# Warpage Deformation Prediction and Optimization in Fused Deposition Modeling Using a Hybrid FFNN and PSO Approach

1st AmirPouya Masoumi
*MISHE Research centre*
*Atlantic Technological University*
*Sligo, Ireland*

2nd Ramen Ghosh
*MISHE Research centre*
*Atlantic Technological University*
*Sligo, Ireland*

3rd Anto Antony Samy
*Engineering Research Institute*
*Ulster University*
*Belfast, UK*

4th Atefeh Golbang
*Engineering Research Institute*
*Ulster University*
*Belfast, UK*

5th Gavin Walker
*Pharmaceutical Manufacturing*
*Technology Centre (PMTC),*
*University of Limerick*
*Limerick, Ireland*

6th Rabah Mouras
*Pharmaceutical Manufacturing*
*Technology Centre (PMTC),*
*University of Limerick*
*Limerick, Ireland*

7th Marion McAfee
*MISHE Research centre*
*Atlantic Technological University*
*Sligo, Ireland*

***Abstract*—Fused deposition modelling (FDM) is a versatile additive manufacturing technique involving extruding thermoplastic polymers layer by layer. FDM enables the fabrication of complex geometries, however prediction and minimization of warpage deformation is critical for high-precision applications such as medical implants. Simulations based on finite element analysis (FEA) have been shown to accurately predict warpage deformation in FDM; however, this approach is computationally intensive and has limitations for process optimisation and monitoring. In this study, a feed-forward neural network (FFNN) model was trained using deformation values from FEA simulations. Input features included nozzle temperature, material deposition rate, bed temperature, layer height, layer number, and spatial coordinates, while warpage deformation served as the output. The trained FFNN was then combined with the particle swarm optimization (PSO) algorithm to find the optimal FDM parameters to minimize the warpage deformation. The combination of a trained FFNN based on FEA with PSO identified optimal FDM parameters, producing a minimum warpage deformation of 0.062 mm. The proposed PSO–FFNN approach demonstrates the feasibility of using machine learning and metaheuristic algorithms to minimize warpage defects in additive manufacturing while reducing computational cost and computation time.**

***Index Terms*—Additive manufacturing; Fused deposition modeling; Warpage deformation; Feed forward neural network; Particle swarm optimization algorithm**

## I. Introduction

Fused Deposition Modeling (FDM) is an additive manufacturing technique that fabricates three-dimensional objects by melting and extruding thermoplastic filaments in a layer-by-layer manner. FDM is widely recognized for its cost-effectiveness, design flexibility, and ease of use. However, despite these advantages, the process has several challenges that can affect mechanical performance, dimensional accuracy, and surface quality of printed parts. Typical issues such as warpage deformation, residual stresses, and geometric inaccuracies often arise from an inappropriate selection of FDM parameters and uneven cooling conditions. To address these challenges, different approaches have been used, including experimental studies, defect detection and classification using deep learning, and use of finite element analysis (FEA) and/or data-driven modelling techniques to predict significant process responses, such as warpage, transient temperature, and mechanical defects. These predictive frameworks provide valuable insight into the complex thermo-mechanical behaviour of FDM and enable process optimization for improved part quality.

