source to selectively sinter or melt raw materials, which is in the form of powder, to build a part in a layer-by-layer manner (Gibson et al., 2010, Chua et al., 2014). Parts produced by PBF consist of thousands of thin layers with thickness ranging from 20 to 100 μm (Sing et al., 2016) resulting in their fine details and superior mechanical properties. As printed parts will be measured for dimension check and a series of post-processing such as heat treatment and machining.

At the preparation stage, powder processing and part placing are involved. The quality of powder needs to be well controlled for producing parts with consistent properties (Cooke et al., 2012). The indices frequently used for powder quality assessment are particle size distribution (PSD) and morphology (Ardila et al., 2014). These powder properties will start to shift when powder is being used and recycled repeatedly. It will be too laborious to keep track of those information for every build using traditional methods like laser diffraction. Therefore, there is a limit on how frequent those data can be captured. As for part placing strategy, it is meaningful to plan in a way to maximize the usage of the substrate plate for cost optimization. However, algorithms that attempt to place as many parts as possible on the plate might fail to consider other factors such as build orientation and tool access during machining.

At the printing stage, the process happens in an enclosed chamber with a vacuum or inert gas environment, which causes difficulty in observing the process and capturing meaningful data. The
fact that limited real-time information can be captured to gain insight into the printing process diminishes the possibility of online failure detection and feedback control. Fail parts are only identified after they were printed. This incurs significant time and cost and are hindrances to the adoption of AM by the industries.

At the post-processing stage, dimension check using Coordinate-Measuring Machine (CMM) is widely accepted in the industries and institutes for its accuracy, with significant drawback in long programming and measuring time. Optical scanner is gaining acceptance due to its advancement in accuracy (Iuliano et al., 2009, Bi et al., 2010), with inherent advantages of fast measuring speed and the capability of measuring complex geometry.

Machine learning in manufacturing
Machine learning is a field of computer science that studies algorithms that can learn from and make predictions on data (Kohavi, 1998). These techniques employ statistical methods to process data and build data-driven models that can improve by themselves without being explicitly programmed (Samuel, 1959, Koza, 1996). In recent decades, it has gain popularity in various sectors for applications in image recognition, data analysis, trend prediction and decision making (Chen et al., 2012, Farrar et al., 2012). There is a rising trend in recent years to apply machine learning and artificial intelligence to the manufacturing sector despite many early researches done (Irani et al., 1993, Monostori et al., 1996). Popular techniques such as Support Vector Machine (SVM), clustering and Artificial Neural Network (ANN) have been implemented for data visualization, demand prediction and decision making to optimize material consumption, improve production yield and manage supply chain, to name a few (Columbus, 2016).

Machine learning in AM
Various studies have been conducted with the aim to solve the technological issues in AM, some of which have shown the potential in combining machine learning with AM to overcome certain challenges. There are several reasons why this combination is meaningful: AM is a highly automated process during the printing stage, which in turn generates numerous system data that are difficult to visualize and interpret by human. Also, the enclosed environment and rapid process add difficulty in analyzing the process. Machine learning could come into play for data visualization, image recognition and system modelling to better understand this process. Moreover, the preparation and post-processing stages involve many labor-intensive processes which can be assisted by process automation with intelligent analysis algorithms for planning and decision making. The entire AM production cycle is a multi-factorial problem which can gain help from machine learning techniques. This article covers the relevant machine learning applications for the three stages in part production cycle using powder bed fusion technology.

MACHINE LEARNING IN PREPARATION STAGE

Powder inspection and characterization
Powder quality verification happens before loading them into the machine for print jobs. It requires speedy inspection method to avoid delay in part production in the production line. Methods like laser diffraction and dynamic image analysis requires significant human involvement which results in long inspection time, potentially bias data introduced by operator and error due to inconsistent handling. Moreover, the PSD results generated by these methods cannot truly define powder properties (Clayton et al., 2015). Research has been done using machine learning and computer vision for powder characterization autonomously (DeCost et al., 2016) to provide more
information about powder properties in an objective and repeatable way. The system first converts image to image representation using computer vision techniques (Figure 1(a)), and k-means clustering was used for feature grouping into classes such as precipitates, grain boundaries and powder particles (Figure 1(b, c)). Subsequently, these image representations will be fed into a support vector machine (SVM) classifier for training a classification model. 95% accuracy was achieved by this model for powder classification of different materials and suppliers. Its application for the industries lies in building a digital library of different classes of powder and when a new batch of powder comes in, it can be quickly compared with the database to verify the quality of powder or make appropriate adjustment to other printing parameters in PBF systems for better part performance. Possible future development includes finding an efficient way in building a library containing powder classes that are established by representative data.

