Application of machine learning methods to improve dimensional accuracy in additive manufacturing

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Abstract. Adoption of additive manufacturing for producing end-use products faces a range of limitations. For instance, quality of AM-fabricated parts varies from run to run and from machine to machine. There is also a lack of standards developed for AM processes. Another limitation is inconsistent dimensional accuracy error, which is often out of the standard tolerancing range. To tackle these challenges, this work aims at predicting scaling ratio for each part separately depending on its placement, orientation and CAD characteristics. Recent attention to machine learning techniques as a tool for data analysis in additive manufacturing shows that such methods as classical artificial neural networks (ANN), such as multi-layer perceptron (MLP), and convolutional neural networks (CNN) have a great potential. For the data collected on polymer powder bed fusion system (EOS P395), MLP outperformed CNN based on accuracy of prediction and mean squared error. The predicted scaling ratio can be used to adjust size of the parts before fabrication.

Keywords: Additive Manufacturing, Artificial Neural Network, Convolutional Neural Network, Deep Learning, Dimensional Accuracy, Machine Learning

1 Introduction

Additive manufacturing is a "process of joining materials to make parts from 3D model data, usually layer upon layer, as opposed to subtractive manufacturing and formative manufacturing methodologies" [1]. There are different types of additive manufacturing processes, categorized after characteristics such as source of energy and type of material. Different AM process categories require optimization of different process parameters. Therefore, AM processes with similar parameters can

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be investigated as one AM group, and results of optimization can be generalized within this group.

Lately, the main attention is set on optimization of additive manufacturing process parameters in order to improve quality of fabricated products. Many studies report that AM is already used to produce end-user products, but quality still remains an issue. For example, dimensional accuracy is still an issue for such AM processes as powder bed fusion AM [2–5]. As compared to the tolerance requirements defined in the DIN 16742:2013 standard [6] for injection molding process, dimensional accuracy error of AM exceeds the defined ranges [4].

Baturynska, I. [4] made an attempt to improve dimensional accuracy by predicting dimensional features (thickness, length and width) based on linear regression. However, just 4 out 12 proposed models (separate models for each dimensional feature and parts' orientation) had accuracy higher than 75%. Based on these results, the author proposed to use more advanced methods for predicting scaling ratio, and hence improving dimensional accuracy. This paper is an extension of the work described in [4], and therefore, more advanced methods are used for data analysis and improvements of dimensional accuracy prediction.

In recent years, machine learning has become a viable option in the additive manufacturing domain as a means for building highly flexible models describing complex relationships between variables. One of the latest reviews on trends of machine learning in additive manufacturing [7] describes five different categories of machine learning application: process parameters, quality enhancement, process monitoring and control, digital security and additive manufacturing in general. The main focus is set on application of ANN, genetic algorithms (GA), support vector machines (SVM). Fewer articles used deep neural networks, principal component analysis (PCA) and particle swarm optimization (PSO) [8–10]. While ANN is used to optimize process parameters, predict mechanical properties and porosity of the object, deep learning techniques were already applied in order "to identify styles of 3D models" based on 2D images rendered from digital 3D models [7].

This paper investigates applicability of two neural network models, namely Multi-layer perceptron (MLP) and Convolution Neural Network(CNN), for predicting scaling ratio for each additively manufactured part separately. The former model constitutes the classical ANN, while the latter is a deep learning model. The chosen techniques are described in Section 3. Comparison of the results of MLP and CNN is done based mean squared error (MSE) and prediction accuracy. As CNN is one of the deep learning models, its performance depends on the amount of training data, but it is less sensitive to noise in data. MLP, on the other hand, is more sensitive to noise, but requires less data for training. Performance of the two chosen methods are compared in Section **Error! Reference source not found.**, and results on scaling ratio prediction are presented in Section 5.

2 Experimental work

In this work, data is collected from the EOS P395 polymer powder bed fusion (PPBF) additive manufacturing process with the material being Polyamide 2200 (PA12). Two identical runs were performed, with 358 samples being fabricated in each build. The build layout is designed in Magics 20.0 software, and is shown in Fig. 1. Each sample is labeled to support identification of each sample after fabrication. More details on the experiment are described in the earlier work [4].

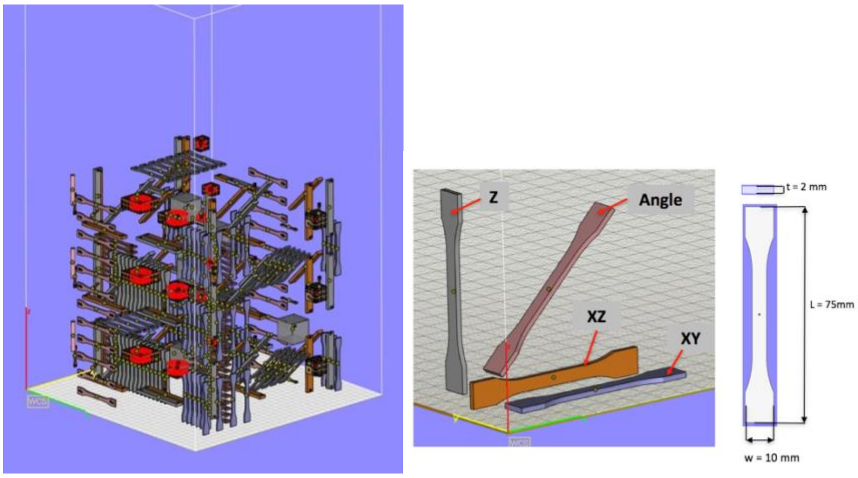

Fig. 1 Placement and orientation of 358 specimens [4]

