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INTEGRATED ANN–GA APPROACH FOR DIMENSIONAL ACCURACY OPTIMIZATION IN FDM ADDITIVE MANUFACTURING

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Abstract: This paper presents an integrated approach based on Artificial Neural Networks (ANNs) and Genetic Algorithms (GAs) for dimensional accuracy optimization in Fused Deposition Modeling (FDM) additive manufacturing. As additive manufacturing technologies are increasingly adopted in functional prototyping and engineering applications, dimensional accuracy becomes a critical requirement for ensuring component performance and assembly reliability.

The study is based on the experimental manufacturing of a functional cylindrical locating pin prototype used in positioning and clamping devices. The selected geometry enables an accurate investigation of the influence of process parameters on dimensional behavior in functionally relevant areas. Experimental specimens were manufactured using Z-ULTRAT material on a Zortrax M200 Plus 3D printer while varying layer thickness, extrusion temperature, and number of profiles.

Based on the experimental dataset, a predictive model was developed using a multilayer perceptron artificial neural network capable of estimating dimensional deviations for different combinations of process parameters. The ANN model was trained, validated, and tested using independent datasets, and its performance was evaluated through correlation coefficients and mean squared error values.

Subsequently, the ANN model was integrated into a multi-objective optimization framework based on genetic algorithms in order to simultaneously minimize dimensional deviations corresponding to two characteristic diameters of the component. The optimization process generated a Pareto-optimal solution set highlighting the trade-offs between the considered objectives and providing a decision-support framework for selecting optimal manufacturing parameters.

The obtained results demonstrate the effectiveness of the hybrid ANN–GA methodology in modeling and optimizing FDM processes, contributing to improved dimensional precision and enhanced process repeatability. The proposed methodology has applicability in both industrial and educational environments, supporting the development of intelligent additive manufacturing strategies.

Keywords: FDM 3D printing, dimensional accuracy, artificial neural networks, genetic algorithms, additive manufacturing

INTRODUCTION

Additive Manufacturing (AM) represents one of the most dynamic development directions in modern engineering, offering high design flexibility and the capability to rapidly manufacture complex geometries. Among AM technologies, Fused Deposition Modeling (FDM) has become one of the most widely used solutions due to its relatively low cost, accessibility, and compatibility with a wide range of polymeric materials [1]. Nevertheless, despite its advantages, dimensional accuracy remains a major challenge, particularly for functional components where geometric deviations directly affect performance and assembly capability.

In engineering applications, dimensional deviations in FDM-manufactured parts are generated by process-specific phenomena such as layer-by-layer deposition, thermal variations, material shrinkage, and anisotropic behavior. These effects lead to differences between nominal and actual geometries, negatively influencing the functionality of mechanical assemblies. Consequently, improving dimensional precision has become an essential requirement for integrating additive manufacturing into functional prototyping and low-volume production applications [2].

The present study addresses this issue through the analysis of a functional component represented by a cylindrical locating pin designed as an educational and experimental support element for positioning systems. The selected geometry enables the investigation of dimensional accuracy in relation to critical functional surfaces, including cylindrical guiding areas and axial support regions. Unlike studies based on simplified geometries, this approach establishes a direct connection with real engineering applications [3].

One of the main challenges in optimizing FDM processes is the nonlinear and complex relationship between process parameters and the resulting dimensional behavior. Parameters such as layer thickness, extrusion temperature, and geometric characteristics interact in a manner that is difficult to model using conventional analytical methods.

To overcome these limitations, recent research has increasingly focused on artificial intelligence techniques and evolutionary optimization algorithms. Artificial Neural Networks (ANNs) have demonstrated high efficiency in modeling the complex relationships between input parameters and dimensional deviations, offering strong predictive capabilities. In parallel, Genetic Algorithms (GAs) provide efficient multi-objective optimization by identifying optimal parameter combinations under compromise conditions between conflicting objectives.

