On the morphing behavior of 4D printed PLA-based parts

Mylene S. Cadete[1,2,a *], Idalina Gonçalves[3,b] and Victor Neto[1,2,c]

[1]Department of Mechanical Engineering, TEMA - Center for Mechanical Technology and Automation, University of Aveiro, Portugal

[2]LASI - Intelligent Systems Associate Laboratory, Guimarães, Portugal

[3]Department of Materials and Ceramic Engineering, CICECO - Aveiro Institute of Materials, University of Aveiro, Aveiro, Portugal

[a]mylene@ua.pt, [b]idalina@ua.pt, [c]vneto@ua.pt

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Abstract. 4D printing integrates additive manufacturing (AM) with smart materials to create structures capable of changing shape over time in response to stimuli, such as temperature. Despite its potential for adaptive systems, this technology faces challenges in controlling the morphing behavior of printed polymers. This study investigates the influence of 3D printing parameters, particularly in fused filament fabrication (FFF), on the morphing behavior of PLA-based polymers. The primary goal is to establish a relationship between printing conditions and shape memory properties to improve the design of adaptive structures. An experimental approach was divided into micro and macrostructural analyses. At the microstructural level, hot programming techniques were used to examine how crystallinity, influenced by extrusion temperature and printing speed, affects morphing capabilities. At the macrostructural level, morphing behavior was directly encoded during the 3D printing process by adjusting parameters such as raster angle, printing temperature, and speed. A design of experiments (DoE) was utilized to feed machine learning algorithms, enabling the correlation of experimental results with processing parameters. Microstructural analyses revealed that extrusion temperature and printing speed significantly impact the crystallinity of PLA. At the macrostructural level, it was observed that samples printed with a 0° raster angle exhibited greater deformation compared to those printed with a 90° raster angle. The machine learning models successfully predicted the shape recovery behavior of printed parts, offering a data-driven tool for optimizing design and manufacturing while minimizing trial-and-error experimentation. These findings contribute to the advancement of 4D printing technology, enabling the creation of adaptive structures with enhanced performance and reliability.

Introduction

Additive Manufacturing (AM), commonly referred to as 3D printing, emerged over three decades ago and has since established itself as a transformative technology in advanced manufacturing. Its ability to fabricate complex structures with precision has led to significant developments in materials, processes, and applications. Building upon these advancements, 4D printing introduces a dynamic aspect to traditional 3D printing by incorporating time as an additional dimension. This novel approach combines AM with stimuli-responsive smart materials, enabling the creation of structures that can change their shape, functionality, or properties when exposed to external stimuli, such as temperature, light, or humidity [1, 2, 3]. Unlike conventional 3D printing, where structures are static, 4D printing exploits the inherent properties of materials to produce programmable, adaptive behaviors.

The concept of 4D printing is based on the interaction between material responsiveness and precise control during the manufacturing process. Shape memory polymers (SMPs), such as poly(lactic acid) (PLA), are commonly used due to their ability to undergo reversible shape changes and their biodegradability. These materials have shown great potential for applications in fields ranging from aerospace and automotive to biomedicine. Momeni et al. [4] describe 4D printing as the convergence of scientific research into smart materials with engineering practices aimed at creating innovative solutions that traditional manufacturing methods cannot achieve.

At the microstructural level, the properties of the material, such as crystallinity, play a crucial role in determining its morphing capabilities. Studies such as those by Xia et al. [5], demonstrate how extrusion temperature and printing speed influence crystallinity, directly affecting shape recovery performance. For example, higher extrusion temperatures were found to enhance crystallinity, resulting in improved shape memory properties. Similarly, Liu et al. [6] analyzed the impact of varying printing speeds on molecular alignment and found a strong correlation between these parameters and the mechanical performance of the printed parts. These findings highlight the importance of controlling microstructural attributes to achieve optimal morphing performance.

At the macrostructural level, parameters such as raster angle, layer thickness, and infill patterns significantly influence the overall deformation and recovery behavior of printed structures. Nam and Pei [7] reported that components printed with a raster angle of 0° exhibit greater deformation compared to those printed at 90°, highlighting the role of directional properties in morphing. Furthermore, Yu et al. [8] demonstrated that thinner layer thicknesses enhance anisotropic properties, allowing for better predictability and control over the shape-changing response. These findings illustrate the importance of optimizing macrostructural parameters to tailor the behavior of adaptive structures.

