Machine Learning assisted response circles for additive manufacturing concerning metal dust bed fusion

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ABSTRACT

Metal Powder Bed Fusion (PBF) has been attracting an increasing attention as an emerging metal Additive Manufacturing (AM) technology. Despite its distinctive advantages compared to traditional subtractive manufacturing such as high design flexibility, short development time, low tooling cost, and low production waste, the inconsistent part quality caused by inappropriate product design, non-optimal process plan and inadequate process control has significantly hindered its wide acceptance in the industry. To improve the part quality control in metal PBF process, this paper proposes a novel Machine Learning (ML)-enabled approach for developing feedback loops throughout the entire metal PBF process. A categorization of metal PBF feedback loops is proposed along with a summary of the critical PBF manufacturing data in each process stage. A generic framework of ML-enabled metal PBF feedback loops is proposed with detailed explanations and examples. The opportunities and challenges of the proposed approach are also discussed. The applications of ML techniques in metal PBF process allow efficient and effective decision- makings to be achieved in each PBF process stage, and hence have a great potential in reducing the number of experiments needed, thus saving a significant amount of time and cost in metal PBF production.

KEYWORDS: additive manufacturing, machine learning, powder bed fusion, feedback loop

1.0 INTRODUCTION

Metal Additive Manufacturing (AM) refers to the manufacturing process in which metal parts are joined or solidified from a feedstock. In recent years, various types of metal AM technologies have been developed and some of them have been commercialised and applied in the production of fully functional parts. In general, AM technologies can be divided into seven categories, including binder jetting, direct energy deposition, material extrusion, material jetting, powder bed fusion (PBF), sheet lamination, and vat photopolymerization. The fundamental theory and mechanism of each AM technology differ significantly from one another [1-11]. The focus of this study is on the most mature and widely applied metal AM technology, i.e. metal PBF.PBF is an AM process that uses a laser or electron beam to selectively melt and fuse areas of a layer of powders, after which the powder bed is moved downwards, another layer of powders is added and the process repeats until the part is built up [12-19]. Widely used metal PBF techniques include Selective Laser Melting (SLM), Electron Beam Melting (EBM) and Direct Metal Laser Sintering (DMLS). Though metal PBF is a relatively new technology compared to traditional subtractive manufacturing, it has shown distinctive advantages in terms of the higher design flexibility, shorter development time, lower tooling cost, and less production waste [20-24]. However, despite these advantages, its widespread adoption is significantly hindered by the variability in part quality with respect to the dimensional accuracy, surface roughness, mechanical and physical properties, porosity, and other defects [25-31]. A typical metal PBF process comprises several stages such as product design, process planning, PBF manufacturing, post-processing (optional), and product quality measurement. The inconsistent part quality can be caused by various reasons in different stages such as inappropriate product design, non-optimal process plan and inadequate process control [32-39]. Therefore, part quality control remains a major challenge for metal PBF. An ideal solution to address this issue is to establish feedback loops (or closed-loop manufacturing) throughout the entire metal PBF process, such that the product design, process planning and process control can be optimized either on-line or off-line based on process monitoring and product quality measurement [40-46]. The development of feedback loops for metal PBF requires a collective effort from various PBF-related research areas such as in-situ process monitoring, process control and optimization, process simulation and product quality measurement. With the advancements in process monitoring and quality measurement technologies, large amounts and various types of manufacturing data become available to be utilized to develop the feedback loops [47-53]. However, traditional statistical methods suffer from their poor capability of analysing the highly heterogeneous and non-linear data. Recent advancements in Machine Learning (ML) provide advanced data analytics tools for processing and analysing the big manufacturing data. Nowadays, ML techniques have been increasingly applied in the manufacturing area as they allow to gain insights of the big manufacturing data and facilitate the decision-making processes. The advantages of ML have shown a great potential in facilitating the development of feedback loops for metal PBF process [54-61]. This study investigates the opportunities and challenges for developing ML-enabled feedback loops for metal PBF process. A literature review on feedback loops and ML applications in PBF is provided in Section 2. The categorization of metal PBF feedback loops and the identification of the critical data are presented in Section 3. Section 4 introduces the ML-enabled feedback loops for PBF, including a generic framework of the ML-enabled feedback loops and some example applications. Section 5 discusses the opportunities and challenges for developing the ML-enabled metal PBF feedback loops. Section 6 concludes the paper.