![Figure 1](image1.png)

**Figure 1. Example of creation of image representation and feature clustering (DeCost et al., 2016)**

**Build orientation optimization**

Selection of build orientation is a relevant field of study for effective part layout planning and has been well studied thus far. Recent research has integrated many relevant determining factors, such as surface roughness (Ra), build time (T), average tensile strength (UTS), Elongation (E) and more, to form multiple objective functions (examples shown in equation (1)) for optimizing build orientation (Brika et al., 2017).

Multi-objective optimization:

\[
\begin{align*}
\text{Minimize } f_1 &= \text{Ra}(\varphi) \\
\text{Minimize } f_2 &= \text{T}(\varphi, \text{SUPP}) \\
\text{Maximize } f_3 &= \text{UTS}(\varphi, \text{HT}) \\
\text{Maximize } f_4 &= \text{E}(\varphi, \text{HT})
\end{align*}
\]  

(1)

where \( \varphi = \{\theta_x, \theta_y\} \) subject to \( 0 \leq \theta_x \leq 360, 0 \leq \theta_y \leq 360 \) referring to the build orientation of part, \( \text{HT} = (A7, \text{HIP}, \text{SR2}) \) referring to heat treatment (annealing, hot isostatic pressing, stress relief), \( \text{SUPP} \) referring to the amount of support structure

Main objective function:

\[\text{Optimize } f = w_1 f_1 + w_2 f_2 + \ldots + w_n f_n\]  

(2)

where \( w_i (i = 1, 2, \ldots n) \) is the weight of the respective objective function \( f_i \)

Each objective was assigned with a weight based on the feedbacks by industry experts according to their importance. A main objective function for this problem was formed by combining individual objective functions with their respective weights (equation 2). The algorithm starts by generating random initial values for \( \{\theta_x, \theta_y\} \), the rotation angles about X- and Y-axis. At this point,
the solution is set to be the optimal solution. The algorithm will then attempt various solutions and compare to the existing optimal one. If the current solution is better based on the evaluation by the main objective function, it will replace the existing one and become the new optimal solution. This iteration continues until the optimal build orientation has been obtained. Using a genetic optimization algorithm, this method is able to consider all these factors simultaneously to determine the best build orientation. This is a good demonstration of solving a multifactorial problem using computational intelligence techniques.

MACHINE LEARNING IN PRINTING STAGE

Online composition monitoring and defects detection
Real-time monitoring during printing stage can possibly provide the most valuable data of what happened during the lay-by-layer additive process. Research (Song et al., 2017) has shown the usefulness of obtaining laser-induced plasma’ spectral signals in predicting composition of parts produced by AM. Using a laser-induced plasma spectroscopy, the obtained spectral line-intensity-ratio and spectral integrated intensity were used to train a support vector regression (SVR) model. Comparing to other statistical and machine learning techniques like partial least square regression (PLSR) and artificial neural networks (ANNs), this operating parameter conditioned SVR is achieving the lowest absolute error of prediction (AEP), relative error of prediction (REP) and relative standard deviation (RSD) for real-time Al concentration measurements, as shown in Table 1. Although this study focuses on directed energy deposition (DED) technology, this monitoring method could still be applicable in PBF with appropriate adjustments. Another research (Grasso et al., 2017) deployed an optical setup outside the build chamber of a selective laser melting (SLM) system to capture image stream which were used for further processing. The use of principal component analysis (PCA) and k-means clustering has been explored to identify defective areas in a layer.

Table 1. Real-time concentration measurement of Al with nominal centration 20.97% (Song et al., 2017)

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<th>Method</th>
<th>AEP (%)</th>
<th>REP (%)</th>
<th>RSD (%)</th>
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<td>PLSR</td>
<td>7.51 – 8.76</td>
<td>35.83 – 41.76</td>
<td>24.05 – 31.93</td>
</tr>
<tr>
<td>ANNs</td>
<td>0.76 – 0.90</td>
<td>3.62 – 4.30</td>
<td>3.86 – 4.13</td>
</tr>
<tr>
<td>SVR</td>
<td>0.60 – 0.77</td>
<td>2.84 – 3.66</td>
<td>3.49 – 3.73</td>
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Visual analysis, pattern recognition of time series sensor data
Another way to understand the printing process is to analyze the data that were generated during the process. These log and sensor data are generally recorded in very short intervals, every second for example. It is a challenging task to visualize those data in a meaningful way due to their multi-dimensional nature, which adds difficulty in the subsequent analyses. The Falcon, a visual analytics system that was created by researchers from Oak Ridge National Laboratory to allow users to visualize data in several different views for efficient knowledge discovery (Steed et al., 2017). It was used for their Arcam Q10 system, which is an electron beam PBF system. The technical focus of this tool is to interactively process and analysis millions of time-series data in multi-dimension to discover patterns related to part defects and AM process issues. The current version includes functions such as variable overview visualization, segmented time series visualization, similarity/dissimilarity indicator alongside with layer image panel and more. Future development will include active learning techniques to automatically learn features of interest based on user’s interaction, computer vision algorithms to facilitate processing of layer images and
other machine learning methods to recommend hidden features in data and improve the efficiency of the analysis process. This is an attempt to understand the printing stage holistically by looking at time-series data captured during the entire build. It illustrated the challenges and possible remedy in understanding this multifactorial process, and can be possibly extended to the entire part production cycle using PBF systems.