Alafaghani et al. [1] optimized FDM parameters to improve dimensional accuracy through an experimental study varying build direction, extrusion temperature, layer height, infill pattern, infill percentage, and print speed. Dimensional accuracy was primarily affected by build direction, nozzle temperature, and layer height, while the other parameters had minor effects. Optimal accuracy was achieved by aligning critical dimensions parallel to the layer orientation, reducing the extrusion temperature to lower thermal distortion, and using smaller layer heights for finer resolutions. A drawback of experimental analysis and optimisation however, is the time_consuming nature of experimentation and the labor_intensive characterisation of microscale defects using contact metrology. As a time-saving solution to defect detection, Bhandarkar et al. [3] utilized convolutional neural networks with camera images to detect warpage defects in polymer parts produced by additive manufacturing. To achieve real-time defect detection, a high-quality camera and an LED lighting setup were used to capture images of printed specimens. The captured images were categorized into warped and unwarped classes to train the convolutional neural network(CNN). The proposed CNN model achieved an accuracy of 99.43% in distinguishing warped from unwarped components. Brion et al. [4] developed a hybrid method for automated detection and correction of warpage deformation in extrusion-based additive manufacturing. The study addressed the problem of residual stresses that cause part distortion and are difficult to prevent due to their delayed manifestation during the printing process. A CNN based on the YOLOv3 architecture was trained on a labelled dataset to detect warp deformation. The model achieved a mean average precision of 88.72% in detecting and localizing warp features. A limitation of the defect detection approaches above, is that they cannot prevent the defect from occuring, and there is no feedback on how to correct the process. On the other hand, using a model based on FEA can minimize experimental expenses and provide diverse mechanical datasets for training data-driven models in order to optimise process parameters prior to printing. For example, [10] minimized FDM warpage deformation using a combined FEA–Taguchi approach to identify key process parameters. Layer thickness and bed temperature were found to be significant factors, contributing about 35% and 40% to total variation, respectively.

However, FEA is a computationally expensive approach, with calculations taking several hours to days depending on the FEA parameters, such as the number of nodes and elements [8]. To address this issue, machine learning and deep learning algorithms based on FEA can be used to reduce computation costs and provide a fast response model for predicting mechanical features [11] [5]. Feng et al. [7] addressed warpage and residual stress in PEEK FDM parts that were caused by thermal gradients using an XGBoost-based surrogate model for FEA simulations. They found that nozzle temperature and infill density had minimal effects on warpage, whereas higher bed temperatures slightly increased residual stress. The speed of the nozzle exhibited a strong non-linear influence and was identified as the most significant factor affecting warpage deformation. The authors did not investigate the application of the XGBoost surrogate model for optimisation of the process. Further, the authors concentrated on prediction of maximum warpage, whereas for many industrial parts the tolerances may be more precise in some critical regions which are not captured by such an approach. Bai et al [2] used deep reinforcement learning based on FEA with for optimizing printing paths in selective laser melting. The approach improved path-generation efficiency by 99.8%, reduced deformation by 64.0%, and reduced stress by 21.8% compared to the traditional raster path, and outperformed other methods such as the genetic-algorithm path and the zigzag path. They did not examine the effects of other process settings on the deformation and residual stress.

Despite previous research efforts, minimising warpage defects in FDM remains time consuming and challenging. The combination of FEA with data-driven approaches is promising for reducing the computational cost of modelling the effect of different process parameters, however the ability to predict 3D warpage deformation in different regions of the part, and identifying the conditions which minimise warpage throughput the part is not yet fully explored. Therefore, this study aims to introduce a data-driven approach based on FEA simulations to predict warpage deformation in 3-dimensional areas of the part that are more prone to warping. Further, this data-driven surrogate model is applied in an optimisation algorithm to identify the process parameters leading to minimal warpage deformation throughout the entire part.

Section II is devoted to introducing FEA, FFNN, and PSO algorithms, which played a significant role in this study's simulation, prediction, and optimization of warpage deformation. In Section III, the geometry and key FDM parameters are discussed, followed by comparisons between various features of the FFNN model used in this research. Finally, the main findings will be presented in Section IV.

## II. Modelling and Optimization Approach

FEA is a numerical technique that has been employed for simulating various physical phenomena by using numerical methods to solve the underlying partial differential equations of e.g. heat transfer, fluid flow, mechanical deformation etc. By discretizing the object into elements and applying the governing mechanical equations, FEA allows for calculation of material responses such as temperature, heat flux, deformation, stress, and strain in response to various stimuli. In this work, FEA is used to predict to 3D warpage values in an FDM printed object under different process settings. The data from the FEA simulations is used to train a FFNN surrogate model which presents a lightweight, fast model for identifying the optimal process settings to minimise warpage. The Particle Swarm Optimisation (PSO) algorithm is used for optimisation. The principles of these algorithms are briefly introduced in the following subsections.