2.0 LITERATURE REVIEW

Development of feedback loops is considered an ultimate goal of a large amount of PBF research, though most of the existing research works focus only on a specific part of the feedback loop such as in-situ process monitoring or process control. This subsection reviews some representative works that are most relevant to the development of PBF feedback loops. Several conceptual PBF feedback loops have been proposed. Based on the hierarchy of PBF parameters, Vlasea et al. proposed four types of PBF feedback control strategies: 1) pre-processing for predictive control, 2) in-situ defect or fault detection and handling, 3) in-situ continuous feedback control, and 4) signature-derived control through plant models or simulations. Aiming to develop closed-loop PBF system, Chua et al. proposed three approaches based on different stages of the inspection and monitoring system, i.e. 1) single layer inspection-based, 2) multi-layer inspection-based, and 3) final product inspection-based feedback loops. Upon the analysis of the control cascades of PBF, Renken et al. proposed three types of feedback control strategies: 1) in-process (vector) control, 2) in-situ (vector sets) control, and 3) in-situ (layer) control [1-17]. Various types of in-situ process monitoring technologies have been utilized to support the development of feedback control of PBF. Renken et al. applied an on-axis high-speed pyrometer on a PBF machine to detect the real-time radiation intensities at the melting point. This signal is used to control the laser power and speed in real time to minimize the temperature deviation. Their experimental results showed that closed-loop control could decrease the temperature deviation by up to 90%. Mireles et al. implemented an infrared (IR) camera on an EBM machine to monitor the in-situ IR thermography of each printed layer [62-71]. Defects detected in the IR thermography are used to trigger a re-melting process to correct the defect, such that an in-situ correction feedback loop is established. Simulation-based (or model-based) feedback loops have been extensively studied. For instance, Wang et al. developed an analytical and control-oriented model that simulates the dynamics of melt pool cross-sectional area during laser scanning. The simulation results are fed back to the controller which adjusts the laser power to regulate the melt pool cross-sectional area during the build process [72-79]. The developed feedback loop reduces defects during the build such as keyhole formation and over-melting. Off-line PBF feedback loops that aim to optimize the product design or process parameters have also been investigated. Based on off-line experimental data and quality measurement results of PBF processes, Brika et al. developed a feedback loop that uses a genetic optimization algorithm to optimize the build orientation while simultaneously considering mechanical properties, surface roughness, support structure and build time and cost [78-83]. Recently, ML techniques have been increasingly applied in metal PBF research to facilitate various types of decision-making processes. Based on the melt pool images captured by a high-speed camera during the PBF process, Yang et al. developed a deep learning-based melt pool classification method to predict the melt pool size in real time. They claimed that the processing time of the developed Convolutional Neural Network (CNN) is reduced by 90% compared to traditional image analysis method [18-24]. To gain insights of how process parameters affect the PBF process, Garg et al. proposed a multi-gene genetic programming method to analyse the hidden relationships between the bead width and some important process parameters such as layer thickness, laser power and scan speed. Scime and Beuth developed a multi-scale CNN that is capable of detecting and classifying seven types of powder bed anomalies based on the powder bed images taken after recoating. Their experimental results showed a 97% detection and classification accuracy, which is higher than traditional image processing methods. To analyse the complex relationships between single track morphology and dynamic process signatures, Zhang et al. proposed two intelligent classification methods, i.e. CNN and support vector machine (SVM), to classify three types of track morphology based on the images of melt pool, plume and spatters captured by a high-speed camera [25-37]. It is noted that their classification methods could only work off-line due to the high computational power requirement. Ye et al. proposed a novel defect detection method for SLM process based on the acoustic signal captured by a microphone in the build chamber. A deep belief network (DBN) framework was developed to predict the melted state of the SLM process based on the acoustic signal. It is noted that ML has been extensively utilised in metal PBF research to solve various types of data analytics problems [38-46]. However, few studies have investigated ML-enabled feedback loops for metal PBF from a systematic perspective. Hence, this study attempts to bridge this research gap by analysing the types of feedback loops in metal PBF process, the critical manufacturing data involved in the feedback loops, and how to apply ML techniques to facilitate the development of the feedback loops [47-53].

3.0 RESEARCH METHODOLOGY

In general, a complete PBF process contains five stages, including product design, process planning, PBF manufacturing, post-processing, and product quality measurement. To analyse the types of feedback loops, the PBF manufacturing stage needs to be broken into more detailed substages considering the process monitoring and control strategies. Since PBF uses a layer-by-layer building process, the control parameters can be adjusted either during recoating or during laser/beam scanning, while the process monitoring is performed at the same time. Furthermore, since there exist various distinctive post-processing technologies (powder removal, heat treatment, machining, etc.), the post-processing stage is not considered in the feedback loops for this study. Hence, in this work, the PBF process is further divided into six stages: 1) product design, 2) process planning, 3) recoating, 4) laser/beam scanning, 5) process monitoring, and 6) product quality measurement. Based on these PBF process stages, we categorise the metal PBF feedback loops into four types, including 1) ex-situ product design optimisation, 2) ex-situ process plan optimisation, 3) in-situ (layer-by-layer) feedback control, and 4) in-process feedback control, as shown in Figure 1. The first two feedback loops are performed off-line, while the last two are conducted during PBF manufacturing process.