Based on this framework, the present paper proposes an integrated ANN–GA methodology for predicting and optimizing the dimensional accuracy of FDM-manufactured components. The ANN model is trained using experimental data, while the genetic algorithm is employed to explore the solution space and identify a Pareto-optimal front corresponding to minimized dimensional deviations.

The novelty of the study lies in combining a functionally relevant geometry with a hybrid modeling and optimization methodology, enabling not only accurate prediction of dimensional behavior but also the formulation of practical recommendations for process parameter selection. The results contribute to improving the reliability and repeatability of FDM processes, with direct applications in functional prototyping and experimental educational activities.

LITERATURE REVIEW

Dimensional accuracy of FDM-manufactured parts has been extensively investigated in the scientific literature due to the increasing adoption of additive manufacturing technologies in engineering applications. Numerous studies have shown that dimensional deviations are influenced by a complex combination of process parameters, material properties, and geometric factors.

One of the most influential parameters is layer thickness. Previous studies indicate that reducing layer thickness generally improves dimensional precision due to finer material deposition resolution.

However, this improvement is associated with longer manufacturing times and potential process instability. Similarly, infill density significantly affects dimensional stability, with higher infill values reducing deformation while increasing material consumption and printing duration [4,5].
Another relevant factor in dimensional accuracy analysis is represented by the geometric configuration of the part, particularly through parameters such as the number of profiles or repetitive constructive features [6]. In cylindrical components or locating devices, the number of profiles influences both local rigidity and material deposition behavior during printing. Increasing the number of profiles may contribute to a more uniform stress distribution and improved dimensional stability, although it may also generate local error accumulation due to frequent extrusion path direction changes. Consequently, this parameter becomes essential in the analysis of dimensional deviations and is strongly correlated with final dimensional precision and geometric fidelity.
Considering the complexity of these interactions, traditional analysis and optimization methods are often insufficient for accurately modeling FDM process behavior. In this context, artificial intelligence-based approaches have gained significant attention.
Artificial Neural Networks (ANNs) are widely employed for predicting dimensional accuracy and mechanical properties, demonstrating strong correlations between estimated and experimental values. In many studies, correlation coefficients exceeding 0.9 have confirmed the capability of ANN models to capture nonlinear relationships between process variables [7].
Simultaneously, Genetic Algorithms (GAs) are frequently utilized for process parameter optimization due to their ability to solve complex multi-objective problems. Hybrid ANN–GA approaches are particularly efficient because the neural network acts as a surrogate model for evaluating candidate solutions generated by the genetic algorithm, significantly reducing computational cost [8–10].
Previous studies have demonstrated the effectiveness of these methodologies in optimizing parameters such as layer thickness, infill density, and geometric tolerances, resulting in reduced dimensional deviations and improved process consistency.
Multi-objective optimization approaches based on Pareto-optimality concepts enable the identification of optimal solutions under compromise conditions between conflicting objectives such as dimensional precision, manufacturing time, and material consumption. Algorithms such as NSGA-II are widely applied for generating optimal solution sets and supporting engineering decision-making processes.
Despite the significant progress achieved, literature still presents several limitations. Most existing studies employ simplified or standardized geometries with limited relevance for real engineering applications. Furthermore, modeling and optimization are frequently treated separately, without integration into a unified methodological framework.
The present study aims to overcome these limitations by employing a functionally relevant geometry and integrating predictive modeling with multi-objective optimization into a unified ANN–GA framework. This approach enables both an in-depth understanding of the involved phenomena and the identification of practically applicable solutions, contributing to the development of intelligent additive manufacturing strategies.

MATERIALS AND METHODS

Materials, Printer and Experimental Conditions

The experimental specimens were manufactured using Z-ULTRAT filament, a technical ABS-based material optimized for the Zortrax ecosystem. The selection of this material was based on its suitability for functional applications, including high impact resistance, structural rigidity, and uniform surface quality.