### A. *Fused Deposition Modelling and Finite Element Analysis*

The Ansys Direct energy deposition (DED) module is used to simulate the FDM process. In DED simulations, a birth–death technique is often employed, in which elements are sequentially activated (birth) and deactivated (death), to mimic the layer-by-layer material deposition process. The workflow begins with the design of a 3D model using computer-aided design software, which is then converted into tool paths through slicing algorithms. These tool paths are translated into G-code, allowing the printer to control nozzle movement and platform positioning along three orthogonal axes. After designing a geometry using CAD, initial process parameters such as nozzle temperature, deposition rate, bed temperature, and minimum mesh size are then specified. The model is discretized into a finite number of elements and nodes, after which the governing thermal and mechanical equations are solved sequentially. This provides comprehensive insights into the process, including temperature distribution, deformation, and residual stress development within the printed part. However, DED simulation can be computationally expensive, as the calculation time increases with the number of elements and nodes. Depending on the model size and complexity, these simulations can take several hours or even days to complete.

### B. Feed-Forward Neural Network and Radial Basis Function

Supervised learning includes a wide range of different algorithms to establish relationships between labeled input and output datasets. Feed-forward neural networks (FFNNs) and radial basis function networks (RBFNs) are well-known algorithms that have been widely used in different research areas. A typical FFNN and RBFN consist of an input layer, hidden layers, and an output layer. The input layer receives the feature data, while the hidden layers perform non-linear transformations to extract relevant patterns and relationships. The output layer generates the final predictions. More information about FFNNs and RBFNs can be found in ref [12]

### C. Particle swarm optimization algorithm

The Particle Swarm Optimization (PSO) algorithm is a widely used and effective optimization technique applied in numerous research studies. Its core concept is inspired by the collective behaviour of birds and fish in nature. In computational terms, PSO consists of multiple particles, each representing a potential solution characterized by two key parameters: position and velocity. The position represents the current state of the particle, while velocity determines how its position changes with each iteration. Initially, both the position and velocity of each particle are assigned randomly or uniformly. The performance of each particle is then evaluated using a fitness function. Among all particles, the one with the highest fitness value is identified as the global best, whereas the best solution found by an individual particle during its search is known as its personal best. During each iteration, particles adjust their velocity and position based on specific mathematical equations. Essentially, a particle's movement is guided by its own best-known position and the globally best position discovered so far. More information regarding the mathematical equations of PSO can be found in ref [6].

## III. Numerical and Surrogate Modelling of FDM

Measuring mechanical properties experimentally in small devices can be both time-consuming and expensive. To address this, FEA was employed to simulate the FDM process under different operating conditions. A data-driven approach was then used to make a bridge between FDM process parameters, critical regions, and the warpage deformation. The following subsections describe the detailed FEA-based simulation of the FDM process, the development of an FFNN to predict warpage deformation, and the search for optimal FDM parameters that minimize the maximum warpage deformation.

### A. Finite element analysis modelling of FDM

To simulate the FDM process, a DED approach was adopted to compute warpage deformation. Cubic geometries with dimensions of $5\,\mathrm{mm} \times 10\,\mathrm{mm} \times 2\,\mathrm{mm}$ and $5\,\mathrm{mm} \times 10\,\mathrm{mm} \times 4\,\mathrm{mm}$ were considered. Polylactic acid (PLA) was selected as the printing material. After generating the geometry and assigning the material properties of PLA, the corresponding G-code was created, which represents the nozzle movements for each printed layer. In this study, a bidirectional raster pattern was employed (see Fig. 1). The maximum warpage deformation in a flat plate typically occurs at corners and edges where uneven cooling is greatest [9]. Accordingly, nine critical regions were identified on each layer for evaluation (see Fig. 2). The mesh sensitivity analysis was then performed to determine the optimal element size, and it was found that a maximum mesh size of 0.2 mm provided a balance between accuracy and computational efficiency for all subsequent simulations. Fig. 3 presents the simulated warpage deformation of the FDM process under the following conditions: nozzle temperature of 220,°C, bed temperature of 60,°C, and a material deposition rate of 2,mm$^3$/s, focusing on region 7 across layers 1, 3, 5, 7, and 9. Since the final magnitude of deformation is of primary interest for warpage evaluation, the steady-state deformation values were extracted and used as output for training the FFNN model. A total of 60 simulations were performed using different parameters of the FDM process, as summarized in Table I, to generate training data for the FFNN model.