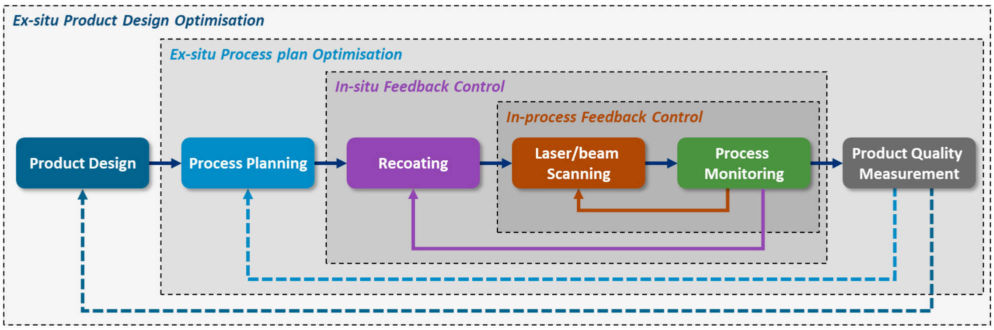

Fig. 1. Categorisation of metal PBF feedback loops

Product design is the initial step of PBF process that determines the material, geometry, and other requirements of the PBF product such as dimensional tolerances and surface roughness. Commonly, the product design cannot be modified in the following manufacturing stages. Hence, product design optimisation is always achieved off-line, where product designers compare the final results from the product quality measurement (sometimes also from the process monitoring) to find the design flaws that cause the product defects, and then perform design optimization to improve the product quality. Process planning is a preparatory step before PBF manufacturing that determines support structures, build position and orientation, and various process parameters such as laser/beam power, scan speed, scan pattern, layer thickness and gas flow rate. In the ex-situ process plan optimisation feedback loop, process planners use data analytics tools to find the relationships between the final product quality (sometimes also the process signatures from process monitoring) and various process parameters to optimise the process plan off-line. Traditionally, process plan optimisation is achieved through the design of experiments or trial and error method. In-situ feedback control is performed during the recoating process, i.e. before the printing of the next layer. Since PBF manufacturing follows a layer-by-layer process, some layerwise process signatures detected from the process monitoring (powder bed image, layerwise temperature distribution, etc.) can only be obtained after the layer is finished. Based on the monitored process signatures, some process parameters can be adjusted (depend on the control system) to improve the quality of the next layer or correct the defects of the previous layer. If fatal errors are detected in process monitoring, the operator can stop the process to prevent further damage of the machine components. In-process feedback control is performed during the laser/beam scanning, where the real-time process signatures (such as melt pool radiation and plume and spatters) are used as the feedback to adjust the laser/beam power, scan speed and scan pattern. In-process feedback control is a very challenging task since it requires real-time data analytics as well as real-time control of the laser/beam power and scan speed. In addition, it is worth mentioning that most commercial PBF machines do not allow operators to adjust the process parameters during scanning. Critical data in PBF feedback loops refer to the manufacturing data in the entire PBF process that can be adjusted, controlled, monitored, or measured to improve the product quality through the proposed four types of feedback loops (Figure 1). Identification of the critical data is a prerequisite for developing feedback loops for PBF process. A comprehensive list of specific metal PBF data in each product lifecycle stage has been reported in our previous work as a metal PBF product data model [22]. In this study, we summarise the critical data that could be monitored, controlled, or measured in each stage of the PBF feedback loops as a fishbone diagram shown in Figure 2.

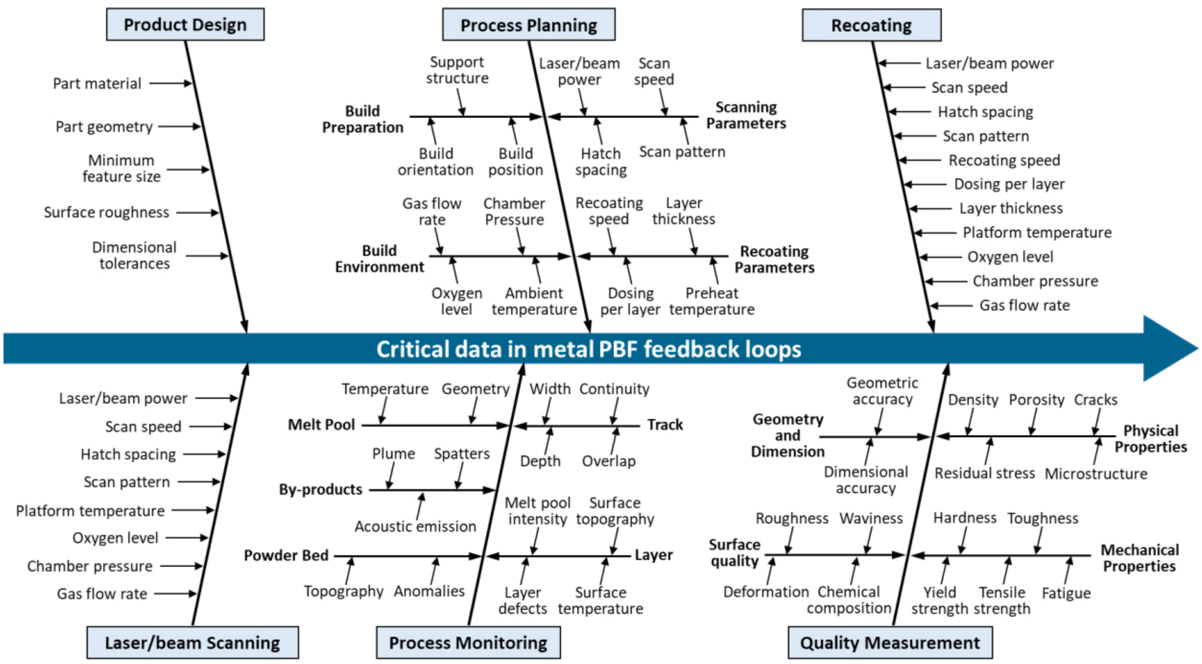

Fig. 2. Critical data in metal PBF feedback loops

Figure 2 does not aim to provide an exhaustive list of critical data in metal PBF feedback loops since there still exist many PBF parameters that have not been studied. However, it includes the most commonly mentioned parameters in existing literatures. Note that process parameters that affect the product quality can be divided into two categories, i.e. predefined and controllable. Predefined process parameters are the parameters that cannot be modified even in the process planning stage such as the powder material properties and some build environment parameters. Hence, for the process planning parameters, we only include the controllable parameters; the predefined parameters are omitted for the feedback loops in this study. For the details of each data item such as the description, data format, unit and methods/devices used to acquire the data, readers are recommended to refer to our previous work.

4.0 RESULT

Figure 2 shows that metal PBF process involves large amounts of heterogeneous manufacturing data with highly complicated relationships. Analysing these data to establish metal PBF feedback loops requires advanced data analytics tools. As recent advancements in ML have shown great potential in solving complicated data analytics problems, this section proposes a ML-based approach to developing metal PBF feedback loops. To explain how to apply ML to support the development of PBF feedback loops, we propose a generic framework of ML-enabled feedback loops for PBF system as shown in Figure 3. This framework is based on the analysis of the types of PBF feedback loops presented in Section 3.1.