All experiments were performed using a Zortrax M200 Plus 3D printer under controlled laboratory conditions. The purpose of maintaining stable process conditions was to ensure experimental reproducibility and complete traceability of the manufacturing sequence.
The printing parameters considered in the experimental plan were:

- Layer thickness: 0.10 mm, 0.15 mm, 0.20 mm;
- Extrusion temperature: 250 °C, 260 °C, 270 °C;
- Number of outer walls: 3, 4, 5;
- Infill density: 50% (solid type);
- Build plate temperature: 80 °C;
- Printing orientation: 0°;
- Support material: disabled.

The selected parameter ranges enabled the investigation of process influence on dimensional precision while maintaining compatibility with the technical capabilities of the printing system.

Geometry of the Experimental Specimens

The analyzed geometry was inspired by real industrial applications where positioning precision and assembly repeatability are essential requirements.
A cylindrical locating pin with a shoulder was designed and manufactured as the central component of an experimental positioning and clamping device. The prototype was intended as a functional educational support for studying positioning principles in technological fixtures and evaluating the influence of constructive solutions on dimensional precision.

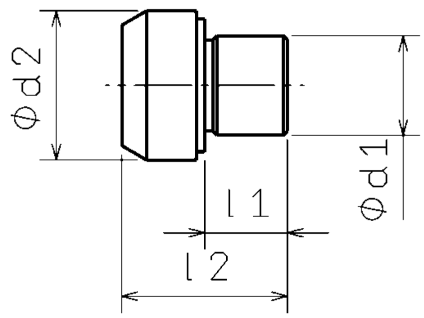

Figure 1. The prototype

From a constructive point of view, the locating pin consists of three functional regions:

- locating area inside the fixture body;
- axial support area (shoulder);
- active positioning region for part orientation.

The geometry was specifically designed to facilitate dimensional analysis in critical functional regions while remaining compatible with the limitations of FDM manufacturing.
Artificial Neural Network Modeling
A predictive model was developed using the Neural Network Toolbox available in MATLAB 2024a. A multilayer perceptron feedforward neural network architecture was implemented, consisting of an input layer, one hidden layer, and an output layer.
The ANN input parameters were:

- layer thickness (LT);
- extrusion temperature (ET);
- Number of Outer Walls (NOW).

