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Artificial Neural Network Based Geometric Compensation for Thermal Deformation in Additive Manufacturing Processes

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Artificial Neural Network Based Geometric Compensation for Thermal Deformation in Additive Manufacturing Processes

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ABSTRACT

Additive manufacturing (AM) processes involve the fabrication of parts in a layer wise manner. The layers of material are deposited using a variety of established methodologies, the most popular of which involve either the use of a powerful laser to sinter/melt successive layers of metal/alloy/polymer powders or, the deposition of layers of polymers through a heated extrusion head at a controlled rate. The thermal nature of these processes coupled with the varying contours of the part at different heights, causes the development of temperature gradients throughout the part and as a result, the part undergoes irregular deformations. These deformations ultimately lead to dimensional inaccuracies in the manufactured part. An Artificial Neural Network (ANN) based methodology is proposed in this research to make the required compensations to the part's geometric design, which will help to counter the thermal deformations in the manufactured part. In this methodology, a feed-forward ANN model is trained using an error backpropagation algorithm to study part deformations resulting in the part during the AM process. The trained network is subsequently implemented on the part Stereolithography (STL) file to effect the required geometrical compensations. Two case studies are presented to illustrate the implementation of the proposed methodology. A novel approach to evaluate the final part profile resulting from the AM process, with respect to the original part CAD model profile has also been developed. This metric is used to quantify the performance of the proposed methodology. The results of the case studies show substantial improvement in the part accuracy and thus validate the ANN based geometric compensation approach.

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1. INTRODUCTION

Additive Manufacturing (AM) technology comprises of several comparable manufacturing processes in which parts are fabricated in a layer wise manner [1]. The layered manufacturing approach allows users to incorporate novel and unconventional features in their part designs, which may be difficult or even unrealistic to manufacture using traditional manufacturing processes. The freedom to manufacture complicated designs with ease, together with the absence of special tooling and reduced assembly requirements have made it one of the most preferred manufacturing process in a several industries, such as toys, electronics, medical equipment, aerospace etc.

Essentially all AM processes follow the same sequence of steps for manufacturing a part. These steps are as listed below:

1. CAD based part design: The digital model of the part or component to be manufactured is designed using a CAD software.

2. STL generation: The CAD model of the part is then converted into the Stereolithographic (STL) file format in which, the geometry of the designed part is approximated using triangular planar facets. The STL file format is globally accepted as the standard design input for AM machines.

3. Input to Machine: The scale, orientation and position of the part in the machine build chamber is then finalized and the file is then input to the machine.

4. Process Parameter Setup: Next, the applicable AM process parameters such as the layer thickness, extrusion head speed, laser power, material constraints etc. are defined by the user.

5. Part Build: The desired part is then manufactured by the machine in a layer wise manner.

6. Part Removal and Post Processing: Once the part is manufactured, it is removed from the build chamber and post-processing operations such as support structure removal, sand blasting, hot isostatic pressing etc. are carried out to clean up the part and mitigate residual stresses.

7. Final Part: The manufactured part is now ready for use.

Figure 1 shows the schematic of the sequence of steps followed by the AM processes of Fused Deposition Modeling (FDM) to manufacture a part.

Figure 1: Schematic of steps involved in Additive Manufacturing

The methodology of material deposition in each layer is used to classify the different types of AM processes. Figure 2 shows a few established AM processes, which are classified based on this scheme.

Figure 2: Classification of AM processes based on material deposition technique

AM processes such as Selective Laser Melting (SLM), Direct Metal Laser Sintering (DMLS) and Selective Laser Sintering (SLS) use a high power laser beam to sinter/melt powdered material in each layer of part. While Rapid Prototyping (RP) or Fused Deposition Modeling (FDM) processes use filaments of material passed through a heated die to deposit the molten material in sequential layers on the build platform. Other AM processes such as 3D Printing and Laminated Object Manufacturing use adhesives to bind together powdered material and metallic sheets respectively to create the layers of the part. The sintered/deposited material adheres to the layer fabricated just before it. Once the current layer of the part has been manufactured, the build platform moves down by the magnitude of the layer thickness specified by the user and the process of material deposition is repeated to fabricate the next layer of the part. This process is repeated

several times during the manufacturing process depending on the number of 2D slice contours generated from the CAD model. **Error! Reference source not found.** [2] and **Error! Reference source not found.** [3] show the schematic setups of the Fused Deposition Modeling and Selective

Figure 3: Schematic of the Fused Deposition Modeling process [2]

Laser Sintering processes respectively.

