

Response to the reviewers

Appreciate your constructive suggestion and the response for the comments of the review #1 written in orange color while the response for reviewer #2 colored by blue color.

Comments of Reviewer #1

The paper describes prediction of deformation of a curved structure based on FEM, linear regression and ET models. The work is entirely computational and future experimental validation is proposed.

1. A single value of elastic modulus is given in Table 1. Because it's highly dependent on temperature, there should be a description of temperature dependency.

Response: Thank you for your constructive comment.

The simulation datasets of training and the Table 1 material properties of Poly lactic acid (PLA) have direct relation. The change of gain mobility of thermal response referred to the melting point of 150-160 °C of PLA to manipulate the stiffness magnitude. The stiffness of PLA is higher below 331 K of glass transition and decreases as thermal stimulus value increases. Consequently, thermal stimulus manipulate the stiffness of elastic modulus variance across shape transformation within 3.2 GPa ultimate young modulus.

2. Glass transition temperature in Table 1 is 58°C. In the text 384-394K is discussed, which is well above this transition temp.

Response: Thank for your supportive comment

The glass transition 331 K (58°C) is the beginning of response temperature while the deformation goes to melting point. However, the appropriate shape transformation demonstrated during the varied magnitude of temperature from 323 - 433 K whereas the 384-394 K value point out the decrement of the stress or the shape response across the model.

3. Why are different temp. Range (50-160C, 273.15-433K etc) and time increment are used (50, 60.1, 105s, etc)?

Response: Apology for inconsistence of information.

The simulation has been pursued for various magnitude of temperature in between 323.15 - 433.15 K and the datasets of COMSOL Multiphysics generated during 0 - 50 s with incremental of 10 s value. However, four individual time setup of 50 s, 60.1 s, and 105 s with 10 s, 0.1 s and 5

s of incremental value were implied to compute the simulation respectively. The shape response of the surface during 0.1 s and 5 s of time setups weren't convenient for undefined temperature change in a range of the interval. Nonetheless, their generated datasets comparatively as similar as the 10 s of incremental value.

4. Please define the dataset explicitly: number of simulations, time steps, total samples, etc.

Response: Thank for you constructive suggestion.

Independently, four number of simulation computed for each 50 s, 60 s, 105 s within 10 s, 0.1s, 5 s of time interval respectively. After comparative simulation, the 628 shear strain and temperature distribution of datasets generated during 50 s of 10 s of increment time setups, across x, y, z -axis.

5. Section 2.3: correct the units.

Response: Done

6. Improve the figure resolution.

Response: Done

Comments of Reviewer #2

1. Is this work new, original?

No - not in terms of clearly demonstrated scientific novelty. Having read the paper, I regard it as an incremental application of established FEA and machine-learning methods to a particular PLA structure. Earlier studies already combined these approaches for 4D-printing prediction and design. The simulations may be the authors' original work, but the paper does not establish a distinctly new method or capability. This is a judgment about novelty, not an allegation of copying.

Response: Thank you for constructive comments and pointing out the weakness.

This computational simulation of 4D printing paper focused on time dependent response with a varied thermal stimulus of PLA where the models of machine learning compared to visualize the gradient magnitude. Yes indeed, a few previous work utilized FEA and machine learning (ML) technique to analysis shape recovery polymer (SMP) especially on active composite responses. The existing review motivated on different materials and mentioned it's applicability for all material and stimuli. However, all computational simulation work is inapplicable for every smart polymer, smart composite properties and stimuli. Besides, the experimental of 4D printing technology is inconvenient with undefined scope of materials while the below Table 1 compare this article with review existing.

Table 1. Comparison of the review existing and this paper.

S.no	Articles	SMP	Stimuli	Models	Validation	Remark
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1	My paper	PLA	Thermal <433 K	Linear regression, XGBoost and Extra Trees	-	Validated by Abebe et al 2026
2	Zolfagharian et al. (2021)	Hyper elastic	Pneumatic pressure	Linear regression, SVM, ANN	Experimented	Temperature and material not Identified
3	Sun et al. (2021)	Composite	Thermal, swelling, magnetism	RNN,CNN, LSTM	-	Temperature and material not Identified
4	Liu et al. (2025)	TPU and Hydrogel	Thermal	-	Experimented	No temperature range
5	Suryavanshi et al. (2023)	p(NIPAM- 4-ABP)- PCL ge	Thermal	DT and MLR model	Experimented	No temperature range

From those point of view, this article dedicated to fill in out the gap of literatures focusing on PLA material predesign, limited thermal stimulus, and latest ML model that utilized random data training. In addition, computed the time dependent response to visualize the real-time transformation through the gradient magnitude of the deformation. Finally, the result has validated by previous published article (Abebe et al 2026).

2. Are previous works in this area adequately reviewed and properly cited?

No—not adequately. The introduction provides broad background references, but it does not critically review the studies most directly related to its FEA—machine-learning approach, i.e.:

- Important direct precedents are missing, including the 2021 study “*4D printing soft robots guided by machine learning and finite element models*” and the 2024 study “*Machine learning-enabled forward prediction and inverse design of 4D-printed active plates.*” Both are relevant to assessing this paper’s novelty.
- Some citations do not adequately support the associated claims. For example, reference [17], on two-dimensional triangular meshing, is cited alongside thermal properties and convective heat-transfer parameters without an evident justification.
- The discussion lacks comparison with previous findings. It does not meaningfully compare prediction accuracy, computational efficiency, or validation with earlier approaches.

Therefore, although relevant literature is cited, the coverage, connection between claims and references, and critical comparison are insufficient to establish the research gap and contribution.

Response: Appreciate for stating out the flaw of introduction and the inconvenient citation.

