PREFERENCE-LEARNING AI FOR THE SELECTION OF FABRICATION-EFFICIENT HIGH-CURVATURE EXTRUSION GEOMETRIES
Under Multi-Objective Fabrication Constraints

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1 INTRODUCTION

Extrusion-based Additive Manufacturing (AM) has unlocked unprecedented geometric freedom in architectural design. However, as designs move towards complex, freeform shapes, fabrication constraints become highly pronounced. High-curvature geometries -specifically surfaces exhibiting negative (anticlastic) Gaussian curvature - create severe bottlenecks in conventional 2.5D planar printing [1]. These zones disrupt continuous extrusion, require extensive support structures, and lead to toolpath inefficiencies, increasing both print time and material waste.

While current research offers structural optimisation or real-time failure correction during printing [2], there is a critical gap in the pre-printing phase. Existing evolutionary optimisation tools produce vast "Pareto Fronts" of potential solutions, but the rationale behind the human designer's final selection is typically discarded [3]. This research proposes a closed-loop, preference-aware AI system that bridges this gap, formalising human intuition and fabrication metrics to optimise high-curvature geometries before printing.

2 METHODOLOGY

The proposed system translates physical fabrication constraints into computable digital metrics using a Grasshopper-based parametric workflow, functioning as a pre-print intelligence layer. The evolutionary algorithm evaluates geometries based on three distinct metrics: **A) Material Consumption:** Extracted via geometric volume and mathematically converted using the density of the printing material (e.g., PLA 1.24 g/cm^3) to estimate mass. **B) Print Time:** Estimated by simulating the slicer environment. The total continuous toolpath length is extracted and divided by the printer's average extrusion speed. **C) Curvature Analysis:** A geometric evaluation classifying surface behaviour based on Gaussian Curvature ($K = \kappa 1 \kappa 2$) [1]. The algorithm calculates the exact percentage of the surface exhibiting anticlastic (saddle-like) curvature, effectively quantifying the "fabrication difficulty" of the model.

Instead of a purely mathematical selection, the system introduces a Preference-Aware Learning Layer. When the algorithm generates a Pareto set of optimal trade-offs, the human designer selects the preferred candidate [3]. The AI logs this decision, learning the implicit weighting the user assigns to aesthetics versus fabrication efficiency, thereby biasing and improving future algorithmic rankings.

3 RESULTS & FUTURE WORK

Initial physical proof-of-concept testing validated the core premise: geometric adaptation directly impacts fabrication efficiency. By testing morphological variations of a high-curvature component, the optimal iteration reduced print time by 3.1% and material consumption by 0.1%, confirming that slight geometric adjustments can bypass toolpath congestion.

Next Steps: The upcoming phase focuses on the full integration of the AI Learning Layer and Preference Data Collection. This will involve capturing selection data from multiple designers to conduct a trend analysis. By visualising this data through statistical charts, the research will identify global preference trends (e.g., determining if human designers systematically prioritise time reduction over material savings when curvature difficulty increases).

4 CONCLUSION

This research shifts the paradigm of computational fabrication from a linear, machine-dictated process to a collaborative Human-AI workflow [4]. By capturing discarded decision data and incorporating curvature analysis directly into the optimisation loop, the proposed framework enables designers to achieve highly complex architectural forms that are inherently sustainable, resource-efficient, and fabrication-ready.

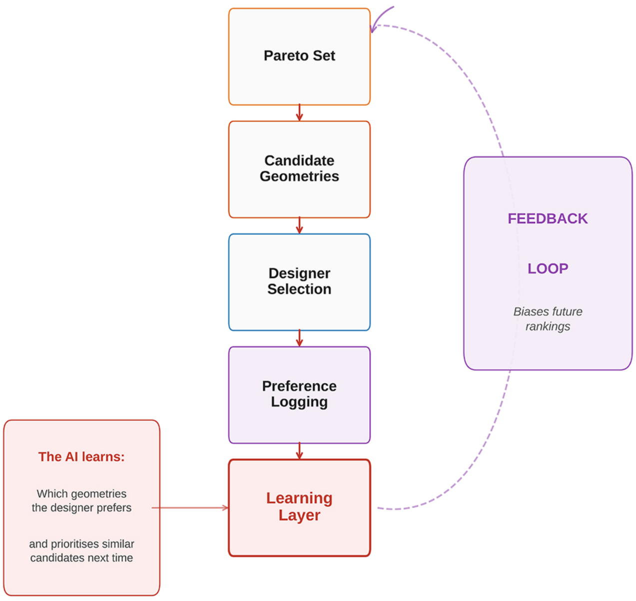

Fig 1.: Feedback loop of the preference-aware learning layer.

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