Figure 4: Schematic of the Selective Laser Sintering process [3]

1.1 Motivation of Research

Over the last decade, AM processes have grown in popularity by several folds in the industry. With the advancements made, both in terms of materials and machines, the capabilities of manufacturing complex and non-conventional designs with AM have become ever more superior. As a result, AM is increasingly being adopted as the primary manufacturing process for fabricating highly precise and critical components, such as aerospace parts and biomedical implants.

However, two of the major limitations associated with AM are the thermal distortions and part shrinkage observed in the manufactured parts. These deformations result primarily because of the constant heating and cooling cycles undergone by the material during the manufacturing process. These can result in severe dimensional inaccuracies and may even hinder the functionality of the manufactured component.

It thus becomes imperative, to consider these thermal effects during the design and preprocessing stages of manufacturing the parts. AM practitioners usually implement a global scaling to the part and/or make manual local modifications to the part geometry, in order to counteract the shrinkage and thermal deformations, respectively. However, currently they rely on their experience and intuition while making these modifications in the part's design. As a result, they often require several trial and error runs of manufacturing the part with the manual modifications before being able to manufacture a part of acceptable quality.

The motivation of this research, was thus to develop an intelligent and more methodological approach towards making the required geometric compensations in an AM part to counteract the shrinkage and deformations resulting from the thermal nature of AM processes.

1.2 Objective and Impact of Research

The heating and cooling of the material in the same layer is often uneven, and is governed in principal by the laser scan/material deposition pattern [4-7]. The cumulative effect of the resulting temperature differences over all the slices of material in the manufactured parts results in anisotropic shrinkage and deformation of the part. As emphasized earlier these thermal deformations cause significant dimensional inaccuracies and often impede the functionality of the part.

Thus, the objective of this research was the development of an automated and intelligent methodology of implementing compensations to a part's design in order to counteract the thermal deformations resulting in the part during the AM process. An Artificial Neural Network (ANN) based approach has been proposed to realize this objective. An established thermo-mechanical AM simulation model from literature was used in this research to simulate the Direct Metal Laser Sintering process of a part. The novel ANN based compensation methodology proposed in this research, was then implemented on the part deformation data acquired from the AM simulation.

The proposed compensation methodology uses a feed-forward ANN trained using back-propagation algorithm to study the geometric data of the original part and the final prototype of the part resulting from the simulation, to learn the differences between the two. The trained network was then used to make the required modifications directly to the part geometry, so that manufacturing the part using the modified geometry counteracts the thermal effects of the process and results in a dimensionally accurate finished product.

Thus, the implementation of the developed ANN based automated geometric compensation approach significantly reduces the number of design and manufacturing iterations required to

ensure the manufacturing of a dimensionally accurate and functional part. **Error! Reference source not found.** shows the implementation process of the ANN based geometric compensation for an example part to be manufactured using AM.

Figure 5: Implementation process flow of the ANN based geometric compensation approach

1.3 Thesis Outline

This research has been divided into five chapters. Chapter 1 presented an introduction to Additive Manufacturing processes. In addition, the motivation, objective and expected impact of this research work was also outlined. Chapter 2 discusses some of the recent research work on the factors affecting thermal deformations of parts in AM processes and approaches developed to compensate for these effects. Chapter 3 presents a comprehensive description of the proposed ANN based geometry compensation methodology. This chapter also describes the developed part profile conformity based performance evaluation metric, which was eventually used to quantify the performance of the proposed methodology. Chapter 4 presents two case studies to show the application and evaluation of the proposed ANN based compensation methodology. The

conclusions derived from the results of the case studies and the scope of future work in this field are presented in Chapter 5.

2. LITERATURE REVIEW

The shrinkage and deformations resulting in an AM part due to the cyclic melting and re-solidification of the material have a significant impact on the part dimensional accuracy, part strength and by extension, on the usability of the final product. As a result, this subject has generated a lot of research interest in the AM community. The current chapter presents a detailed review of the available literature on the topic of thermal deformations resulting from AM processes. The review is divided into three sub-sections, (i) effect of process parameters on thermal deformations in AM, (ii) development of computational models for simulating the AM process and (iii) compensation methodologies established to counteract the thermal deformations.