TABLE I
Parameter ranges for FDM of PLA

| **Category** | **Process and Geometric Parameters** | |
|---|---|---|
| | ***Parameter*** | ***Range*** |
| Process | Nozzle Temperature (°C) | 180 - 220 |
| | Deposition Rate (mm$^3$/s) | 0.3 - 2.0 |
| | Bed Temperature (°C) | 50 - 60 |
| Geometric | Layer Height (mm) | 0.2 - 0.4 |
| | Number of Layers | 1 - 10 |

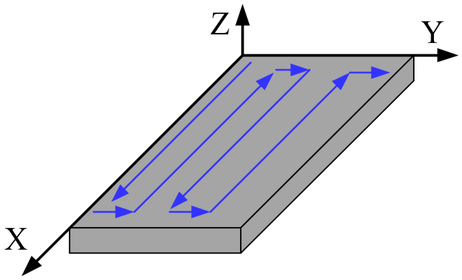


Fig. 1. Rectangular raster pattern of FDM

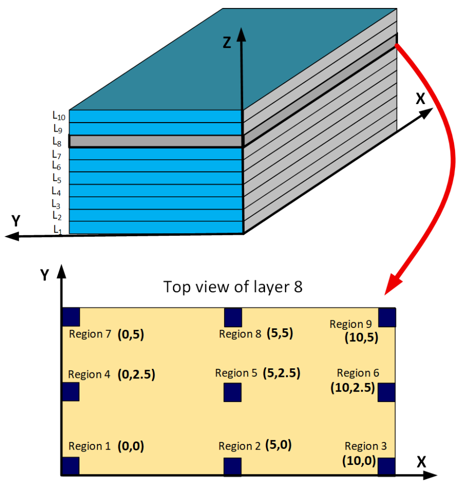


Fig. 2. Geometry of the 10 layer cubic FDM specimen with critical regions

## B. Feed-forward neural network modelling of FDM

The deformation values obtained from the nine regions in each layer under various FDM parameters were used to train an FFNN that captures the relationship between FDM parameters and deformation. A total of 42, 9, and 9 simulation cases were used for the training, validation, and test subsets, respectively. The FFNN model includes seven input features: nozzle temperature, bed temperature, material deposition rate, layer height, layer number, and the

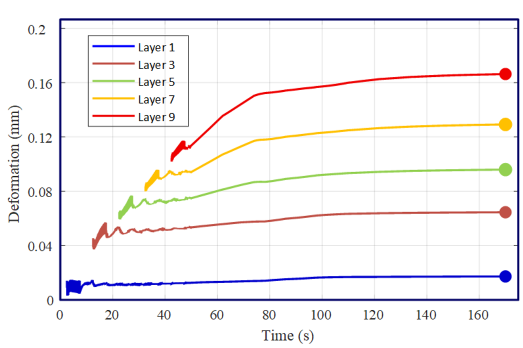


Fig. 3. Deformation in FDM part with Nozzle: 220°C, Bed: 60°C, Deposition: 2 mm³/s, Region 7, layers 1, 3, 5, 7, 9.