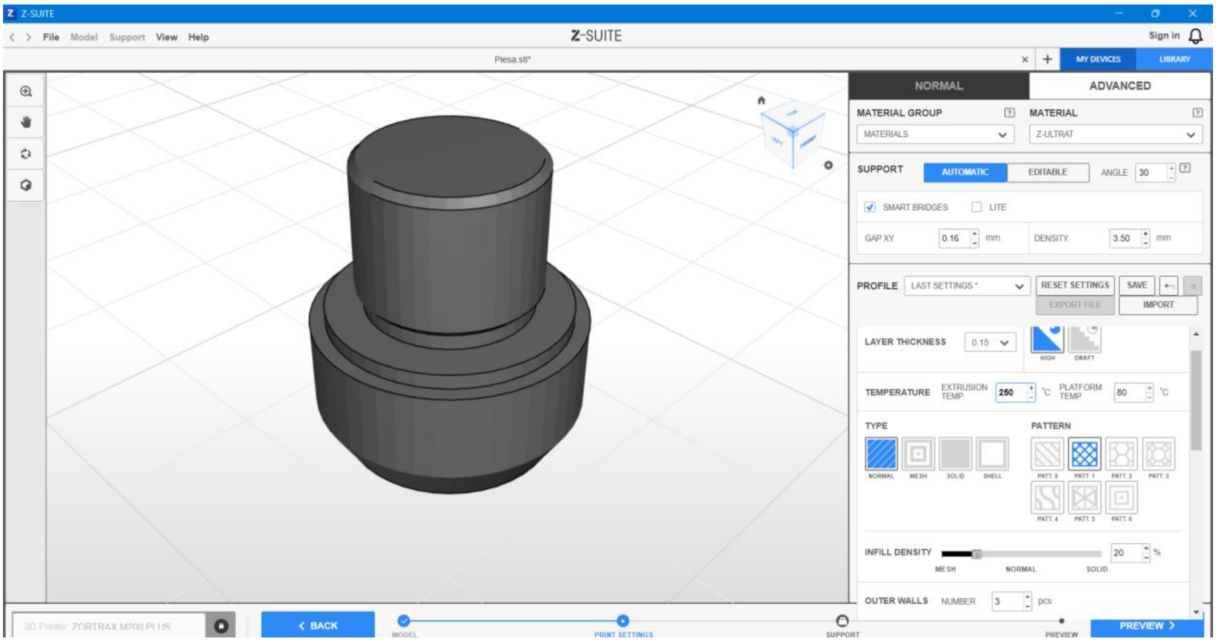

Figure 2. The virtual prototype in Z-Suite environment

The network outputs corresponded to the dimensional deviations obtained for diameters:

- dev_d1;
- dev_d2.

Table 1. The dataset for the experiment

	Input variables			Obtained dimensions		Output variables	
No.	**Layer Thickness [mm]**	**Extrusion Temperature [°C]**	**Number of Outer Walls**	**d1 mm**	**d2 mm**	**dev_d1 mm**	**dev_d2 mm**
1	0,10	250	3	11,89	17,91	0,11	0,09
2	0,10	250	3	11,89	17,91	0,11	0,09
3	0,10	250	3	11,87	17,89	0,13	0,11
...							
28	0,20	260	5	11,72	17,77	0,28	0,23
29	0,20	260	5	11,71	17,76	0,29	0,24
...							
53	0,15	270	4	11,83	17,84	0,17	0,16
54	0,15	270	4	11,80	17,87	0,20	0,13

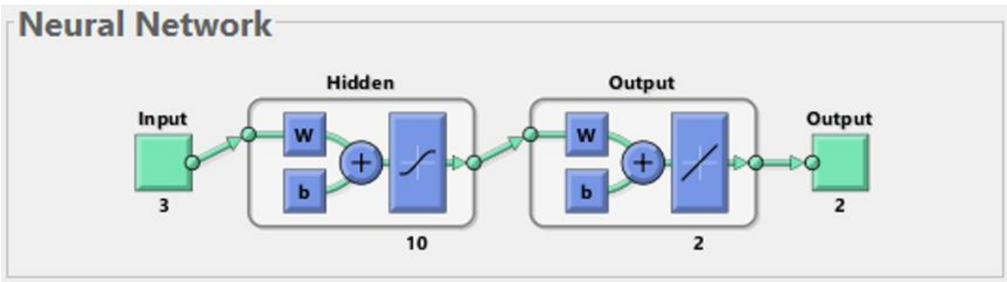

Figure 3. The ANN architecture

The dataset was randomly divided into:

- 60% training data;
- 20% validation data;
- 20% testing data, figure 4.

The hidden layer employed a tangent sigmoid activation function, while the network training process was performed using the Levenberg–Marquardt backpropagation algorithm.