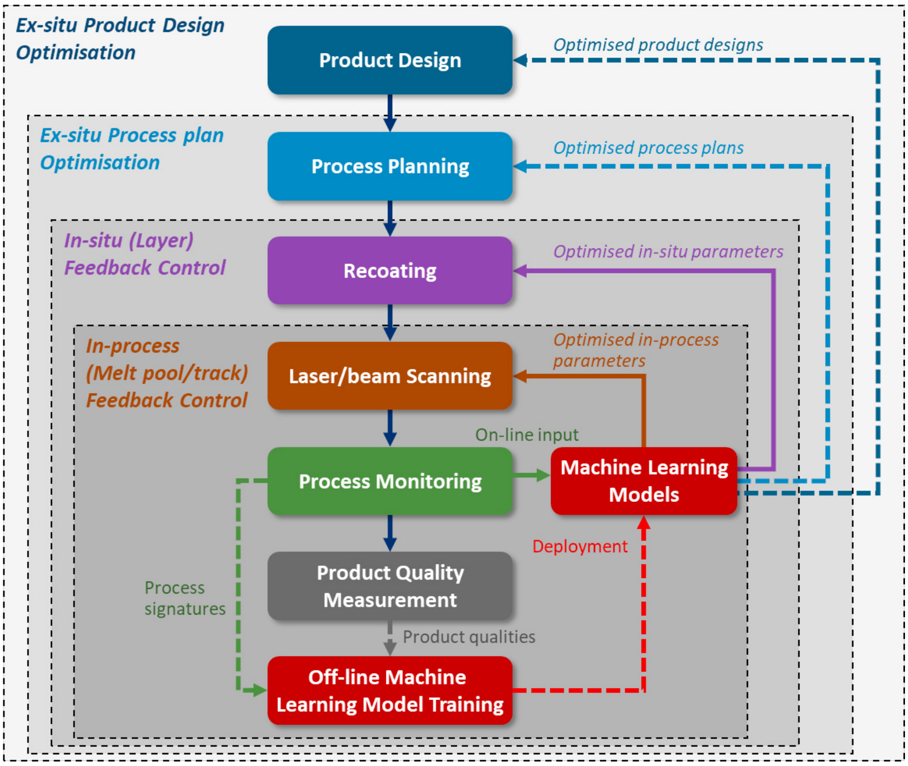

Fig. 3. Generic framework of Machine Learning-enabled feedback loops for PBF process

In general, ML techniques can be applied to support all the four types of PBF feedback loops by making use of critical manufacturing data mentioned in Section 3.2. The designed process parameters, the monitored process signatures, and the measured product qualities are used as the dataset for the off-line ML model training. The trained ML model is then deployed in the PBF process to predict either the in-situ process signatures or the final product qualities and provide the optimised parameters as the feedback to each PBF stage. Details of each ML-enabled feedback loop are explained along with some example applications as follows. In the in-process (melt pool/track) feedback control loop, the melt pool/track signatures (melt pool radiation, track width, etc.) and the measured melt pool/track qualities (melt pool size, track geometry, etc.) are used as the dataset for the off-line ML model training. The trained ML model is then deployed as an in-process quality control model that uses the real-time process signatures to predict the quality of the melt pool/track and optimise the in-process control parameters in real time. Due to the real-time processing requirement, high-performance supervised ML models that can deal with image data such as various CNN models are commonly used to assist this feedback loop. An example is the work mentioned in the literature review, where high-speed melt pool images are used to predict the melt pool size with a trained CNN model in real time. The predicted melt pool size can be used to provide optimised laser power and scan speed as the in-process feedback control. The in-situ (layer) feedback control loop works in a similar way as the in-process feedback control loop, but uses the layer signatures (powder bed image, layer temperature distribution, etc.) and layer qualities (layer porosity, layer deformation, etc.) to train the ML model. After one layer is built, the trained ML model uses the in-situ layer signatures to predict the layer quality and optimise the laser power or scan speed for the next layer, or perform a re-melt to correct the defects of the previous layer. In this feedback loop, since the prediction is made layer-by-layer, the computational requirement of the ML model is as critical as the in-process feedback loop. Various types of supervised ML models that deal with image data can be applied. An example is from where layerwise images and CT scans of the final part are used to train different ML models that predict the layer defects after one layer is built. The predicted defects can provide suggestions for optimising the control parameters for the next layer. In the ex-situ process plan optimisation loop, ML models are developed to find the complicated relationships between the process plan (support structure, laser/beam power, scan speed, scan pattern, layer thickness, gas flow rate, etc.) and the final product qualities (density, geometry deformation, tensile strength, etc.). Since this is an off-line feedback loop, various types of supervised ML models can be applied. A typical example of this feedback loop is reported in, where the process parameters and the measured part density are used to train ML models to define a good process window for the scan speed. Moreover, since there is no well-developed simulation model for metal PBF process, ML techniques can also be integrated with physics-based simulation to achieve the process plan optimisation. The ex-situ product design optimisation loop works in a similar way as the ex-situ process plan optimisation but focuses on finding the complex relationships between the product design features (material, geometry, feature size, etc.) and the final product qualities. Various types of supervised ML models can be applied to analyse the relationships between the heterogeneous manufacturing data. An example of this feedback loop is reported by Zhang et al. in which they developed ML models for predicting the manufacturability of metal PBF parts with different materials, geometric structures, and sizes.

5.0 DISCUSSION

An emerging idea in computer-aided engineering science is hybrid modelling, or physics-informed machine learning. The premise is to make use of a simplified representation of the physics involved in the engineering process to be controlled, and to complement this representation by machine learning, using data acquired on-the-fly to further increase the predictive capabilities of the digital system. This can be achieved in many ways. For instance, inputs of physics-based PBF simulators such as inherent strains or convection coefficients may be linked to machining parameters though a non-parametric regression, leading to a hybrid model represented by a neural network whereby the last layer is made of the physical models. Advanced differentiation techniques developed in the field of modelling with partial differential equations may subsequently by used to obtain the quantities required to perform back propagation. Similarly, physical measurements such as porosities or microstructure states may be predicted via a neural network that takes the output of a physical model as input, for instance the solution predicted by a transient thermal problem. Finally, hybridisation may also be obtained by allowing the parameters of the physical model to change with time, using time filtering approaches. For such advanced digital twinning approaches to be feasible, robust data-to-simulation pipelines must be constructed so that inference algorithms may be deployed to compare simulated outputs and measurements so that the corresponding error may be minimised during the calibration or manufacturing process. This pipeline must also be able to provide real-world feedback to control the manufacturing process inputs thus numerically optimised, or to automatise the acquisition of new data, in an active learning fashion. Optimising parameters from massive amount of data collected is typically tackled by offline learning, i.e. supervised or unsupervised learning. However, it has always been an interesting subject to explore how a model can be established for on-line PBF process control optimisation. One promising approach is to deploy the technique of deep reinforcement learning (DRL) that models the sequential decision-making problem by an agent, which determines the next action to interact with the environment given the observation (i.e. state) with the goal of maximising long term rewards towards an optimal solution. The most well-known application with DRL is the success of AlphaGo, which beats the world champion of the GO game and several recent publications, especially the work reported by DeepMind, claiming human-level intelligence for game environment such as Atari. For PBF process control specifically, the problem is considerably more complicated. First, the Go or Atari environments are represented in discrete space, where Deep Q-