The introduction part has remodified and re-structured with additional relevant literature. Also, the inconvenient citation of [17] has removed.

3. Does the title of the article reflect its content?

Partly. The title correctly identifies computational simulation, time-dependent behavior, and machine learning as the main subjects. However, “predict shape transformation” is broader than what is convincingly demonstrated, since the analysis mainly predicts displacement and strain components from simulated data.

A more precise title would be:

“Finite element simulation and machine-learning prediction of thermally induced deformation in a PLA structure for 4D-printing applications.”

Response: Thank you for pointing out the inadequacy of interpretation on predicting shape transformation.

However, this paper’s computational pipeline start with CAD/CAM solid work modelling to demonstrate the FEA. The FEA of COMSOL Multiphysics analyzed the time dependent deformation of PLA’s using thermo-mechanical properties where the melting properties of PLA limited to less than 433 K. Through the analysis, the tune thermal response of PLA exchange between boiled water and the model surface determine the X, Y, and Z direction nodes change. In parallel, mathematical relation of temperature dependent displacement $U(T)$ and $(X, Y, Z, T, \text{ and } t)$ support the linear regression and Extra Trees shape prediction with incremental of time setups.

Consequently, the feature of new deformation $U' = X + U(t)$ observed on the spatial deformation while the real time response was validated with a previous published article, Abebe et al 2026. The anticipation of this article was minimizing the difficult of PLA implication in soft robot through aforementioned progresses. The process indicates, rather than weak interpretation of computational simulation and shape prediction the article included the necessary steps of time function shape transformation. Nevertheless, from this point of view, the title has been modified to “Computational simulation and machine-learning prediction of 4D printing: Modeling PLA's time-dependent deformation using thermal response”.

4. Is the abstract informative?

Partly—it describes the tools used and gives numerical results, but it does not clearly explain what was learned or why it matters. I would consider it technically detailed but insufficiently informative as a scientific abstract.

Its main weaknesses are:

- Unclear research question and novelty: It does not identify the specific gap being addressed or what distinguishes this work from previous FEA–machine learning studies.
- Poorly defined structure and outcome: We are not told what was modelled, its dimensions, the intended transformation, or exactly what the machine-learning model predicts.
- Numbers without context: A displacement of 45 mm and stress of 0.463 MPa are difficult to interpret without the geometry and loading conditions. The RMSE lacks units or a defined target.

- Unclear validation: “All COMSOL input data were trained” does not explain the training/test split, independent testing, or whether physical experiments were performed. $R^2 = 0.99$ does not mean “99% accuracy.”
- Unsupported conclusions: Neither design optimization, computational time savings, nor functional soft-robot performance is demonstrated by the results presented.

Some wording also obscures the meaning: “machine learning enhanced the response” could mean improved prediction or improved physical behavior—very different claims.

The abstract should allow the reader to answer: What was predicted, how was it validated, and what new capability resulted? At present, those essential points remain unclear.

Response: [Appreciate your supportive comments and the correction has done.](#)

5. Is the content of the article relevant for the conference topics?

Yes. The article is directly relevant to COTech 2026, particularly Topic 6: “Design Optimization, Additive Manufacturing Technologies & Applications.”

On page 1, this topic explicitly includes:

- 3D/4D printing of smart materials.
- Modelling and analysis of additively manufactured parts.
- Generative design and AI applications in additive manufacturing.

The paper’s thermal simulation of PLA structures and machine-learning prediction of deformation fit this scope clearly.

Response: [done](#)

6. Are all drawings and tables necessary and readable?

No—not all are necessary or sufficiently readable in their present form.

- Table 1 and Figure 2: Relevant and generally readable; they provide the material properties, geometry, and mesh.
- Figure 1: Overcrowded, with very small labels, and largely repeated figures presented later. It could be simplified or omitted.
- Figures 3 and 4: The workflow diagrams overlap in purpose and could be consolidated. Figure 4’s text is particularly small and blurred.
- Figures 5–8: Relevant to the results, but axes, legends, color scales, and numerical annotations need larger fonts and sharper reproduction. Figure 5 should identify each simulation time directly and preferably appear on one page.
- Figure 9: Its necessity is not clearly established. The three panels need individual labels and clearer explanations of the quantities, units, and connections to the conclusions.

The figures require improved resolution, clearer labelling, and more informative captions; redundant material should be reduced.

Response: [Done](#)

7. Are the conclusions supported by the data obtained?

Only partly. The results support the limited conclusion that machine-learning models can approximate selected displacement and shear-strain outputs from the COMSOL simulation. They do not adequately support the broader claims.

- Physical shape recovery is not validated: No experiments confirm that the simulated PLA structure behaves as predicted; experimental validation is explicitly deferred to future work.
- Computational savings are not demonstrated: No runtime comparison is reported.
- Design optimization is not demonstrated: No defined optimization procedure or comparison between initial and optimized designs is presented.
- Soft robot functionality remains speculative: Actuation performance is not tested.
- Numerical reporting is inconsistent: The conclusion gives a maximum stress of 0.456 MPa, whereas the abstract and results report 0.463 MPa. The reported R^2 values range from approximately 0.92 to 0.99, so emphasizing only 0.99 overstates the consistency of performance.

The conclusions should be restricted to preliminary computational findings and distinguish agreement with simulation outputs from validation of real-world behavior.

Response: [Thank you for supportive comments and pointing out the inconsistency of numerical reports.](#)

[The computational and prediction of the model referred the previously published article, Abebe et al 2026 for validation and the comparison will be deferred for future experimental work. However, the comparison of shape transformation explained in Section.3.2.1 and section. 4](#)

8. Have you information if content of this article is published elsewhere in the current form?

No – no information!

Response: [Done](#)