Fraunhofer Institute for Production Systems and Design Technology (IPK) also developed the Condition Monitoring Tool (CMT) to process the sensor data and realize pattern recognition for fault detection and diagnostics applications. More specifically, this tool is able to perform signal pre-processing, feature extraction and selection, and data classification or clustering (Uhlmann et al., 2017) for data extracted from a SLM machine, which is a laser PBF system. In CMT, the input data will flow into two streams and get processed separately. In the first stream, data are manually categorized to 3 groups, namely “finished perfectly”, “finished with errors” and “not finished, and used for training and validation of classifiers. In the training data set, features that can show the best separability of different categories are shortlisted as the chosen features for subsequent analyses. Classification using Bayes Classifier and SVM in this case outperforms other techniques such as Nearest Neighbor and neural network and achieve near 100% accuracy in identifying parts that were “finished perfectly” in 271 sample data. In the second stream, k-mean clustering is used on the same set of data without any groupings to verify the appropriateness of the categories formed in the first stream, and discover potential hidden patterns. The algorithm identified 3.5 categories from the data which is close to the manual grouping done in the first stream, proving the appropriateness of using 3 categories for this data set. This work shows the potential of applying machine learning techniques in predicting part’s condition using existing sensor data which are already available in the PBF system. By implementing these algorithms on a real-time basis, online monitoring and failure prediction for PBF could become possible without additional sensors.

MACHINE LEARNING IN POSTPROCESSING STAGE

Dimensional inspection and classification

After the printing stage, parts will usually undergo dimensional inspection to ensure the geometry variation is within the specified tolerance. As mentioned earlier, CMM is favored for its accuracy but suffers from long measuring time and significant programming effort. Laser scanning is gaining interest and research has been done to improve the efficiency of AM part measurement by using laser scanner in conjunction with machine learning techniques. The approach developed by Tootooni (Tootooni et al., 2017) only takes 5% of the 2 million 3D point cloud data captured by a laser scanner to quickly determine the degree of dimensional variation in tens of microns. It is achieved by extracting features from point cloud data using a novel method and feed them in supervised classification based models for each class representing different degree of geometric variation. The objective of this research is to reduce the measurement burden so that the quality of AM parts in terms of geometry accuracy can be quickly assessed on the shop floor. When this idea is further improved with greater accuracy and integrated with geometric dimensions and tolerance (GD&T), it will become more relevant to the industries using AM for part production.

DISCUSSION OF POTENTIAL GAP

The previous session has reviewed on several machine learning applications that are either directly implemented in or relevant to the part production cycle in PBF systems. Further research is
worthwhile in many areas for realization of these methodologies in the industries. For powder feedstock inspection, a more efficient way of collecting representative powder data and building a digital library containing various powder classes will benefit companies in accumulating knowledge along the course of production, speeding up powder validation process and gaining confidence in powder quality assurance. For real-time monitoring, it is expected that the scope of monitoring will keep expanding to obtain more information during the printing process. A more powerful monitoring approach can be devised by combining these advancements in sensors and algorithms developed thus far. For dimensional inspection techniques, effort could be put into improving the resolution of detecting dimensional variation and integrating GD&T (Tootooni et al., 2017) in order to turn this approach into a real solution and gain adoption on the shop floors.

Additionally, the fragmented applications of machine learning in different processes of PBF can potentially be combined and form a powerful tool for part production cycle analysis. The Falcon system mentioned in the review has shown the capability of visualizing multi-dimensional data captured by PBF systems during the printing process. There is a possibility in expanding its scope to encompass more data obtained from powder, build planning, printing process and part quality and dimension. This improvement will facilitate researchers in visualizing data from a holistic view and understand the entire process chain. To perform analysis on this multifactorial process with the help from machine learning techniques, methodology raised by Brika (Brika et al., 2017) regarding build orientation optimization, in which multi-objective function was established and solved for optimization result, can be explored and built upon. To achieve this idea, it is essential to transform data from each field to respective data representations that are not only able to preserve the important features of raw data, but comparable and processable by algorithms.

CONCLUSION

This paper has reviewed several machine learning applications that are relevant to PBF systems. In the three different stages of part production cycle, potential gaps have been discussed individually and collectively, with the aim to better comprehend the entire process. Although the focus of this paper is on PBF systems, many of the methodologies are transferable to other AM technologies as many of them shared the same or similar processes, such as powder inspection and dimensional check. Overall, the recent trend of applying machine learning in AM has been illustrated. Researches have shown the capabilities of machine learning and continuous effort is needed for creating solutions with better accuracy, reliability and efficiency.

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REFERENCES