2.1 Effects of AM Processes Parameters on Thermal Deformation of Parts

Process parameters are of primary importance for all manufacturing processes as they have a significant impact on the quality of parts being manufactured and the success of the manufacturing process as a whole. In AM processes, some of the process parameters governing the part quality and its manufacturability are the build orientation, slice thickness and laser scan speed/ material deposition rate [1]. From the perspective of thermal deformations and part shrinkage, parameters such as the scan pattern, raster lengths and microstructure of material used are found to be the most important [8-10]. As a result, several researchers have investigated the impact of these parameters on the manufactured part and reported their findings in literature.

Pohl et al. [8] used the DMLS process to manufacture sample flat plates to study the effect of parameters such as the laser scan pattern, and input energy on the development of residual stresses in the part. It was found that using shorter scan lengths to manufacture the layers of the part significantly reduced the resulting deformation. Zhu et al. [9] investigated the shrinkage

observed during the SLS process for Cu based metal powder. The shrinkage performance was analyzed for four variants of Cu powder, by varying the laser power, scan speed, scan spacing and the slice thickness sequentially one at a time. The shrinkage observed was anisotropic and its largest magnitude was along the z-axis (build direction). Ning et al. [10] investigated the effect of geometric shapes on the part shrinkage during DMLS process; and proposed a compensation approach by dynamic adjustment of laser scan speed based on part geometry.

2.2 Development of Computational Models for Simulating the AM Process

A significant amount of research effort has also focused on the development of computational models to simulate AM processes with the objective of predicting and analyzing the thermal stresses induced in the part during manufacturing. Wang and Kruth [11] developed an analytical model based on ray tracing approach to simulate the absorption and penetration of input laser energy during the SLS process of Fe-Cu powder mixture. This model was also employed by Wang et al. [12] to study the SLS of WC-Co hard metal powders. Matsumoto et al. [13] developed a finite element method for analyzing temperature distribution and thermal stresses distribution within a single metallic layer manufactured using SLS process. Jamshidinia et al. [14] developed and used a 3D model to simulate thermal fluid flow to investigate the melt pool geometry and temperature distribution in Electron Beam Melting (EBM) process. Roberts [15] developed a comprehensive FEA based model to simulate and study thermal stresses and resulting deformations in metal powder melting based AM processes. Paul and Anand [16] used an analytical method to evaluate the effect of part shrinkage on the form error during AM processes. Paul et al. [17] developed a thermo-mechanical FEA model to simulate the AM process and

investigate part thermal deformation based on process parameters such as material properties, slice thickness, scanning speed and part build orientation.

2.3 Previous Thermal Compensation Approaches for AM Processes

Over the years, several geometric compensation methodologies have also been developed to counteract the shrinkage and the thermal deformations resulting from the thermal effects of the AM processes. Tong et al. [18, 19] developed STL and slice based, compensation approaches for machine/geometric errors in parts fabricated using Rapid Prototyping process. Raghunath et al. [20] studied the impact of different process parameters on part shrinkage during SLS process, and used Taguchi method to develop scaling models along x, y and z directions to compensate for the shrinkage. Huang et al. [21, 22] investigated the offline shape-shrinkage compensation for the individual layer contours using a statistical approach. Wang et al. [23] reported a Neural Network based approach for establishing the relation between AM process parameters and shrinkage ratio for parts fabricated using SLS. Senthilkumaran et al. [24] proposed a part geometry and beam offset based shrinkage model and a CAD slice contour shrinkage compensation approach for polymer parts manufactured using SLS.

All the compensation approaches mentioned above counteracted the shrinkage and thermal deformation of the manufactured parts by identifying and implementing a global scaling factor for the part design and by implementing a single-plane slice contour compensation approach respectively. However, the shrinkage and deformations resulting in the part during the AM process, as established in the previous sections, are highly anisotropic. As a result, by implementation of these compensation approaches, the localized shrinkage and out of plane deformations in the manufactured part are not accounted for. Thus, there is a need for a more

robust compensation methodology to counteract these defects. The ANN based geometric compensation methodology proposed in this research is unique in this regard, since it implements a feed-forward neural network model to study the geometric difference between the part resulting from the AM process simulation and its original design. The trained network also implements the appropriate geometric compensations to the part's geometry in a localized manner, thereby ensuring the manufacturing of a dimensionally accurate part.