In addition to experimental investigations, predictive modeling and simulation have become indispensable tools in the development of 4D printing technologies. Bodaghi et al. [9] utilized finite element modeling to simulate the thermo-mechanical behavior of PLA-based structures, achieving results that closely align with experimental observations. Similarly, Su et al. [10] employed machine learning algorithms to predict morphing behavior based on geometric and processing parameters, significantly reducing the need for trial-and-error experimentation. These approaches demonstrate the potential of combining computational tools with experimental data to accelerate innovation in 4D printing. Additionally, machine learning algorithms offer an innovative approach to predicting complex behaviors in responsive materials, enabling the integration of experimental and computational data in an efficient and practical manner, thus reducing the reliance on trial-and-error experimental methodologies.

This study focuses on exploring the influence of fused filament fabrication (FFF) processing parameters on the morphing behavior of PLA-based materials. By analyzing the interplay between microstructural and macrostructural factors, it provides a comprehensive understanding of how these parameters affect the shape memory properties of printed parts. The integration of experimental methodologies with predictive modeling further aims to establish robust frameworks for optimizing 4D printing processes. The insights gained from this work contribute to the advancement of 4D printing technologies, enabling the design of intelligent, adaptive structures for a wide range of applications. By addressing current challenges in controlling morphing behaviors, this research lays the groundwork for innovations in fields such as aerospace, healthcare, and sustainable manufacturing.

Microstructural Analysis

This section examines the interplay between microstructural attributes, such as crystallinity and thermal properties, and their role in determining the morphing behavior of PLA-based materials. The study specifically utilized hot programming, a 4D printing technique, to investigate the relationship between printing parameters and shape-memory capabilities (Fig. 1). This technique involves post-printing deformation of the material at elevated temperatures, followed by cooling to fix a temporary shape. Upon reheating, the material recovers its original shape, providing insight into its morphing performance.

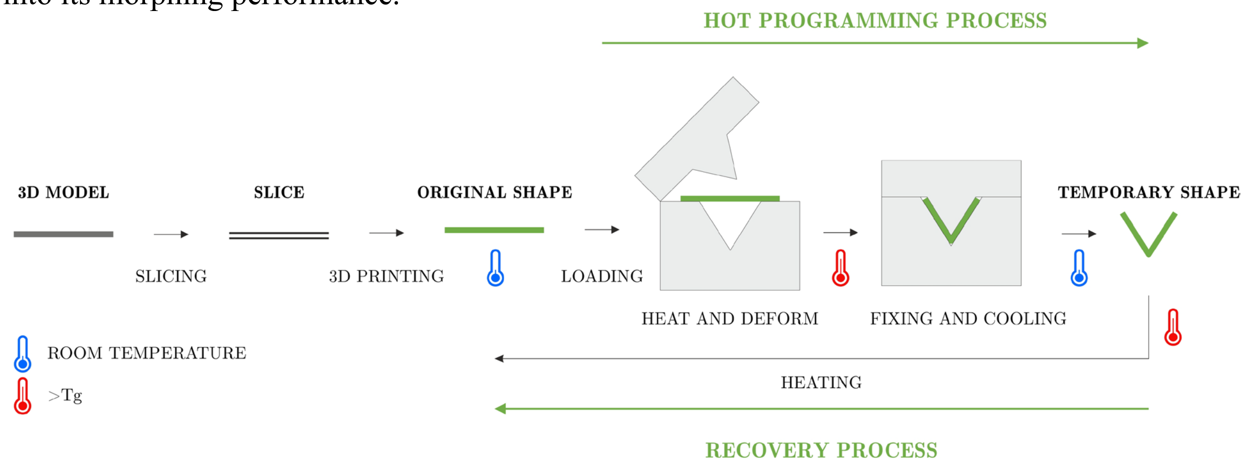

Figure 1 – Schematic representation of hot programming process. Adapted from [11].