TABLE II
BEST 5 FFNN AND RBF STRUCTURE FOR PREDICTING WARPAGED DEFORMATION IN FDM

| *Structure* | *RMSE (mm)* | *Number of Epoch* |
|---|---|---|
| FFNN: 7-32-16-1 | 0.001 | 1231 |
| FFNN: 7-16-16-1 | 0.015 | 975 |
| RBF: 7-700-1 | 0.019 | 700 |
| FFNN: 7-32-32-1 | 0.021 | 1013 |
| FFNN: 7-64-1 | 0.049 | 678 |

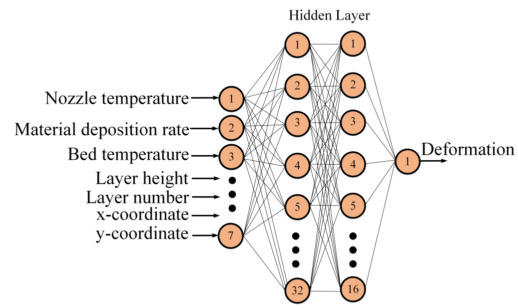


Fig. 4. Architecture of the FFNN model for deformation prediction

$x$–$y$ coordinates of the critical regions. The network output is the predicted deformation value. Determining the optimal number of neurons and hidden layers was achieved through a trial and error method. The network was trained using the Adam optimizer with a mini-batch size of 32 and a learning rate of 0.001. Several FFNN architectures were evaluated, and the five best-performing configurations, based on minimum RMSE for warpage deformation prediction, are listed in Table II. The architecture with a structure of 7–32–16–1 achieved the lowest RMSE and was therefore adopted for deformation modelling (see Fig. 4). For visual analysis of the FFFN performance, it was used to predict the warpage in a test case (not seen in training or validation), with a nozzle temperature of 220 °C, bed temperature of 50 °C, and material deposition rate of 1 mm$^3$/s at layer number 9. The prediction results of the trained FFNN were compared with those obtained from FEA. As shown in Fig. 5, the trained FFNN can predict the deformation in critical regions.

## C. Optimization of FDM

Particle Swarm Optimization is applied to the trained (7–32–16–1) FFNN model to determine the optimal FDM process parameters to minimize warpage deformation. The cost function of PSO was defined as minimizing the maximum warpage deformation across all 90 critical regions 1. The PSO algorithm was executed with 50 particles, 100 iterations, and cognitive and social gains of 2. As can be seen in Fig. 6, the minimum warpage deformation of 0.062 mm in critical regions occurs with a layer height of 0.2 mm, bed temperature of 60 °C, nozzle temperature of 180 °C, and material deposition rate of 0.3 mm/s. Based on the

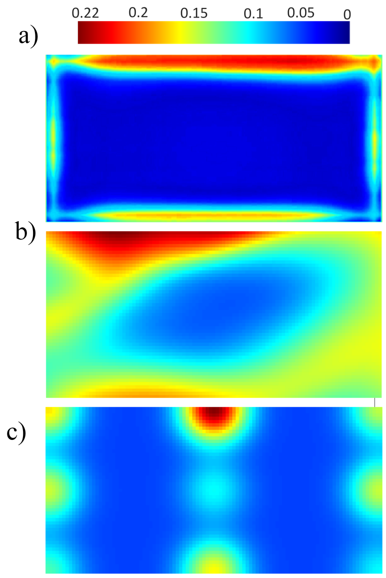


Fig. 5. Comparing deformation distribution from top view for (a)FEA , (b)FFNN and (c)RBF with nozzle temperature of 220 $^{\circ}$C, bed temperature of 50 $^{\circ}$C, material deposition rate of $1\ \mathrm{mm}^3/\mathrm{s}$, and layer 9 from top view

optimization analysis, when the nozzle speed is low, the temperature difference between the nozzle and the bed is small, and the layer height is minimal, warpage deformation can be effectively reduced. For validation, FEA simulations were conducted using both optimal and non-optimal FDM parameters. The parameters used for simulations that were not included in the training phase are listed in Table III. As shown in Fig. 7, the FEA with optimal FDM parameters exhibits a maximum warpage deformation of 0.070 mm, which is close to the PSO–FFNN prediction (0.062 mm). In addition, increasing the nozzle temperature and polymer deposition rate increases the maximum deformation to 0.138 mm, which is approximately double the value of the maximum warpage deformation under optimal FDM conditions.