3. METHODOLOGY

This chapter elaborates on the proposed methodology of using an ANN model for making direct modifications to the geometry of a given part CAD model. The applied geometric modifications help compensate for thermal shrinkage and deformations during the AM process. Figure 6 shows the schematic overview of the compensation methodology.

Figure 6: Methodology for ANN based geometric compensation approach for AM processes

The process begins with modeling a part in any available CAD software. A thermo-mechanical FEA model was then used to simulate the AM process for the part with a defined set of process parameters. The simulation returns the part deformation data as its output. The part surface data prior to and post deformation, resulting from the AM process simulation was used to create the datasets for the ANN model training. This surface data was then used by the ANN model to train on/learn the direction and magnitude of deformation at different regions of the part. The learning process for the network is equivalent to the approximation of a deformation function for the part under consideration.

The trained network was then applied on the part STL to generate the compensated STL geometry, which would compensate for the thermal effects induced in the part during the AM process. The AM process simulation was repeated for the modified geometry and the result of the simulation was used to quantify and evaluate the performance of the proposed method in reducing the thermal deformation and shrinkage of the part.

The subsections of this chapter are organized as follows: First, the thermo-mechanical simulation model of the AM process used to generate the part deformation data is discussed. This part deformation data was used to create training data for the ANN. Next, a brief introduction to ANNs, the implemented feed-forward ANN architecture and the network training methodology is presented. This is followed by the explanation of the ANN training methodology on the part thermal deformation data obtained from the AM process simulation. Following which, the method of implementing the trained network to make geometric compensations to the part is presented. Finally, the novel metric developed to evaluate the geometric errors in the manufactured part with respect to the original CAD model is described in detail.

3.1 Surface Data Generation Using a Finite Element Thermo-Mechanical Model

The first step of the proposed geometry compensation methodology is to create datasets to train the defined ANN model. Since point cloud data is considered one of the most primitive and closest representation of a 3D geometry, it serves as an efficient means for studying the part deformations and shrinkage due to thermal effects of the AM process. As a result, it was decided to use the point cloud representation of the part, as training data for the ANN model.

In this approach, the 3D thermo-mechanical finite element model developed by Paul et al. [17] was implemented using ANSYS as the FE solver. The model was used to simulate the laser sintering of Ti6Al4V powder for generating the required surface data for the manufactured part. The FE model uses the element birth and death technique, for simulating the creation of layers of solid material during the AM process [15, 25]. The model operates in two sequential steps:

- (i) In the first step, the temperature history and thermal gradients across all layers are calculated.
- (ii) In the second step, the information from step (i) is used to determine the overall deformation induced in the part.

Figure 7 shows the comparison of the original geometry of Example Part 1 and the deformed geometry after the execution of the thermo-mechanical model. The 3D point location co-ordinates of the part nodes defined by ANSYS before and after the simulation were used as the required input training datasets for the ANN model.

Figure 7: Comparison of the CAD geometry and the deformation resulting from the AM process

3.2 The ANN Model Architecture

Artificial Neural Networks [26] refers to a group of advanced mathematical modeling tools, which have been proven to be capable of approximating any function from given set of input observations. These bionic models were inspired by the functioning of the central nervous system of living organisms. They are widely used in applications like regression analysis, classification, pattern recognition, control systems etc. The uniqueness of these models is their capability to learn from data. ANNs are generally represented as a set of interconnected functional nodes or neurons, which are capable of exchanging data between themselves through weighted connections. These weights are continuously evaluated and updated, as the data instances are input to the network, and this process is called network training. This makes the network mesh adaptive to the input data and thus imparts a learning-from-data capability to the model. Based on the defined network architecture and application requirement, there exists a wide variety of ANN models.

For application of ANN intelligence in the proposed geometric compensation application, a feed-forward neural network model was selected. The architecture of a generic feed-forward ANN model is as shown in Figure 8. The neurons are arranged in sequential layers. The first layer is the input layer, followed by one or more hidden layers and the final layer is the output layer. Input data instances are presented sequentially to the network at the input nodes following which, it is transferred from one layer of functional nodes to another through the weighted inter-nodal connections.