Learning Network (DQN) can be used directly. However, for real-world metal PBF processes, we need to operate the manufacturing processes in a continuous space, i.e. parameters of laser power, exposure time, scan path, and so on. Many attempts have been made for learning in continuous space and the most prominent method is the Deep Deterministic Policy Gradient (DDPG) network. DDPG is an actor-critic-based network, allowing, on one hand, DQN-like off-policy learning for efficient updating of the value functions from experience buffer and, on the other hand, train a policy network simultaneously. Second, a compact representation of the states will be required. With the Atari games, raw pixel-wise state representations are used. However, it is still considered less challenging than the PBF processes, considering the possible state space of the environment with not only 3D geometric information, but also all the relevant dynamic physical attributes of the process. Abstracted parameters of the product, such as dimensions, densities, statistical information of defects or quality and so on, could be potentially considered for representing the states. Another challenge is that the simulation is highly time-consuming and learning meaningful rewards from such a reward-sparse environment will be very difficult. Thus, how to accelerate the process of learning needs to be addressed. Such mechanisms may include providing human demonstrations from experts with prior expert knowledge. Challenges for the development of ML-enabled metal PBF feedback loops have also been recognised from the current limitations of the related technologies. It is noted that most of the commercial metal PBF machines provide very limited controllability for the users. As a result, the on-line process control feedback usually cannot be achieved due to the closed control system. Another issue with current metal PBF machine is the poor data interoperability. While traditional subtractive manufacturing has taken advantage of open and unified data communication standards such as MTConnect and OPC UA [28,29], there is currently no unified data communication protocol for metal PBF machines. This not only poses challenges for the field-level manufacturing data acquisition, but also limits the transferability of the developed feedback loops between different metal PBF machines. Development of ML models usually requires large amounts of manufacturing data. For metal PBF process where manufacturing data is obtained from practical experiments, the time and cost for the experiments have to be taken into account. The poor interpretability, explainability and trustability of some deep learning models may also limit their application in the manufacturing environment. Moreover, the on-line ML models usually require very high computation capability in the field level, which is also a challenge for current shop floors. The limitations of current process monitoring and quality measurement technologies also hinder the development of ML-enabled metal PBF feedback loops. Though various types of in-situ monitoring techniques have been developed in the past several decades, detecting the real-time process signature accurately, efficiently, and cost-effectively has always been a major challenge. Besides, the limitations of current non-destructive testing (NDT) technologies also pose challenges for labelling the PBF manufacturing data. For example, measurement and localisation of internal defects such as porosity of a large-sized high-density metal part remains a critical challenge.

6.0 CONCLUSIONS

Metal PBF has been attracting an increasing attention as an emerging metal AM technology. Despite its distinctive advantages compared to traditional subtractive manufacturing such as high design flexibility, short development time, low tooling cost, and low production waste, the inconsistent part quality caused by inappropriate product design, non- optimal process plan and inadequate process control has significantly hindered its broad acceptance in the industry. To improve the part quality control in metal PBF process, this study proposes a novel ML-enabled approach for developing metal PBF feedback loops. First, a categorisation of the types of metal PBF feedback loops is proposed based on the metal PBF process stages. The critical manufacturing data that affect the final product quality in each stage are identified. Second, a generic framework of ML-enabled metal PBF feedback loops is proposed and each feedback loop is explained in detail with some practical examples. Finally, the opportunities and challenges of the proposed approach are discussed. The proposed ML-enabled feedback loops enable the vision of closed-loop manufacturing for metal PBF processes, in which the in-situ process signatures monitored during the manufacturing stage and the measured product qualities are fed back to product design, process planning and on-line process control stages to ensure the process stability and optimise the final product quality. The applications of ML techniques in metal PBF process allow efficient and effective decision-makings to be achieved in each PBF process stage, and hence have a great potential in reducing the number of experiments needed, thus saving a significant amount of time and cost in metal PBF production. The proposed ML-enabled feedback loop approach is also in line with the emerging concepts in Industry 4.0 and Smart Manufacturing such as Digital Twin and Cyber-Physical Machine Tool. It can be applied as a generic ML-enabled feedback loop solution for other types of manufacturing systems to facilitate the development of the envisioned Cyber-Physical Production System (CPPS) and Smart Factory in the era of Industry 4.0.

REFRENCES

[1] Qi, Xinbo, et al. "Applying neural-network-based machine learning to additive manufacturing: current applications, challenges, and future perspectives." Engineering 5.4 (2019): 721-729.

[2] Johnson, N. S., et al. "Invited review: Machine learning for materials developments in metals additive manufacturing." Additive Manufacturing 36 (2020): 101641.

[3] Sadi, Mehdi, Yi He, Yanjing Li, Mahabubul Alam, Satwik Kundu, Swaroop Ghosh, Javad Bahrami, and Naghmeh Karimi. "Special Session: On the Reliability of Conventional and Quantum Neural Network Hardware." In 2022 IEEE 40th VLSI Test Symposium (VTS), pp. 1-12. IEEE, 2022.

[4] Qin, Jian, et al. "Research and application of machine learning for additive manufacturing." Additive Manufacturing (2022): 102691.

