

Generative Diffusion Modeling for Predictive Digital Twins of Sustainable Nanoparticle Electronics Printing

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Motivation

Aerosol Jet Printing (AJP)'s significant role in promoting sustainability

AJP's Nanoparticle Printing Mechanism



https://youtu.be/phyGNdj9iOI

- Customization and Additive Manufacturing
- Material Efficiency and Waste Reduction
- Energy Efficiency
- Environmentally Friendly Materials
- > Lightweight, Flexible Electronics
- Integration with Sustainable Technologies

Motivation

Generative Diffusion Modeling Driven Predictive Digital Twins (DTs)

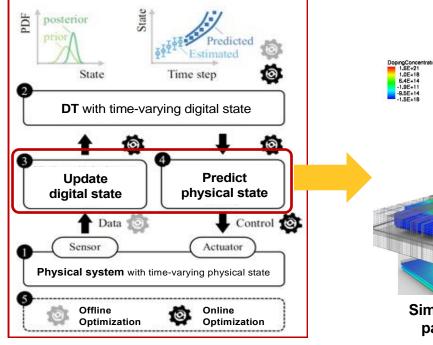
DT = F(PS, DS, P2V, V2P, OPT)

PS: a physical system, DS: a digital system, P2V: an updating engine, V2P: a prediction engine, and OPT: an optimization dimension

-1.9E+11 -9.5E+14 -1.5E+18

Simulation-based

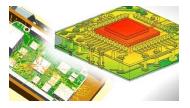
part modeling



Thelen, Adam, et al. "A comprehensive review of digital twin-part 1: modeling and twinning enabling technologies." Structural and Multidisciplinary Optimization 65.12 (2022): 354.

Previous Approaches

Input: Process parameters Output: Final geometry and the concentrations of all the dopants. (CRC Electronic Design Automation for IC Handbook, Chapter 24)



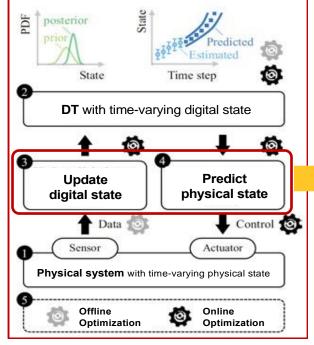
Improving Thermal Accuracy with **Electronics Digital Twin**

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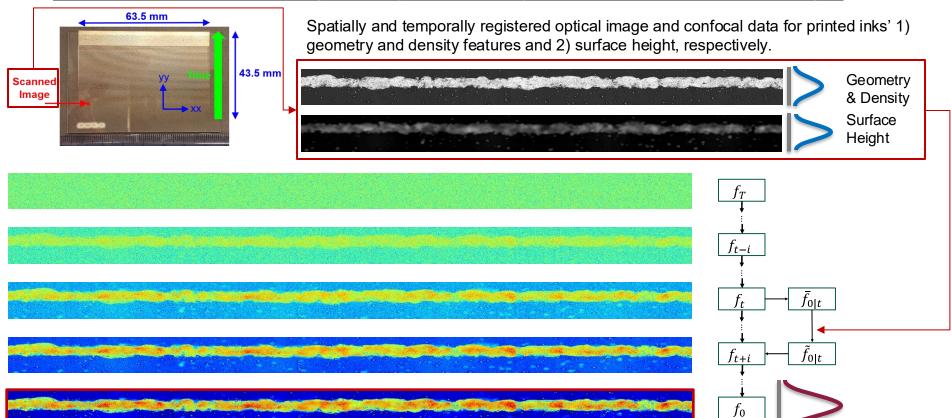
Generative AI-Driven Opportunity



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Case Study & Result

Fusion of printed inks' 1) geometry and density features and 2) surface height



Discussion

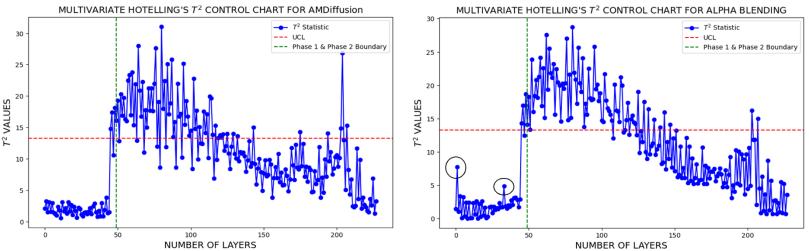
Diffusion vs. Non-Generative

Hotelling's T2 Control Chart Results

- Phase I: The proposed method shows higher stability, with alpha blending presenting more outliers.
- Phase II: In-control statistics: Alpha Blending: 99 vs Proposed method: 111 (12.12% improvement). The proposed method demonstrates more consistent process monitoring.

Diffusion-Driven Predictive DT for AJP

Generative AI benefits: The DT represents hidden linkages between geometry, density, and surface height in synthesized fused images. The proposed generative model not only preserves sensor data but also introduces new hidden features \rightarrow Novel predictive DT method.





- 1. Elhambakhsh, F., Ko, H., Yang, Z. & Lu, Y., 2024. *AMDiffusion: Denoising Diffusion Modeling Based Causal Data Fusion For Predictive Additive Manufacturing Digital Twins*. IEEE Robotics and Automation Society, under review.
- 2. Yoo, D., Mahoney, C.M., Deneault, J.R., Grabowski, C., Austin, D., Berrigan, J.D., Glavin, N. and Buskohl, P.R., 2022. Optical microscopy and confocal data of aerosol jet printed lines over a 16-hour print duration. Data in Brief, 42, p.108080.

Thank you. For more questions, please contact Hyunwoong.Ko@asu.edu.