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ANN-based modelling of dimensional accuracy in L-PBF

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Abstract

Laser-based powder bed fusion (L-PBF) is one of the AM techniques that has continued to gain an increased market acceptance and penetration, particularly in a wide range of industrial applications that include automotive, aerospace, medical/dental and robotics. However, in spite of its unstoppable rise in popularity, the L-PBF process still poses some technological challenges that need addressing in order to improve the robustness and repeatability of parts produced. In particular, when compared to other conventional manufacturing technologies, AM and L-PBF in particular lags behind when it comes to being able to predict different quality marks of the parts produced, such as dimensional accuracy and surface quality. In this context, the aim within this paper is to implement a systematic approach to improve precision of printed parts through predictive process modelling and experimental-based study. The methodology of a comprehensive Design of Experiments (DoE) study to improve process knowledge of down-facing surfaces is presented along with the methodology used to generate the dataset with regards to dimensional inaccuracy. The acquired results are used to build process models based on Artificial Neural network (ANN). The prediction accuracy of the proposed model is discussed, and the feasibility of the proposed approach is demonstrated. The outcome of this paper helps understand the L-PBF method and the influence of the governing parameters to further develop high precision L-PBF processes.

L-PBF; ANN; AM; dimensional accuracy; process parameters

1. Main section heading

Additive Manufacturing (AM) technologies represent a change in the paradigm of the manufacturing Industry [1]. They are considered a key enabling technology for the current trends of automation and digitalisation within the manufacturing industry known as Industry 4.0. Industry 4.0 comprises of various digital technologies such as; the internet of things (IOT), Augmented reality, virtual reality, autonomous robots, big data analytics, machine learning and artificial intelligence (AI) [2].

AM technologies have seen increased adoption for industrial production in recent years. Especially in the aerospace, automotive and medical industry where the benefits of AM such as design freedom, reduction in lead-time, supply chain optimisation, mass customisation etc. are much appreciated [3-5]. However, precision aspects of laser based powder bed fusion (L-PBF) are still an area where there is considerable room for improvement [6]. Therefore, there exists a need for effective process modelling techniques for improving the predictability and controllability of the process.

Previous research efforts have shown that the effect of L-PBF process parameters on the quality of printed parts is interdependent as well as non-linear and with a certain degree of uncertainty and anisotropy [7, 8]. Therefore, it makes it challenging to employ conventional modelling approaches for this process. However, the usage of more computational intelligence proves promising. The usage of Artificial Neural Networks (ANN) is recognised as an effective tool to model, identify and control non-linear processes.

ANNs are powerful tools that mimic the structures and processes of biological neural systems. They are especially able to process large input/output data sets and to visualise complex non-linear associations within this data. Which then makes it possible to create complex process models for the purpose of optimisation and control.

More recently ANNs have been used to model many different manufacturing and machining processes especially due to their high degree of accuracy in prediction [9, 10]. They are also highly suitable for processes that generate a large amount of continuous data for big data analytics. Nevertheless, looking at the literature, only few attempts to model the L-PBF process using ANN can be found [11]. In this context, this paper presents an attempt at using ANN for modelling of the L-PBF parts. Especially with regards to the modelling of down-facing process parameters to predict dimensional inaccuracy in down-facing surfaces. Dimensional inaccuracies in down-facing surfaces are primarily caused by the formation of dross. Dross formation takes places due to the creation of a over-heated zone where the laser scans over lose powder [12].

Following this introduction, the next section describes the methodology that was followed for the printing of the parts, as well as the method of analysis used for generating the data that was used to train the ANN model. This is followed by a description of the first results achieved in the training of the model. Finally, conclusions derived from the results are presented along with the direction of future work.

2. Methodology

2.1. Part fabrication

The test samples that were the focus of this study, were designed to have a 45° overhanging surface with a thickness of 2.12 mm. The various process parameters that were considered for these test pieces were four quantitative parameters (laser power, scan speed, scan spacing and layer thickness) and one qualitative (discrete) parameter (scan strategy). The various levels of the process parameters can be seen in Table 1.

Table 1 List of process parameters and levels

Process Parameter	**Levels**
Laser power (W)	50, 90, 150, 210, 250
Scan speed (mm/s)	200, 465, 850, 1235, 1500
Scan spacing (µm)	50, 60, 75, 90, 100
Scan Strategy	Strips, Rectangular cells, Hexagonal cells
Layer thickness (µm)	60, 90

The aforementioned process parameters were only varied within the down-facing area of the part as show in Fig. 1. The rest of the bulk of the part was printed using the same parameters for all test pieces. This was done in order to make sure that the thickness of the test pieces were solely affected by the down-facing process parameters.