$$\text{Cost Function} = \min\left(\max_{i=1,\ldots,90}(Warpagedefprmation)\right) \quad (1)$$

TABLE III
PROCESS PARAMETERS AND RESULTS FOR SIMULATION CASES

| Parameter | Case A | Case B | Case C |
|---|---|---|---|
| Layer Height (mm) | 0.4 | 0.2 | 0.2 |
| Bed Temperature ($^{\circ}$C) | 50 | 50 | 60 |
| Nozzle Temperature ($^{\circ}$C) | 220 | 220 | 180 |
| Maximum Deformation (mm) | 0.260 | 0.138 | 0.070 |

## IV. Conclusion and Future Work

FDM enables the fabrication of complex geometries but high precision remains challenging due to issues with

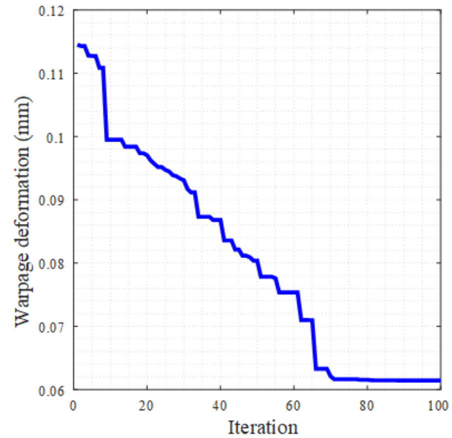


Fig. 6. Convergence of PSO_FFNN to minimize the warpage deformation

warpage deformation that are primarily caused by uneven cooling and suboptimal process parameters. Accurate modelling and optimization of warpage deformation are therefore essential for improving dimensional precision in printed components. However, capturing the nonlinear thermo-mechanical behavior of FDM through FEA is computationally expensive. To overcome this, an FFNN model was developed in this study to predict warpage deformation based on FEA. The trained FFNN demonstrated high prediction accuracy (RMSE of 0.001mm) comparing to trained RBF and drastically reduced computation time compared to FEA, indicating strong potential for use in process optimization and control. Furthermore, integrating the FFNN with a PSO algorithm enabled the identification of parameter sets that minimize warpage deformation. These results confirm that data-driven models can effectively approximate the deformation behavior of FDM and support parameter optimization for improved part quality.

The limitation of the current approach lies in its dependency on the geometry and material used for training. When applied to other materials such as ABS or polypropylene, or to more complex geometries, the deformation patterns differ. Future research will therefore focus on using transfer learning to adapt the trained model to different materials and geometries. Additionally, incorporating real-time sensor data such as temperature, deposition rate, and nozzle movement could enable dynamic prediction and compensation of warpage deformation during printing. Extending the model to predict additional defects, such as residual stress accumulation, would further enhance its applicability for improving the overall structural integrity of FDM printed parts.

## Acknowledgment


The research leading to these results has received funding from Science Foundation Ireland under grant number 21/FFP-A/9152. For the purpose of Open Access, the authors

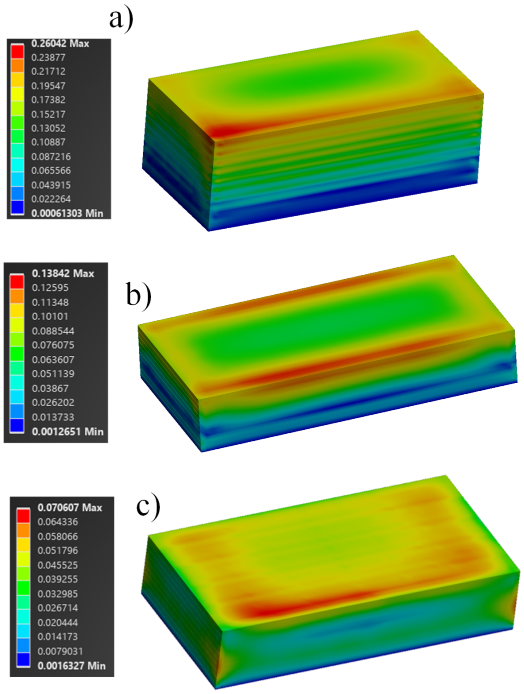


Fig. 7. Comparison of FEA simulation results for warpage deformation using optimal and non-optimal FDM process parameters