In order to minimize a dimensional accuracy error for each part separately, scaling ratio for thickness, width and length was calculated as follows:

$$sr_i = y_i - y_i' \qquad (1)$$

where $i \in \{1, 2, 3\}$ (1 stands for thickness, 2 for width and 3 for length), sr_i is a scaling ratio of feature i, y_i is the designed dimension of feature i and y_i' is measured dimension of feature i.

Predicted value for each dimensional feature should be added to the designed value before fabricating it. For more complex design, a different type of scaling ratio should be proposed.

3 Computational intelligence techniques for improvement of dimensional accuracy

3.1 Data pre-processing

Data analysis always requires clean and normalized data beforehand. This step is especially important in case when parameters' values are different. Application of machine learning requires normalization of features in the training data. In this study, an impact of 20 different parameters on three dimensional features (thickness, width and length) are investigated (see Table 1). Part orientation is represented as four different groups, and thus value of this parameter varies from 1 to 4, while value of number of mesh triangles starts at ca. 1200 and increases up to ca. 7000. These ranges in parameters' values has to be scaled to zero mean and unit variance.

Table 1 Description of input and output parameters

Input parameters				Output
cent_coord_X	Orient_Z	min_coord_X	max_coord_X	**Thickness**
cent_coord_Y	Orient_group	min_coord_Y	Num_mesh_trian	
cent_coord_Z	Weight	min_coord_Z	Num_mesh_points	**Width**
Orient_X	Build_numb	max_coord_X	Volume	**Length**
Orient_Y	Shape_group	max_coord_Y	Surface	

The work underlying this paper is based on Scikit-learn and TensorFlow with Keras frontend. The original data is split to training (541 samples) and testing (136 samples) sets using `train_test_split`. Before training the models, the training data is scaled to zero mean and unit variance using `StandardScaler`.

3.2 Multilayer Perceptron

Artificial Neural Networks constitute a class of machine learning models that allows to define complex non-linear relationship between input and output. The core idea behind ANNs is in constructing a complex model as a network of processing functions and learning the parameters of these functions using backpropagation. The latter constitutes a method for computation of gradients of a cost function with respect to functions' parameters by propagating the error back through the network architecture and applying the chain rule for differentiation.

Multilayer Perceptron (MLP) is the classical neural network model, based on a sequence of fully connected layers of neurons, where the lineal layer-to-layer mapping is activated with a non-linear function. In this work, MLP neural network is designed with Scikit-learn. In order to obtain stable prediction every time, MLP architecture was optimized by trial and error approach: different combinations of number of hidden layers and number of nodes in each layer, as well as various available activation functions, has been manually tuned and applied in order to predict scaling ratio of thickness, width and length.

The stability of this neural network was evaluated based on 5 runs given the same architecture but different randomly chosen training and testing sets (Table 2). The final architecture of MLP ANNs consists of one hidden layer with a size of 35 nodes, 20 parameters are used as input and 3 dimensional features as outputs. Rectified Linear Unit (ReLU) activation function is chosen because of best performance.

Table 2 Stability evaluation of Multilayer Perceptron architecture

	Number of runs	MLP performance metrics		MLP number of iterations
		MSE	Accuracy	
	1	0.0006358	0.919135	1131
	2	0.0006402	0.868677	1333
	3	0.0006770	0.839951	1553
	4	0.0007860	0.865166	2271
	5	0.0006876	0.892730	1664
Mean		**0.0006853**	**0.87713**	**1590**

3.3 Convolutional Neural Network

Convolutional Neural Networks are a class of deep neural networks. Their architecture is comprised of a series of convolutional layers, followed by flattening the multi-dimensional output tensor and feeding it to a series of fully-connected layers (the same as in an MLP). The convolutional layers provide space invariance by sliding a filter with shared weights over data. These models are typically used in image recognition, language processing, and similar types of application. The main interest in deep learning techniques is attributed to possibility of ignoring the noise in data, and therefore minimizing time spent on data preprocessing.

Contrary to the traditional use cases, in this paper a CNN is used for regression, and trained with relatively small amount of data. The input data is one dimensional (1D) that was beforehand preprocessed (more details in Section 3.1) The final architecture for Convolutional Neural Network (see Fig. 2) was chosen in the same way as for ANN.