Figure 8: Schematic representation of a feed forward ANN model

There are several learning or training techniques currently being used for training different ANN models. The Error Backpropagation algorithm [27] is one of the most commonly used network-training approaches for ANNs. The objective of this algorithm is to minimize the error between the desired output and the required output of the network. This is accomplished by back propagating the errors from the output layer to the hidden layers and subsequently making the

required adjustments to the inter-nodal weights. The training methodologies also combines the ANN training together with an optimization routine such as the steepest descent method [28] to speed up the convergence of the network output towards the optimal solution.

The MATLAB Neural Network Toolbox [29] was used to simulate the experiments for the designed ANN model. The toolbox uses Levenberg-Marquardt [30] variant of the Error Backpropagation Algorithm for training the feed-forward network, which carries out the network training in conjunction with two optimization routines: the Steepest Descent [28] and the Gauss-Newton algorithms [31].

Trials were carried out to determine the optimal network architecture to be used for the ANN based geometric compensation methodology. The number of hidden layers and the number of neurons in each hidden layer were varied over three trials and the average mean squared error between the actual and desired outputs of the network and computational time needed for the network training were recorded. The trial results for the point cloud data from Example Part 1 is shown Table 1. The trials were carried out on a PC with Intel Core i7 Processor with 8 GB RAM. It was observed that the mean squared error reduces with an increase in the number of hidden layers and the number of neurons in each layer. However, there was a significant increase in the computational time with every increase in number of hidden layers and number of neurons in each hidden layer. Thus, the final network architecture selected for the proposed geometry compensation ANN model is as shown in Figure 9. It consists of an input layer with three input nodes, a hidden layer with fifteen neurons and an output layer with three neurons. The selected architecture was able to keep the mean squared error between the desired output and the actual output of the network within an acceptable range at a relatively inexpensive computational time cost.

Table 1 : ANN Architecture Trial Results

Network Architecture	Average Mean Squared Error (3 Trials)	Average Computational Time in Seconds (3 Trials)
1 Hidden Layer, 10 Neurons	1.25E-04	130
1 Hidden Layer, 15 Neurons	7.24E-05	175
1 Hidden Layer, 20 Neurons	4.71E-05	296
2 Hidden Layer, 10 Neurons	4.53E-05	290
2 Hidden Layer, 15 Neurons	2.27E-05	457
2 Hidden Layer, 20 Neurons	1.54E-05	582
3 Hidden Layer, 10 Neurons	2.89E-05	475
3 Hidden Layer, 15 Neurons	2.09E-05	587
3 Hidden Layer, 20 Neurons	1.12E-05	641

3.3 Network Training

Once the 3D co-ordinates of the nodes and the deformed nodes are obtained from the FE model, the ANN model training process was started. Considering the case of a single node defined on the part. Let $[x \ y \ z]$ be its 3D co-ordinate, and $[x' \ y' \ z']$ be the co-ordinates of the same node in its deformed state. The deformed node location, $[x' \ y' \ z']$ was presented as input to the network and at the same time, the original node location $[x \ y \ z]$ was presented to the network as the desired output for the given input data. The input data was transferred sequentially from the input nodes to the hidden layer neurons and finally to the output neurons through the weighted inter-nodal connections.

The output of the network was evaluated, and the weights of the inter-nodal connections were updated based on the difference in the desired and the actual output of the network for the given input point location. In this manner, all the nodes defined by ANSYS were evaluated sequentially and the training process was iterated until the network has minimized the mean squared error of the network outputs or a maximum number of iterations, set to 1000, was completed. The main objective of this approach was to train the ANN efficiently such that it can model the part deformation data as a function of the point location in the 3D co-ordinate space. Figure 9 shows the complete set up for training the designed ANN model. Figure 10 shows the regression plot of the ANN model training process. It was observed that the trained network is able to fit the geometric deformation data of the given part geometry as a function of surface point locations very accurately.

Figure 9: Architecture of the feed-forward ANN model to be used for geometric compensation

Figure 10: Regression Plot of the ANN training process performance for Example Part 1

3.4 CAD Geometry Compensation

After the network training was completed, the next step in the geometry compensation approach is to implement the trained network to deliver a compensated design of the part. The compensated design after AM would result in a finished part that is dimensionally accurate and conforms to the original CAD design of the part. AM machines in general, use the STL format of part CAD designs as input for manufacturing. The STL format is a close representation of the CAD surfaces using planar triangular facets.