[5] Caggiano, Alessandra, et al. "Machine learning-based image processing for on-line defect recognition in additive manufacturing." CIRP annals 68.1 (2019): 451-454.

[6] Bahrami, Javad, Mohammad Ebrahimabadi, Jean-Luc Danger, Sylvain Guilley, and Naghmeh Karimi. "Leakage power analysis in different S-box masking protection schemes." In 2022 Design, Automation & Test in Europe Conference & Exhibition (DATE), pp. 1263-1268. IEEE, 2022.

[7] Yao, Xiling, Seung Ki Moon, and Guijun Bi. "A hybrid machine learning approach for additive manufacturing design feature recommendation." Rapid Prototyping Journal (2017).

[8] Bahrami, Javad, Viet B. Dang, Abubakr Abdulgadir, Khaled N. Khasawneh, Jens-Peter Kaps, and Kris Gaj. "Lightweight implementation of the lowmc block cipher protected against side-channel attacks." In Proceedings of the 4th ACM Workshop on Attacks and Solutions in Hardware Security, pp. 45-56. 2020.

[9] Sing, S. L., et al. "Perspectives of using machine learning in laser powder bed fusion for metal additive manufacturing." Virtual and Physical Prototyping 16.3 (2021): 372-386.

[10] Ahmadinejad, Farzad, Javad Bahrami, Mohammd Bagher Menhaj, and Saeed Shiry Ghidary. "Autonomous Flight of Quadcopters in the Presence of Ground Effect." In 2018 4th Iranian Conference on Signal Processing and Intelligent Systems (ICSPIS), pp. 217-223. IEEE, 2018.

[11] Ko, Hyunwoong, et al. "Machine learning and knowledge graph based design rule construction for additive manufacturing." Additive Manufacturing 37 (2021): 101620.

[12] Wang, Chengcheng, et al. "Machine learning in additive manufacturing: State-of-the-art and perspectives." Additive Manufacturing 36 (2020): 101538.

[13] Zhu, Zuowei, et al. "Machine learning in tolerancing for additive manufacturing." CIRP Annals 67.1 (2018): 157-160.

[14] Shafaie, Majid, Maziar Khademi, Mohsen Sarparast, and Hongyan Zhang. "Modified GTN parameters calibration in additive manufacturing of Ti-6Al-4 V alloy: a hybrid ANN-PSO approach." The International Journal of Advanced Manufacturing Technology 123, no. 11 (2022): 4385-4398.

[15] Meng, Lingbin, et al. "Machine learning in additive manufacturing: a review." Jom 72.6 (2020): 2363-2377.

[16] Sarparast, Mohsen, Majid Ghoreishi, Tohid Jahangirpoor, and Vahid Tahmasbi. "Experimental and finite element investigation of high-speed bone drilling: evaluation of force and temperature." Journal of the Brazilian Society of Mechanical Sciences and Engineering 42, no. 6 (2020): 1-9.

[17] Li, Zhixiong, et al. "Prediction of surface roughness in extrusion-based additive manufacturing with machine learning." Robotics and Computer-Integrated Manufacturing 57 (2019): 488-495.

[18] Jin, Zeqing, et al. "Machine learning for advanced additive manufacturing." Matter 3.5 (2020): 1541-1556.

[19] Jiang, Jingchao, et al. "Machine learning integrated design for additive manufacturing." Journal of Intelligent Manufacturing (2020): 1-14.

[20] Sarparast, Mohsen, Majid Ghoreishi, Tohid Jahangirpoor, and Vahid Tahmasbi. "Modelling and optimisation of temperature and force behaviour in high-speed bone drilling." Biotechnology & Biotechnological Equipment 33, no. 1 (2019): 1616-1625.

[21] Xiao, Qingyang, et al. "An ensemble machine-learning model to predict historical PM2. 5 concentrations in China from satellite data." Environmental science & technology 52.22 (2018): 13260-13269.a

[22] Baumann, Felix W., et al. "Trends of machine learning in additive manufacturing." International Journal of Rapid Manufacturing 7.4 (2018): 310-336.

[23] Gu, Grace X., et al. "Bioinspired hierarchical composite design using machine learning: simulation, additive manufacturing, and experiment." Materials Horizons 5.5 (2018): 939-945.S

[24] Bahrami, Javad, Mohammad Ebrahimabadi, Sofiane Takarabt, Jean-luc Danger, Sylvain Guilley, and Naghmeh Karimi. "On the Practicality of Relying on Simulations in Different Abstraction Levels for Pre-Silicon Side-Channel Analysis."

[25] Yang, Xiaoxue, et al. "Evaluation of short-term freeway speed prediction based on periodic analysis using statistical models and machine learning models." Journal of Advanced Transportation 2020 (2020).

[26] Hadiana, Hengameh, Amir Mohammad Golmohammadib, Hasan Hosseini Nasabc, and Negar Jahanbakhsh