A design of experiments (DoE) approach was used to evaluate the effects of five critical 3D printing parameters: extrusion temperature, bed temperature, printing speed, fan speed, and flow rate (Table 1). PLA specimens were fabricated under controlled conditions and analyzed for their crystallinity using Differential Scanning Calorimetry (DSC). Shape-memory performance was tested using the hot programming method, where samples were deformed to a temporary shape in a water bath at 60°C and subsequently allowed to recover their original form upon reheating.

Table 1 – Parameters and levels for the 2^5 full factorial design in 3D printing experiments. Adapted from [11].

Factor	Low level	High level
A – Printing temperature (°C)	180	220
B – Bed temperature (°C)	40	80
C – Speed (mm/s)	10	80
D – Fan speed (%)	0	100
E – Flow (%)	100	150

Key findings revealed that bed temperature and printing speed had significant interactions affecting crystallinity. Higher bed temperatures promoted crystallinity by reducing cooling rates, whereas increased printing speeds reduced crystallinity due to accelerated inter-layer solidification. Fan speed and flow rate also influenced crystallinity; lower fan speeds and moderate flow rates facilitated slower cooling and consistent material deposition, leading to enhanced crystallinity.

Shape-memory behavior varied significantly with the printing parameters. All specimens exhibited shape recovery, with recovery ratios ranging from 71% to 99% and recovery times between 8 and 50 seconds. Optimal shape recovery was achieved using a combination of high extrusion temperature (220 °C), low bed temperature (40 °C), high printing speed (80 mm/s), and minimal fan speed (0%), resulting in a recovery ratio of 98.6% and a recovery time of 17.8 seconds. The balance of parameters proved critical, as interactions between bed temperature and printing speed were the most influential on crystallinity and, consequently, morphing performance.

The hot programming technique enabled an understanding of the interplay between residual stresses, thermal activation, and shape recovery. This method underscores the importance of fine-tuning 3D printing parameters to optimize the morphing behavior of PLA. High recovery rates and short recovery times can be achieved by fine-tuning microstructural properties, providing a foundation for the design of adaptive and functional 4D-printed materials.

Macrostructural Analysis

This section explores the influence of macroscopic parameters on the morphing behavior of PLA-based materials in 4D printing. The study employed the printing programming technique, a method that directly incorporates shape-memory properties during the printing process by adjusting key parameters (Fig. 2). By analyzing the interplay between factors such as raster angle, thickness, length, printing speed, bed temperature, and printing temperature, the aim was to optimize bending behavior and establish guidelines for programmable morphing structures.

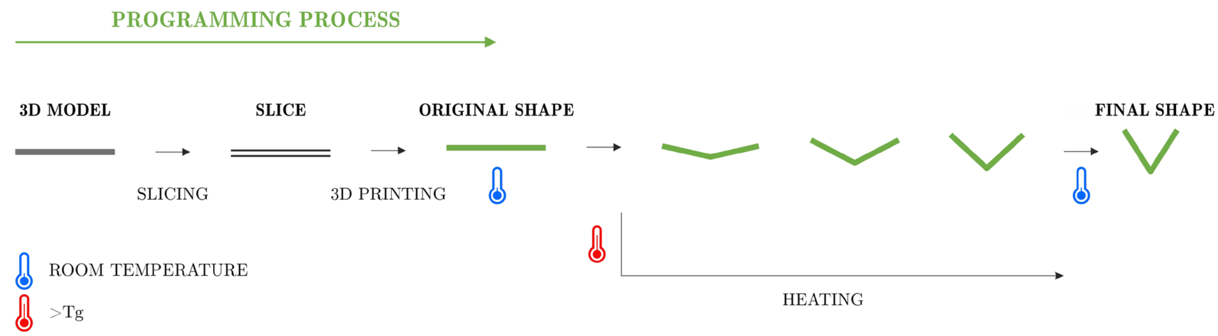

Figure 2 – Schematic representation of hot programming process.

A DoE was implemented to evaluate the effects of five critical 3D printing parameters: bed temperature, printing speed, printing temperature, thickness, and length, on the morphing behavior of wPLA samples with raster angles set at 0° and 90°, Table 2.

Table 2 – Printing parameters for wPLA samples. This table summarizes the parameters tested to study the influence of raster angle (0° and 90°) on morphing behavior.