Thus, to obtain a compensated part design that is ready for processing by AM machines, the trained ANN model network was applied on the vertices of the part STL facets. The 3D co-ordinates of the STL vertices were sequentially input into the trained network. The network then processed the input data using the optimal weights determined from the ANN training process. This procedure results in the compensated 3D co-ordinate location for each STL vertex. The *stlwrite* MATLAB function [32] was used to finally bring together the compensated STL vertices

and output the complete STL model of the compensated geometry. The *stlwrite* function takes the compensated STL vertices and generates a valid error free STL file. Figure 11 shows the implementation schematic of the trained ANN based CAD geometry compensation methodology.

Figure 11: Schematic of compensated STL file generation using trained ANN model

3.5 Point Cloud to Part Conformity Score

To evaluate the performance of the compensation methodology, the conformity of the part profiles resulting from the FE simulations were compared with that of the actual CAD model. For this process, a novel point cloud data based conformity metric is defined in this section. The schematic of the performance evaluation process is shown in Figure 12. First, points were discretized on the CAD model surface. This point cloud serves as the reference against which the manufactured part profiles will be compared. An NX Open API application in Siemens NX 8.5 was used to discretize points on the CAD surface. The application was used to identify all the surfaces for the given part within the CAD environment, after which points were uniformly discretized on each surface patch. The manufactured part profiles were represented by the

deformed/compensated surface nodes resulting from the FE model based simulations of the AM process.

The second step in the evaluation process is the registration of each of the two sets of manufactured point cloud data (deformed and compensated nodes) with the CAD surface point cloud. The registration was carried out in two sequential sub-steps:

- (i) Point cloud data alignment using a classical user defined marker based approach. The open source mesh-processing tool – Mesh Lab [33] was used for this process;
- (ii) Fine registration of the point cloud data using Iterative Closest Point Algorithm [34].

Figure 12: Schematic of Point Cloud to Part Conformity Score calculation methodology

Next, a design space was defined by considering a bounding box for the CAD surface point cloud. This design space serves as the common base for the conformity evaluation for all three sets of point cloud data and thus, the extremities of the bounding box were extended by a user-defined tolerance to account for the part deformations. The design space was then divided into a user defined three-dimensional grid specified by the number of cells along x, y and z-axes. The cells were assigned cell IDs depending on their position in the design space along x, y and z directions. For example, the cell at the minimum x, y and z positions was assigned the cell ID of [1, 1, 1]. Rest of the cell IDs were assigned relative to this cell. The CAD surface points were then introduced in this design space and the cell IDs of the cells filled by one or more of the CAD surface points were extracted. Next, the deformed and the compensated nodes were introduced sequentially into the design space and the cell IDs filled by both separate sets of point cloud data were determined. The final step is to compare the similarity of cell IDs filled by both the CAD surface points and the deformed/compensated point clouds. Based on this comparison, each point cloud set is given a point cloud to part profile conformity score (CS) on a 1 to 100 scale as follows,

$$CS_{deformed} = \left(\frac{N_{d-CAD}}{N_{CAD}} \right) \times 100 \quad (1)$$

and

$$CS_{compensated} = \left(\frac{N_{c-CAD}}{N_{CAD}} \right) \times 100 \quad (2)$$

where $CS_{deformed}$ and $CS_{compensated}$ are the compensation scores for the deformed and the compensated surfaces respectively. N_{d-CAD} and N_{c-CAD} are the number of filled cells IDs common for the CAD surface points with the deformed and compensated surface points respectively, and N_{CAD} are the number of cells filled by the CAD surface points.

Next, the reduction of conformity error due to compensation was determined. The error (ε) in conformity to CAD surface for the deformed and compensated point cloud was respectively calculated as,

$$\varepsilon_{deformed} = 100 - CS_{deformed} \quad (3)$$

and

$$\varepsilon_{compensated} = 100 - CS_{compensated} \quad (4)$$

The percentage reduction ($\Delta\varepsilon$) in conformity error was then calculated as,

$$\Delta\varepsilon = \left(\frac{\varepsilon_{deformed} - \varepsilon_{compensated}}{\varepsilon_{deformed}} \right) \times 100 \quad (5)$$

4. CASE STUDIES AND RESULTS

The proposed ANN model for geometry compensation was tested on two sample parts and the results obtained from these tests are presented in this section.