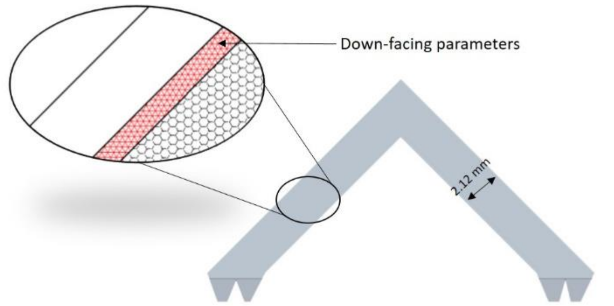

Figure. 1 Depiction of area where down-facing parameters were used

The parts were pre-processed on 3DXpert software and printed using a 3DSystems ProX DMP320. The parts were printed using the Ti6AL4V, which is a high strength Titanium alloy with good mechanical and thermal properties [13]. All parts were put through a stress relief heat treatment process before they were removed from the build platform. This was done in order to prevent any warpage.

2.2. Experimental design

The analysis of the thickness was carried out in order to calculate the dimensional deviation as a result of the varied process parameters. The measurements were obtained by capturing an image of each printed part and performing an image processing technique to measure the thickness. The methodology of the image processing is described as follows. The captured images are first grey-scaled and a threshold is applied in order to detect the edges of the part. The developed algorithm then scans the image vertically as well as horizontally and extrapolates a straight line from the detected edge points. Knowing the scale of the image makes it possible to calculate precisely the distance between the lines, which gives the thickness of the test pieces.

The error in the thickness was calculated by comparing the measured value to the CAD design data. Thereby, providing the data set fed into the ANN. The DoE can be seen in Table 2.

Table 2 Experimental design

Trial	Laser Power (W)	Scan Speed (mm/s)	Scan Spacing (µm)
1	90	465	60
2	90	465	90
3	90	1235	60
4	90	1235	90
5	210	465	60
6	210	465	90
7	210	1235	60
8	210	1235	90
9	50	850	75
10	250	850	75
11	150	200	75
12	150	1500	75
13	150	850	50
14	150	850	100
15 - 24	150	850	75

Meaning the above table represents 24 samples printed using one type of scanning pattern and layer thickness. The results for dimensional error used for training the ANN consider 3 different scanning patterns, which were fed into the ANN model as discrete levels (-1, 0 and 1) and 2 layer thicknesses. Therefore, a total of 144 (entailing 90 dataset and 9*6 replicates) samples were fabricated and tested.

3. Results

3.1 Algorithm for Error Estimation for Metal AM

This section is devoted to the design of the Artificial Neural Network (ANN) to model the relationship between the input and output parameters based on the experimental results. ANN was utilised in this study due to its high ability to tackle complex non-linear problems, whether classification or regression problems, which are very difficult to solve using other techniques [XXX]. In this paper, the proposed ANN model works to estimate the error of metal additive manufactured parts. The data was split into input parameters (features) data as "Laser Power, Scan speed, Scan Spacing, Scan Strategy, and Layer Thickness" and label (response) data as "Error%".

The ANN Algorithm works as follows. Input data and label data were stored into two matrixes 5x90 and 1x90, respectively. Then, the entire data sets were divided randomly into training data, validation data, and testing data. The proposed algorithm was developed using the Neural Network toolbox in MATLAB. Different ANN designs were tested and evaluated for the minimum error between the expected and estimated results. Accordingly, the proposed ANN was designed based on five neurons for input layer, 1 hidden layer with three and one neuron for the output layer as shown in Figure 2. The Levenberg–Marquardt was selected as neural network algorithm.

For the training phase of the ANN algorithm, random values for initializing weight and bias of neural network, 1000 epochs (training step) and 0.1 learning rate were set.

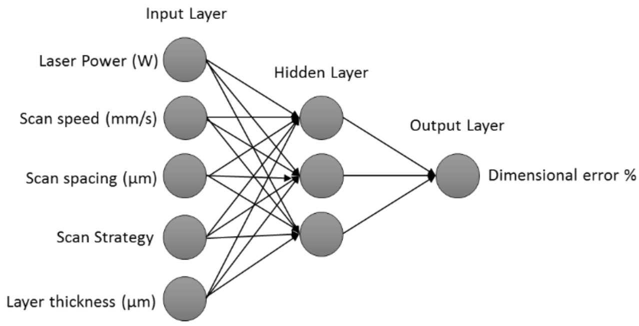

Figure. 2. Optimal structure of the proposed ANN

Further to the development of the training session, Figure 14. The proposed training ANN model was updated with the newly generated weights and bias that minimize the training error in order to estimate the correct response “Errors%” of the 3D printed parts.