Parameter	Raster angle 0°/90°
Bed temperature (°C)	30, 40, 50, 60
Printing speed (mm/s)	40, 60, 80, 100
Printing temperature (°C)	200, 210, 220, 230
Thickness (mm)	0.8, 1.2, 1.6, 2
Length (mm)	40, 60, 80, 100

The printing programming technique was employed to program shape changes directly during fabrication. This approach relied on inducing internal stress through the careful adjustment of printing parameters. After 3D printing, the samples were thermally activated in a water bath at 80 °C, and their bending ratio was measured. The bending ratio represents the percentage of shape change, quantifying the extent of deformation.

Key findings revealed that the raster angle had the most significant impact on the bending ratio, with samples printed at 0° exhibiting higher bending ratios (42.8–286%) compared to 90° (0.02–42.3%). This difference arises from the alignment of layers at 0°, which allows for greater internal stress accumulation and more pronounced shape changes upon activation.

In addition to raster angle, thickness and length played significant roles. Thinner samples (0.8 mm) demonstrated higher bending ratios compared to thicker ones (2 mm) due to reduced structural stiffness. Similarly, longer samples (100 mm) amplified the bending ratio at 0° but exhibited reduced deformation at 90° due to increased rigidity.

Bed and printing temperatures also influenced morphing behavior. Lower bed temperatures (30 °C) and higher printing temperatures (230 °C) enhanced the bending ratio by promoting greater internal stress accumulation. Conversely, higher bed temperatures (60 °C) and lower printing temperatures (200 °C) resulted in reduced deformation due to slower cooling rates and improved interlayer adhesion. Finally, printing speed affected the bending ratio, with faster speeds (100 mm/s) inducing greater deformation at 0° due to reduced heat dissipation and increased residual stresses. However, at 90°, the influence of speed was less pronounced, emphasizing the importance of layer orientation in shaping morphing behavior.

These findings underscore the importance of carefully tuning printing parameters to achieve optimal morphing performance. By leveraging the printing programming technique, it is possible to design adaptive structures with tailored bending behavior. The insights gained in this study provide valuable guidelines for advancing 4D printing applications in responsive devices and programmable materials.

Morphing Prediction

This section explores the development and evaluation of predictive models to forecast the morphing properties of PLA-based materials in 4D printing. Experimental data from both hot programming and printing programming processes were used to train and evaluate various machine learning algorithms, including Support Vector Machine (SVM), K-Nearest Neighbors (KNN), XGBoost, Random Forest (RF), and Decision Trees (DT). These models aimed to predict key properties such as recovery ratio (RR), recovery time (Rtime), and bending ratio.

The process began with data preparation, where output variables were discretized into classes to enhance model performance. Predictive models were trained using experimental data, incorporating key printing parameters such as printing temperature, bed temperature, speed, raster angle, thickness, and length. For the hot programming process, recovery ratio and recovery time were the primary targets, while for the printing programming process, the focus was on the bending ratio. Model performance was evaluated using metrics such as precision, recall, and F1-score, with the best-performing algorithms identified based on these metrics.

For the hot programming process, the SVM algorithm demonstrated the best performance for recovery ratio prediction, achieving an F1-score of 0.73. The model excelled in classes with greater variability, such as Classes 0 and 3, but faced challenges in distinguishing between Classes 1 and 2, which had narrower value ranges and closer distributions. These findings underscore the difficulty in separating overlapping classes, particularly near decision boundaries. Recovery time predictions were most accurately handled by the XGBoost algorithm, which achieved a weighted F1-score of 0.84. XGBoost performed particularly well in Classes 0 and 2, where recovery times were more distinct, but struggled with the broader range and dispersion of values in Class 3.

In the printing programming process, the bending ratio was the target property. Initial modeling included all geometric and printing parameters, but this introduced significant variability due to the impact of thickness and length, which were later excluded from the final model. The Decision Tree algorithm emerged as the best performer, achieving an F1-score of 0.91. By focusing on printing parameters such as raster angle, bed temperature, printing speed, and printing temperature, the model demonstrated robust performance in predicting bending ratio classes. However, inconsistencies were observed near class boundaries, highlighting the need for additional data to refine the model further.