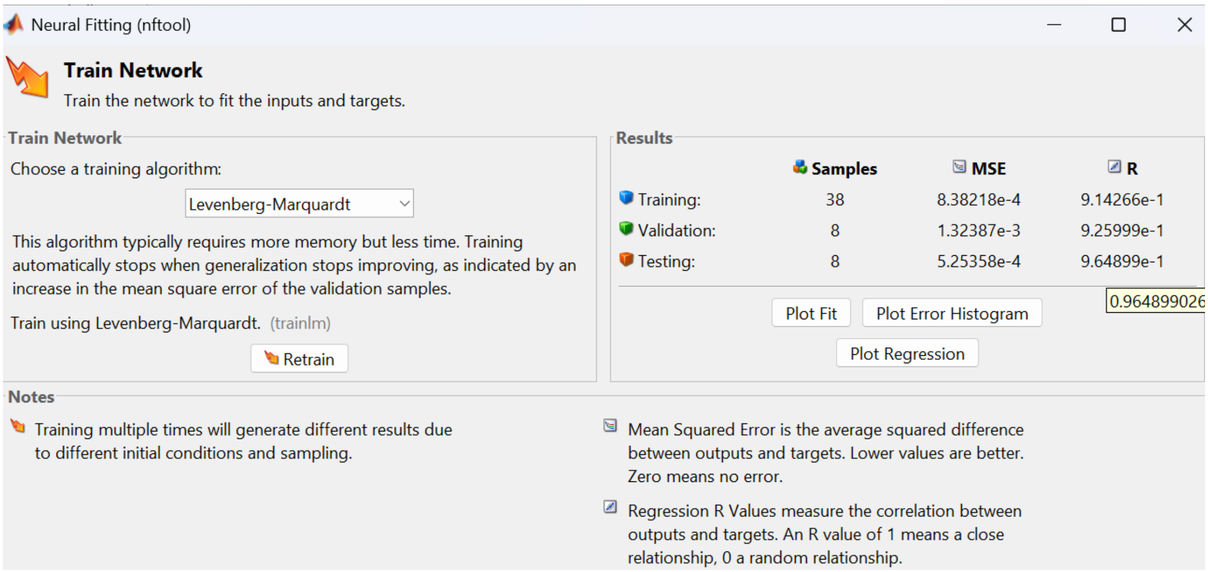

Figure 4. The ANN training, validation and testing process

The trained network was subsequently employed as a predictive model in the multi-objective optimization stage.

3.4. Multi-Objective Optimization Using Genetic Algorithms

The multi-objective optimization process was performed using the MATLAB gamultiobj solver. The ANN model was integrated as the objective evaluation function.

The decision vector was defined as:

$$x = [LT, ET, NOW]$$

where:

- LT = layer thickness;
- ET = extrusion temperature;
- NOW = Number of Outer Walls.

The optimization objectives were:

- minimization of deviation at diameter d1;
- minimization of deviation at diameter d2.

The optimization process generated a Pareto-optimal solution set describing the compromise relationships between the considered objectives.

Table 2. Pareto Solutions, Objective Functions and Decision Variables

Pareto front - function values and decision variables

Index	f1	f2	x1	x2	x3
1	0,03	0,037	0,1	251,476	3,813
2	0,03	0,037	0,1	251,477	3,811