Javidd. "Time Parameter Estimation Using Statistical Distribution of Weibull to Improve Reliability." (2017).
[27] Jiang, Jingchao, et al. "Achieving better connections between deposited lines in additive manufacturing via machine learning." Math. Biosci. Eng 17.4 (2020): 3382-3394.
[28] Zavareh, Bozorgasl, Hossein Foroozan, Meysam Gheisarnejad, and Mohammad-Hassan Khooban. "New trends on digital twin-based blockchain technology in zero-emission ship applications." Naval Engineers Journal 133, no. 3 (2021): 115-135.
[29] Li, Rui, Mingzhou Jin, and Vincent C. Paquit. "Geometrical defect detection for additive manufacturing with machine learning models." Materials & Design 206 (2021): 109726.
[30] Baturynska, Ivanna, Oleksandr Semeniuta, and Kristian Martinsen. "Optimization of process parameters for powder bed fusion additive manufacturing by combination of machine learning and finite element method: A conceptual framework." Procedia Cirp 67 (2018): 227-232.
[31] Bozorgasl, Zavareh, and Mohammad J. Dehghani. "2-D DOA estimation in wireless location system via sparse representation." In 2014 4th International Conference on Computer and Knowledge Engineering (ICCKE), pp. 86-89. IEEE, 2014.
[32] Gobert, Christian, et al. "Application of supervised machine learning for defect detection during metallic powder bed fusion additive manufacturing using high resolution imaging." Additive Manufacturing 21 (2018): 517-528.
[33] Blockeel, Hendrik, and Joaquin Vanschoren. "Experiment databases: Towards an improved experimental methodology in machine learning." European Conference on Principles of Data Mining and Knowledge Discovery. Springer, Berlin, Heidelberg, 2007.
[34] Amini, Mahyar, Koosha Sharifani, and Ali Rahmani. "Machine Learning Model Towards Evaluating Data gathering methods in Manufacturing and Mechanical Engineering." International Journal of Applied Science and Engineering Research 15.4 (2023): 349-362.
[35] Paul, Arindam, et al. "A real-time iterative machine learning approach for temperature profile prediction in additive manufacturing processes." 2019 IEEE International Conference on Data Science and Advanced Analytics (DSAA). IEEE, 2019.
[36] Pineau, Joelle, et al. "Improving reproducibility in machine learning research: a report from the NeurIPS 2019 reproducibility program." Journal of Machine Learning Research 22 (2021).
[37] Amini, Mahyar, and Aryati Bakri. "Cloud computing adoption by SMEs in the Malaysia: A multi-perspective framework based on DOI theory and TOE framework." Journal of Information Technology & Information Systems Research (JITISR) 9.2 (2015): 121-135.
[38] Mahmoud, Dalia, et al. "Applications of Machine Learning in Process Monitoring and Controls of L-PBF Additive Manufacturing: A Review." *Applied Sciences* 11.24 (2021): 11910.
[39] Amini, Mahyar. "The factors that influence on adoption of cloud computing for small and medium enterprises." (2014).
[40] Khanzadeh, Mojtaba, et al. "Quantifying geometric accuracy with unsupervised machine learning: Using self-organizing map on fused filament fabrication additive manufacturing parts." *Journal of Manufacturing Science and Engineering* 140.3 (2018).
[41] Amini, Mahyar, et al. "MAHAMGOSTAR.COM AS A CASE STUDY FOR ADOPTION OF LARAVEL FRAMEWORK AS THE BEST PROGRAMMING TOOLS FOR PHP BASED WEB DEVELOPMENT FOR SMALL AND MEDIUM ENTERPRISES." Journal of Innovation & Knowledge, ISSN (2021): 100-110.
[42] Liu, Rui, Sen Liu, and Xiaoli Zhang. "A physics-informed machine learning model for porosity analysis in laser powder bed fusion additive manufacturing." *The International Journal of Advanced Manufacturing Technology* 113.7 (2021): 1943-1958.
[43] Amini, Mahyar, et al. "Development of an instrument for assessing the impact of environmental context on adoption of cloud computing for small and medium enterprises." Australian Journal of Basic and Applied Sciences (AJBAS) 8.10 (2014): 129-135.
[44] Ward, Logan, et al. "Including crystal structure attributes in machine learning models of formation energies via Voronoi tessellations." Physical Review B 96.2 (2017): 024104.
[45] Golmohammadi, Amir-Mohammad, Negar Jahanbakhsh Javid, Lily Poursoltan, and Hamid Esmaeeli. "Modeling and analyzing one vendor-multiple retailers VMI SC using Stackelberg game theory." Industrial Engineering and Management Systems 15, no. 4 (2016): 385-395.
[46] Motalo, Kubura, et al. "evaluating artificial intelligence effects on additive manufacturing by machine learning procedure." Journal of Basis Applied Science and Management System 13.6 (2023): 3196-3205.
[47] Fu, Yanzhou, et al. "Machine learning algorithms for defect detection in metal laser-based additive manufacturing: a review." *Journal of Manufacturing Processes* 75 (2022): 693-710.
[48] Amini, Mahyar, et al. "The role of top manager behaviours on adoption of cloud computing for small and medium enterprises." Australian Journal of Basic and Applied Sciences (AJBAS) 8.1 (2014): 490-498.
[49] Stathatos, Emmanuel, and George-Christopher Vosniakos. "Real-time simulation for long paths in laser-based additive manufacturing: a machine learning approach." *The International Journal of Advanced Manufacturing Technology* 104.5 (2019): 1967-1984.
[50] Amini, Mahyar, and Nazli Sadat Safavi. "Critical success factors for ERP implementation." International Journal of Information Technology & Information Systems 5.15 (2013): 1-23.