4.1 Example 1

An engineering bracket was chosen as the part to be studied for Example 1 as shown in Figure 13. The dimension of the given part along x, y and z-axes is 14.4mm x 10.9 mm x 4.50mm. The maximum deviation observed for the given part after simulating the AM process using the FE model was 0.81 mm.

Figure 13: CAD model of the bracket used for Example 1

Figure 14(i) shows the deformed part geometry resulting from the AM process simulation using the FE model. Figure 14(ii) compares the deformed part nodes with the designed CAD model surface points.

Figure 14: (i) Results of the AM process simulation with the original geometry of the Example Part 1; (ii) Comparison of the part resulting from the AM process simulation (red) and the original geometry (blue)

Figure 15 shows the compensated STL resulting from the ANN based geometry compensation methodology. Figure 16(i) shows the part geometry resulting from the FE thermal model using the compensated geometry. Figure 16(ii) shows the comparison between the nodes resulting from the AM simulation using the compensated STL and the CAD surface points.

The point cloud to part conformity evaluation described above was used to evaluate the performance of the compensation model, and it was found that the pre-compensation conformity score of the deformed nodes for Example Part 1 was 75.70, while post compensation the conformity score increased to 91.25. These conformity scores translate to a reduction in conformity error by 63.99%.

Figure 15: Compensated STL file for Example Part 1 generated using the ANN based geometric compensation approach

Figure 16: (i) Results of the AM process simulation with the compensated geometry of Example Part 1; (ii) Comparison of the part resulting from the AM process simulation (green) and the original geometry (blue)

4.2 Example 2

The flange shown in Figure 17 was selected as the sample part to be studied for Example 2. The dimension for the given part along x, y and z-axes is 19 mm x 7.5mm x 19mm and the maximum deviation was found to be 0.51mm.

Figure 17: CAD model of the flange used in Example 2

Figure 18 (i) shows the deformed part geometry resulting from the FE model. Figure 18 (ii) shows the comparison of the deformed part geometry resulting from the AM simulation and the CAD surface points the given for part geometry.

(i)

(ii)

Figure 18: (i) Results of the AM process simulation with the original geometry of Example Part 2; (ii) Comparison of the part resulting from the AM process simulation (red) and the original geometry (blue)

The ANN geometry compensation model was used to generate the compensated STL as shown in Figure 19. The geometry resulting from the FE model using the compensated STL is shown in Figure 20 (i). The comparison between the compensated nodes resulting from the AM simulation and the CAD surface points is as shown in Figure 20 (ii).

Figure 19: Compensated STL for Example Part 2 resulting from the ANN based geometric compensation approach

Figure 20: (i) Results of the AM process simulation with the compensated geometry of Example Part 2; (ii) Comparison of the part resulting from the AM process simulation (green) and the original geometry (blue)

Next, the previously described point cloud to part-conformity evaluation methodology to evaluate the performance of the compensation model was applied. It was found that the pre-compensation conformity score of the deformed nodes with the part was 81.45 while post compensation the conformity score increased to 92.37. Thus, the reduction in conformity error for this part was determined to be 58.86%.

5. FUTURE WORK AND CONCLUSIONS

5.1 Future Scope

As shown in the previous chapter, the ANN based geometric compensation approach successfully made the required changes to the part geometry in order to counteract the shrinkage and deformation effects of the AM processes. The significant reduction in the conformity errors for the two case studies also validate the performance of this approach. The next logical step in advancing this research is to use real world manufacturing data to train the ANN model for the required geometric compensation. This would involve defining a set of AM process parameters to be used in manufacturing a part, followed by actually manufacturing the part with these defined parameters. The part shrinkage and deformation data can be acquired by using a high precision laser scanner to scan the manufactured part's geometry.

In this regard, a third case study was conducted to test the performance of the ANN based geometric compensation approach, by using real world manufacturing data. Figure 21 shows the turbine blade design used for this case study.

Figure 21: CAD model of the Turbine blade

This part was manufactured using a predefined set of process parameters by the Direct Metal Laser Sintering process. The manufactured part geometry was then scanned using a laser scanner and points were extracted from the surface of the CAD model using an NX Open API application. These two point clouds were used to create the training datasets for the ANN based geometric compensation approach. Figure 22 (i) and (ii) show the surface points from the CAD model surface and the surface points obtained from the manufactured part surface using a laser scanner, respectively.