As shown in Figure 3, the results of the training gradient was calculated to be 0.05733 at epoch 11 and the best validation results are at epoch 5 with a mean square error of 0.2855 as shown Figure 5.

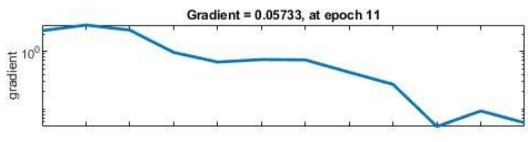

Figure. 3 Results of Training gradient

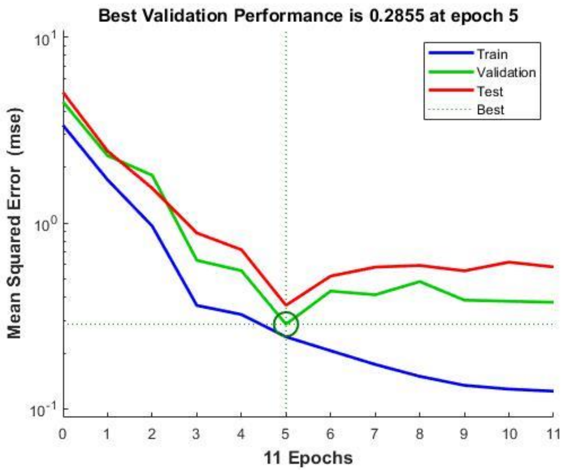

Figure. 4 Validation performance of neural network

Figure 5 shows the performance of the ANN algorithm developed to predict the error of AM fabrication process. In particular, the proposed ANN model successfully estimates the error percentage in the MAM products for different input parameters. This is clearly revealed considering the trend and distribution of plotted data around the fit line in the training, validation and testing phases of the proposed ANN model.

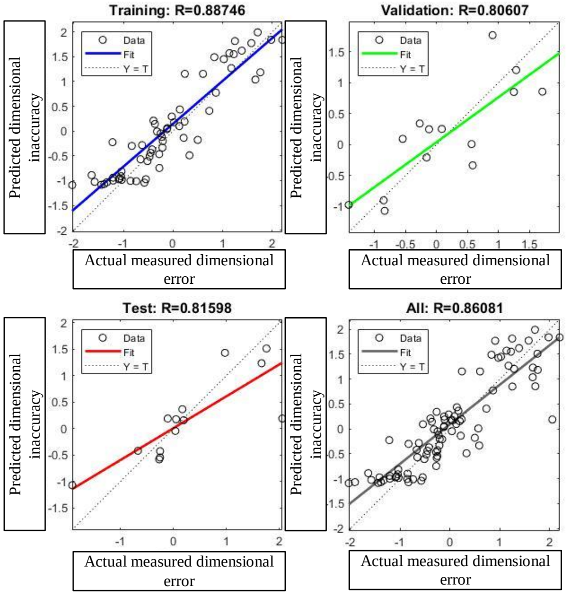

Figure. 5. Regression algorithm performance

4. Conclusions

The current work has utilised ANNs for predictive process modelling of the L-PBF process. A DoE study was conducted and the printed test pieces were measured for dimensional error % using an image processing technique. The process parameters and the measured error % were used to train a ANN. An ANN model was then developed for the prediction of the error % of the process based on the training data. This model was validated and tested and it showed the best performance at a Mean Squared Error of 0.2855 after 5 epochs. However, this current ANN model is the result of a limited dataset for ongoing work. A larger data sets are being prepped in order to train the ANN model as it is even further. Therefore even more accurate predictions are expected at the end of the current work, in order to optimise the L-PBF using a genetic algorithm technique. The results of this larger ANN training model and the identified optimal processing parameters will be presented during the SIG meeting after the work has been finalised. The current state of the work along with the small error in prediction accuracy point towards a promising direction for the usage of ANN for the process modelling of L-PBF parts. Finally one can conclude that developing of highly accurate predictive models for L-PBF process are important in the context of greater adoption of AM in the manufacturing industry. The application of artificial techniques such as ANN to manufacturing processes have shown much promise to develop precision, quality and predictability.

5. Acknowledgements

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