The results demonstrate the potential of data-driven approaches to predict and optimize morphing behavior in 4D printing. While the models showed strong overall performance, challenges in classifying overlapping and boundary cases indicate opportunities for further improvement. Increasing the dataset size and diversity, along with refining model parameters, could enhance accuracy and robustness. These predictive tools represent a significant step toward automating design decisions and improving control over morphing effects in 4D printing, supporting the development of programmable materials for advanced applications.

Conclusion

This study explores the morphing behavior of PLA-based materials in 4D printing, integrating experimental and data-driven approaches to optimize shape-memory properties. At the microstructural level, hot programming demonstrated how parameters such as extrusion temperature and printing speed influence crystallinity, enhancing recovery ratios and reducing recovery times. At the macrostructural level, the printing programming technique revealed that parameters like raster angle, thickness, and length significantly impact bending behavior, with 0° raster angles achieving superior deformation.

Machine learning models, including SVM, XGBoost, and Decision Trees, successfully predicted morphing properties, offering a robust tool for minimizing trial-and-error and improving design efficiency. While models performed well for distinct classes, challenges in boundary and overlapping cases highlighted the need for expanded datasets and refinement.

This work contributes to advancing 4D printing by providing a framework that integrates experimental insights with predictive tools, enabling the design of adaptive structures with tailored morphing behaviors. Future research could explore multi-material systems and refine models for complex applications, further pushing the boundaries of programmable materials.

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References

[1] F. Mehrpouya, A. Pourjamshidi, M. Ding, 4D printing of smart materials: Evolution and applications, Addit. Manuf. 36 (2020) 101577. https://doi.org/10.1016/j.addma.2020.101577

[2] M. Ding, Y. Zhao, B. Zhang, Advances in the evolution of 4D printing: Materials, applications, and challenges, Prog. Mater. Sci. 107 (2019) 100577. https://doi.org/10.1016/j.pmatsci.2019.100577

[3] Cadete, M.S., Gomes, T.E.P., Gonçalves, I., & Neto, V. Controlling Morphing Behavior in 4D Printing: A Review About Microstructure and Macrostructure Changes in Polylactic Acid. 3D Printing and Additive Manufacturing, 10 (2023) 6. https://doi.org/10.1089/3dp.2022.0088

[4] F. Momeni, X. Liu, J. Ni, 4D printing—An evolution from 3D printing: Techniques, materials, and applications, Mater. Des. 122 (2017) 42-79. https://doi.org/10.1016/j.matdes.2017.03.051

[5] Y. Xia, M. Fang, D. Wang, 4D printing of shape memory polymers: Structure–property relationships and their role in application, J. Mater. Chem. A 9 (2021) 39-59. https://doi.org/10.1039/D0TA08846G

[6] Y. Liu, T. Zhao, J. Xu, Effect of processing parameters on shape memory behavior in PLA 3D printed structures, Polym. Eng. Sci. 59 (2019) 881-892. https://doi.org/10.1002/pen.25092

[7] S. Nam, E. Pei, Analysis of raster angle effects on 4D printed PLA components using FFF technology, Addit. Manuf. 34 (2020) 101235. https://doi.org/10.1016/j.addma.2020.101235.

[8] K. Yu, Q. Qi, Z. Zhou, Layer thickness control and anisotropy effects in 4D printing of PLA-based structures, Adv. Mater. Technol. 5 (2020) 1900853. https://doi.org/10.1002/admt.201900853

Materials Research Proceedings 54 (2025) 337-343 https://doi.org/10.21741/9781644903599-37

[9] M. Bodaghi, M. Damanpack, A. L. Ghaffar, Finite element analysis and experimental validation of thermo-mechanical behaviors in 4D printed structures, Smart Mater. Struct. 28 (2019) 055021. https://doi.org/10.1088/1361-665X/ab0dc5

[10] H. Su, C. Wang, S. Zhang, Machine learning for 4D printing: Predicting morphing behavior of active structures, Soft Robot. 7 (2020) 735-744. https://doi.org/10.1089/soro.2019.0130

[11] Cadete, M.S., Gomes, T.E.P., Gonçalves, I., & Neto, V. Influence of 3D-printing deposition parameters on crystallinity and morphing properties of PLA-based materials. Progress in Additive Manufacturing. 10 (2025) 127–137. https://doi.org/10.1007/s40964-024-00608-x