## References

[1] A. Alafaghani, A. Qattawi, B. Alrawi, and A. Guzman, "Experimental optimization of fused deposition modelling processing parameters: A design-for-manufacturing approach," *Procedia Manufacturing*, vol. 10, pp. 791–803, 2017, 45th SME North American Manufacturing Research Conference, NAMRC 45, LA, USA.

[2] R. Bai, S. Shi, C. Chen, Y. Ren, J. Yuan, W. Lyu, H. Naceur, D. Coutellier, J. Luo, L. Wang, and H. Pu, "Printing path optimization in selective laser melting: Deep reinforcement learning with an enhanced reward function," *Journal of Manufacturing Processes*, vol. 155, pp. 760–774, 2025.

[3] V. V. Bhandarkar, A. Kumar, and P. Tandon, "Warpage detection in 3d printing of polymer parts: a deep learning approach," *Journal of Intelligent Manufacturing*, vol. 36, no. 5, pp. 3129–3141, 2025.

[4] D. A. Brion, M. Shen, and S. W. Pattinson, "Automated recognition and correction of warp deformation in extrusion additive manufacturing," *Additive Manufacturing*, vol. 56, p. 102838, 2022.

[5] S. Deokar, N. Kumar, and R. P. Singh, "A comprehensive review on smart manufacturing using machine learning applicable to fused deposition modeling," *Results in Engineering*, vol. 26, p. 104941, 2025.

[6] J. Fang, Z. Wang, W. Liu, L. Chen, and X. Liu, "A new particle-swarm-optimization-assisted deep transfer learning framework with applications to outlier detection in additive manufacturing," *Engineering Applications of Artificial Intelligence*, vol. 131, p. 107700, 2024.

[7] Q. Feng, W. Maier, and H.-C. Möhring, "Application of machine learning to optimize process parameters in fused deposition modeling of peek material," *Procedia CIRP*, vol. 107, pp. 1–8, 2022.

[8] M. Roy and O. Wodo, "Data-driven modeling of thermal history in additive manufacturing," *Additive Manufacturing*, vol. 32, p. 101017, 2020.

[9] A. A. Samy, A. Golbang, E. Harkin-Jones, E. Archer, D. Tormey, and A. McIlhagger, "Finite element analysis of residual stress and warpage in a 3D printed semi-crystalline polymer: Effect of ambient temperature and nozzle speed," *Journal of Manufacturing Processes*, vol. 70, no. June, pp. 389–399, 2021.

[10] D. Syrlybayev, B. Zharylkassyn, A. Seisekulova, A. Perveen, and D. Talamona, "Optimization of the warpage of fused deposition modeling parts using finite element method," *Polymers*, vol. 13, no. 21, p. 3849, 2021.

[11] W. Yong, G. Zhang, J. Wang, Y. Gui, C. Fu, and H. Fu, "Finite element modeling and simulation of in738 laser powder bed fusion process assisted via machine learning," *Materials Today Communications*, vol. 40, p. 109848, 2024.

[12] A. Zaidan, A. Alnoor, O. S. Albahri, R. Mohammed, A. H. Alamoodi, A. S. Albahri, B. Zaidan, S. Garfan, H. Hameed, M. S. Al-Samarraay *et al.*, "Review of artificial neural networks-contribution methods integrated with structural equation modeling and multi-criteria decision analysis for selection customization," *Engineering Applications of Artificial Intelligence*, vol. 124, p. 106643, 2023.