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv1d_1 (Conv1D)            (None, 20, 12)            36
_________________________________________________________________
conv1d_2 (Conv1D)            (None, 20, 12)            300
_________________________________________________________________
max_pooling1d_1 (MaxPooling1 (None, 10, 12)            0
_________________________________________________________________
dropout_1 (Dropout)          (None, 10, 12)            0
_________________________________________________________________
conv1d_3 (Conv1D)            (None, 10, 36)            900
_________________________________________________________________
max_pooling1d_2 (MaxPooling1 (None, 5, 36)             0
_________________________________________________________________
dropout_2 (Dropout)          (None, 5, 36)             0
_________________________________________________________________
conv1d_4 (Conv1D)            (None, 5, 48)             3504
_________________________________________________________________
max_pooling1d_3 (MaxPooling1 (None, 2, 48)             0
_________________________________________________________________
dropout_3 (Dropout)          (None, 2, 48)             0
_________________________________________________________________
flatten_1 (Flatten)          (None, 96)                0
_________________________________________________________________
dense_1 (Dense)              (None, 32)                3104
_________________________________________________________________
dense_2 (Dense)              (None, 3)                 99
=================================================================
Total params: 7,943
Trainable params: 7,943
Non-trainable params: 0
```

Fig. 2 The final architecture of Convolutional Neural Network

CNN model is comprised of four convolutional layers, three max-pooling layers and three dropout layers. The latter are added to prevent overfitting. The output from the last dropout layer is flattened and fed to two fully connected layers. where the first layer is activated with ReLU, and the second one – with softmax. The Adam optimizer were chosen due to its computational efficiency and low memory requirements.

4 Prediction of scaling ratio of dimensional features by using MLP and CNN

Dimensional accuracy error can be caused by different variations in the process, such as temperature distribution in the build chamber. One normally requires deep knowledge of the process and the material in order to mathematically define this phenomenon. Typically, a single scaling ratio is proposed for the whole build chamber or one for each coordinate axis (x, y and z). However, due to different temperature distribution at different places in the build chamber, dimensional error will still be present, especially in the corners (see Fig. 1).

This work applies MLP and CNN to predict scaling ratio for each part separately. Using machine learning techniques allows incorporating any type of relationship between input and output and providing better prediction accuracy with lower mean squared error (MSE). Comparing the performance metrics for MLP and CNN, it is evident that prediction accuracy and MSE are better for MLP. As it is shown in Table 3, the known (measured) values for dimensional features, presented as *Y original*, range between -1.0 and 1.0, and therefore value of MSE should be smaller than 0.001 in order to minimize accuracy error in the future.

Table 3 Prediction of scaling ratio for thickness, width and length using MLP and CNN techniques for a sample of 10 data points from the test set

MLP predicted	Y original	CNN predicted
[0.2289, 0.2626, -0.9517]	[0.218 0.274 -0.95]	[0.2342, 0.4075 , 0.3582]
[-0.1189, 0.1878, 0.1135]	[-0.085 0.249 0.22]	[0.4603, 0.52578, 0.0139]
[-0.0233, 0.1945 0.2757]	[-0.055 0.098 0.28]	[0.1739, 0.4218, 0.4043]
[-0.0115, 0.0163, -0.2164]	[-0.005 0.101 -0.12]	[0.1574, 0.3943, 0.4482]
[-0.0328, -0.1823, 0.1669]	[-0.012 -0.281 0.18]	[0.3194, 0.4055, 0.2749]
[-0.2750, 0.0320, 0.0865]	[-0.279 0.025 0.22]	[0.2845, 0.2184, 0.4972]
[-0.1224, 0.1965, 0.3019]	[-0.075 0.177 0.21]	[0.1976, 0.4104, 0.3920]
[0.1235, 0.1964, 0.3570]	[0.147 0.202 0.34]	[0.1454, 0.4223, 0.4324]
[-0.0796, 0.0938, 0.0186]	[-0.099 0.11 0.06]	[0.2689, 0.3832, 0.3479]
0.0005877	*MSE*	*0.097392*
0.887624	*Accuracy*	*0. 764705*

Although, results for CNN is not as good as for MLP, it is very important to keep in mind that amount of data is an important factor to train deep learning models. As a rule of thumb, the more data is used to train a machine learning model, the better performance it will have. As such, for data set less than 1000 points, CNN results are relatively good, and they can be improved upon in the future when more data from experiments is accumulated.

At the same time, the trained MLP can already be used to predict scaling ratio for dimensional features even considering parts with simple but different shapes. Such industries as automotive, aerospace and medical can already benefit from the results described in this article. Incorporating presented algorithms will allow decreasing dimensional accuracy error, while fully utilizing build chamber space and thus decreasing cost per part in one build.

5 Conclusion

In this work, data was collected from the experiment performed on EOS P395 polymer powder bed fusion process. Two identical runs with the same process, build and material parameters were executed with 358 samples in each run. This data was preprocessed and divided into training and testing samples. As an input for algorithm training, 20 different parameters were chosen and scaling ratios for 3 dimensional features were defined as an output. Two machine learning algorithms were applied for data analysis, and their results were compared based on two metrics (MSE and accuracy).

Multi-layer perceptron outperformed convolutional neural network and should be used in the future in order to minimize dimensional accuracy error. However, results for convolutional neural network show the possibility of using this method in the future after more data is accumulated. Additional experiments with different material, process and build parameters will be beneficial for both the MLP and CNN algorithms.

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