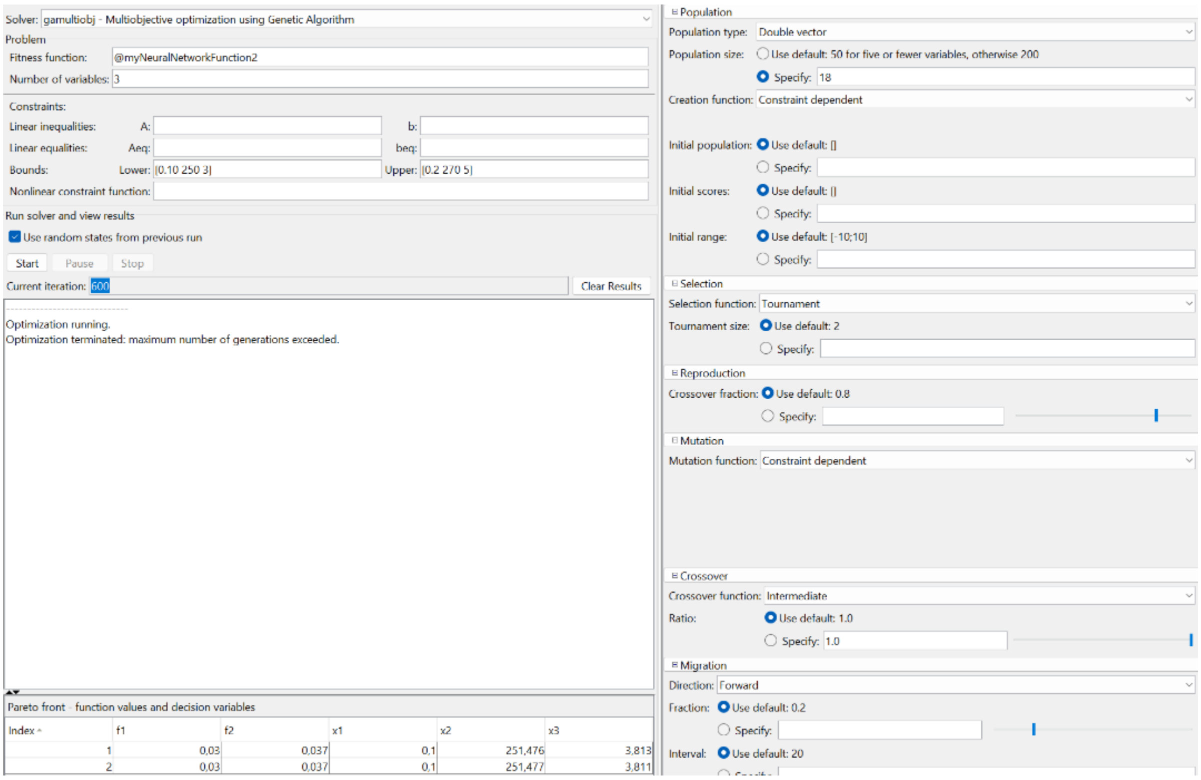

Figure 5. Gamultiobj settings and the obtained Pareto Front

The GA configuration included:

- population size: 18 individuals;
- tournament selection;
- crossover fraction: 0.8;
- mutation strategy: constraint dependent.

The optimization terminated after 600 iterations when the average Pareto front spread variation dropped below the imposed tolerance threshold.

RESULTS AND DISCUSSION

The optimization process generated two Pareto-optimal solutions corresponding to different trade-offs between the considered dimensional objectives.

One of the selected optimal solutions obtained through the genetic algorithm corresponded to:

- layer thickness = 0.10 mm;
- extrusion temperature = 251.476 °C;
- number of outer walls = 3.813.

Since the obtained values were continuous and could not be directly implemented using the printer settings, the parameters were discretized according to the practical capabilities of the Zortrax M200 Plus printer:

- layer thickness = 0.10 mm;
- extrusion temperature = 251 °C;
- number of outer walls = 4.

Simulation using the trained ANN predicted dimensional deviations (*dev_sim_d*) of:

- dev_sim_d1 = 0.034;
- dev_sim_d2 = 0.040.

A new specimen was experimentally manufactured using the discretized parameters. The measured dimensional deviations (*dev_m_d*) were:

- dev_m_d1 = 0.050;
- dev_m_d2 = 0.030.

The results indicate that the ANN model overestimated the deviation for one diameter while underestimating the deviation for the other. This behavior suggests different sensitivities of the dimensional characteristics to process parameters and highlights the influence of factors not explicitly included in the model, such as local cooling conditions, micro-variations in extrusion flow, and cumulative trajectory effects.

Nevertheless, the obtained results confirm the capability of the ANN–GA methodology to capture the general dimensional behavior of the FDM process and to provide a reliable framework for intelligent parameter selection.

CONCLUSIONS

The present study proposed and experimentally validated an integrated ANN–GA methodology for dimensional accuracy optimization in FDM additive manufacturing.

The main conclusions are:

- dimensional accuracy in FDM manufacturing is strongly influenced by layer thickness, extrusion temperature, and geometric configuration;
- artificial neural networks provide reliable predictive capabilities for estimating dimensional deviations;
- genetic algorithms effectively identify Pareto-optimal parameter combinations for multi-objective optimization problems;
- the integrated ANN–GA methodology improves process repeatability and supports intelligent parameter selection;
- experimental validation confirmed the applicability of the proposed methodology for functional engineering components.

Future research will focus on extending the methodology through the inclusion of additional process variables, larger experimental datasets, and finite element analysis integration for enhanced predictive capabilities.

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