Figure 22: (i) Points discretized on the surface of the CAD model of the turbine blade; (ii) Points extracted from the surface of the manufactured part using a laser scanner

As evident from Figure 22, there was a significant difference between the densities of the two point clouds. Therefore, only those regions of the part where surface data could be acquired both from the CAD model and from the laser scan data of the manufactured part were used to create the training datasets for the ANN model to be used for implementing the geometric compensations. These regions were isolated using voxels and are presented in Figure 23. An

approximation methodology was then used to correlate data points from the two point clouds in order to create the training data set for the ANN model. Specifically, the centroid of the points within a considered voxel from the first point cloud was associated with the centroid of the corresponding points within the same voxel for the second point cloud.

Figure 23: Regions of the geometry to be considered for ANN training

Using the points from the two point clouds pertaining to these regions of the geometry, a feed-forward ANN model was trained to learn the shrinkage and deformations in the manufactured part. The trained network was then implemented on the original CAD model's STL file to generate the compensated STL model, as shown in Figure 24.

Figure 24: Compensated STL file for the Turbine Blade generated using the ANN based geometric compensation approach.

The compensated STL file was then used to manufacture the turbine blade with the pre-defined set of process parameters. The manufactured part was scanned using a laser scanner and the surface data extracted is shown in Figure 25.

To evaluate the performance of the ANN based geometric compensation approach, the point clouds from the laser scans of the part with and without compensation were evaluated one at a time with respect to the point cloud extracted from the surface of the CAD model. The root mean squared (RMS) error was used as the metric to compare the similarity of the point clouds from the CAD model and the manufactured part laser scans. The results from the evaluation are presented below in Table 2.

Figure 25: Points acquired from the surface of the manufactured part after compensation was implemented

Table 2: Performance evaluation of the ANN based compensation for the Turbine Blade

Pre-Compensation RMS error	0.0105295 in
Post Compensation RMS error	0.0086708 in
Reduction in RMS error	17.65%

As seen from Table 2, the implementation of the ANN based geometric compensation methodology showed a 17.65% reduction in the RMS error between the point clouds sampled from the surfaces of the CAD model and the manufactured part. The results of this experimental case

study present a successful proof-of-concept for the implementation of the ANN based geometric compensation methodology on real world manufacturing data.

5.2 Conclusions Derived from the Research

An Artificial Neural Network (ANN) based geometry compensation methodology was proposed in this research for counter-acting the thermal deformations in AM parts, resulting from the temperature gradients caused during the AM process. The methodology uses a feed forward neural network trained using the error back propagation technique. Surface data from the CAD model of the part and the manufactured part surface form the input data for the ANN model. An established FE model was used to simulate the deformations in the AM part and thus helps generate the surface data for the manufactured part surface data. The trained network was then used on the STL file of the part CAD model to impart the required geometrical compensations to the part design. A new point cloud based part conformity metric was also presented to evaluate and quantify the performance of the proposed compensation methodology. Tests were carried out on two sample parts and a significant reduction has been recorded in the error in manufactured parts' conformity to the CAD design, thereby confirming the successful use of the defined ANN model for direct geometry correction to counter thermal deformations in AM parts. The proposed ANN based geometry compensation methodology serves as an efficient complementary tool to all the FE based thermal deformation prediction models for AM processes available in literature.

An experimental case study to validate the performance of the ANN based geometric compensation methodology was also presented. The experimental case study used surface data from the CAD model and its manufactured prototype extracted using 3D scanning techniques to generate the training dataset for the ANN model. The implementation of the ANN based geometric

compensation methodology with real world manufacturing data provided a successful proof-of-concept of the developed methodology.

Additional steps are required to further improve the methodology and make it more robust for implementation with real world manufacturing data. A few possible steps in this direction could involve (i) removal of noise from the 3D scanned point cloud data, (ii) better registration of the scanned point cloud with the CAD surface point cloud to ensure accurate comparison of deformation data and (iii) matching of individual points in the two-point cloud data sets. However, at this stage, the matching of point cloud data from the CAD model surface and the 3D scan of the manufactured part, which serves as the input data for the ANN model, presents an open and non-trivial problem to be resolved. Other potential areas of improvement could be the refinement of the proposed ANN model architecture or even the use of other established ANN models.

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