[51] Petrich, Jan, et al. "Multi-modal sensor fusion with machine learning for data-driven process monitoring for additive manufacturing." *Additive Manufacturing* 48 (2021): 102364.
[52] Amini, Mahyar, et al. "Agricultural development in IRAN base on cloud computing theory." International Journal of Engineering Research & Technology (IJERT) 2.6 (2013): 796-801.
[53] Snow, Zackary, et al. "Toward in-situ flaw detection in laser powder bed fusion additive manufacturing through layerwise imagery and machine learning." *Journal of Manufacturing Systems* 59 (2021): 12-26.
[54] Amini, Mahyar, et al. "Types of cloud computing (public and private) that transform the organization more effectively." International Journal of Engineering Research & Technology (IJERT) 2.5 (2013): 1263-1269.
[55] Akhil, V., et al. "Image data-based surface texture characterization and prediction using machine learning approaches for additive manufacturing." *Journal of Computing and Information Science in Engineering* 20.2 (2020): 021010.
[56] Amini, Mahyar, and Nazli Sadat Safavi. "Cloud Computing Transform the Way of IT Delivers Services to the Organizations." International Journal of Innovation & Management Science Research 1.61 (2013): 1-5.
[57] Douard, Amélina, et al. "An example of machine learning applied in additive manufacturing." *2018 IEEE International Conference on Industrial Engineering and Engineering Management (IEEM)*. IEEE, 2018.
[58] Amini, Mahyar, and Nazli Sadat Safavi. "A Dynamic SLA Aware Heuristic Solution For IaaS Cloud Placement Problem Without Migration." International Journal of Computer Science and Information Technologies 6.11 (2014): 25-30.
[59] Ding, Donghong, et al. "The first step towards intelligent wire arc additive manufacturing: An automatic bead modelling system using machine learning through industrial information integration." *Journal of Industrial Information Integration* 23 (2021): 100218.
[60] Amini, Mahyar, and Nazli Sadat Safavi. "A Dynamic SLA Aware Solution For IaaS Cloud Placement Problem Using Simulated Annealing." International Journal of Computer Science and Information Technologies 6.11 (2014): 52-57.
[61] Zhang, Wentai, et al. "Machine learning enabled powder spreading process map for metal additive manufacturing (AM)." *2017 International Solid Freeform Fabrication Symposium*. University of Texas at Austin, 2017.
[62] Sharifani, Koosha and Amini, Mahyar and Akbari, Yaser and Aghajanzadeh Godarzi, Javad. "Operating Machine Learning across Natural Language Processing Techniques for Improvement of Fabricated News Model." International Journal of Science and Information System Research 12.9 (2022): 20-44.
[63] Du, Y., T. Mukherjee, and T. DebRoy. "Physics-informed machine learning and mechanistic modeling of additive manufacturing to reduce defects." *Applied Materials Today* 24 (2021): 101123.
[64] Sadat Safavi, Nazli, et al. "An effective model for evaluating organizational risk and cost in ERP implementation by SME." IOSR Journal of Business and Management (IOSR-JBM) 10.6 (2013): 70-75.
[65] Chen, Lequn, et al. "Rapid surface defect identification for additive manufacturing with in-situ point cloud processing and machine learning." *Virtual and Physical Prototyping* 16.1 (2021): 50-67.
[66] Sadat Safavi, Nazli, Nor Hidayati Zakaria, and Mahyar Amini. "The risk analysis of system selection and business process re-engineering towards the success of enterprise resource planning project for small and medium enterprise." World Applied Sciences Journal (WASJ) 31.9 (2014): 1669-1676.
[67] Yaseer, Ahmed, and Heping Chen. "Machine learning based layer roughness modeling in robotic additive manufacturing." *Journal of Manufacturing Processes* 70 (2021): 543-552.
[68] Sadat Safavi, Nazli, Mahyar Amini, and Seyyed AmirAli Javadinia. "The determinant of adoption of enterprise resource planning for small and medium enterprises in Iran." International Journal of Advanced Research in IT and Engineering (IJARIE) 3.1 (2014): 1-8.
[69] Chen, Lequn, et al. "Rapid surface defect identification for additive manufacturing with in-situ point cloud processing and machine learning." Virtual and Physical Prototyping 16.1 (2021): 50-67.
[70] Safavi, Nazli Sadat, et al. "An effective model for evaluating organizational risk and cost in ERP implementation by SME." IOSR Journal of Business and Management (IOSR-JBM) 10.6 (2013): 61-66.
[71] Guo, Shenghan, et al. "Machine learning for metal additive manufacturing: Towards a physics-informed data-driven paradigm." Journal of Manufacturing Systems 62 (2022): 145-163.
[72] Khoshraftar, Alireza, et al. "Improving The CRM System In Healthcare Organization." International Journal of Computer Engineering & Sciences (IJCES) 1.2 (2011): 28-35.
[73] Ren, K., et al. "Thermal field prediction for laser scanning paths in laser aided additive manufacturing by physics-based machine learning." Computer Methods in Applied Mechanics and Engineering 362 (2020): 112734.
[74] Abdollahzadegan, A., Che Hussin, A. R., Moshfegh Gohary, M., & Amini, M. (2013). The organizational critical success factors for adopting cloud computing in SMEs. Journal of Information Systems Research and Innovation (JISRI), 4(1), 67-74.
[75] Zhu, Qiming, Zeliang Liu, and Jinhui Yan. "Machine learning for metal additive manufacturing: predicting temperature and melt pool fluid dynamics using physics-informed neural networks." Computational Mechanics 67.2 (2021): 619-635.
[76] Amini, Mahyar and Ali Rahmani. "Agricultural databases evaluation with machine learning procedure." Australian Journal of Engineering and Applied Science 8.6 (2023): 39-50-10.
[77] Newiduom, Ladson, et al. "Machine learning model improvement based on additive manufacturing process for melt pool warmth predicting." International Journal of Applied Science and Engineering Research 15.6

(2023): 240-250.
[78] Jackson, Keypi, et al. "Increasing substantial productivity in additive manufacturing procedures by expending machine learning method." International Journal of Mechanical Engineering and Science Study 10.8 (2023): 363-372.
[79] Opuiyo, Atora, et al. "Evaluating additive manufacturing procedure which was using artificial intelligence." International Journal of Science and Information System 13.5 (2023): 107-116.
[80] Amini, Mahyar, and Ali Rahmani. "Machine learning process evaluating damage classification of composites." Journal 9.12 (2023): 240-250.
[81] Pham, Anh-Duc, et al. "Predicting energy consumption in multiple buildings using machine learning for improving energy efficiency and sustainability." Journal of Cleaner Production 260 (2020): 121082.
[82] Yun, Chidi, et al. "Machine learning attitude towards temperature report forecast in additive manufacturing procedures." International Journal of Basis Applied Science and Study 9.12 (2023): 287-297.
[83] Shun, Miki, et al. "Incorporated design aimed at additive manufacturing through machine learning." International Journal of Information System and Innovation Adoption 16.10 (2023): 823-831.