How Do We Learn to Use Learning in Manufacturing Systems?

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intelligent. control. innovation.

Conference on Decision and Control

Cancún, Mexico

Dec. 7th, 2022

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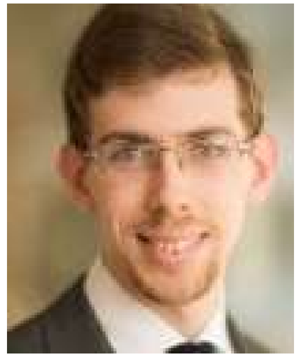
Lucid Motors

Berk Altin
NVIDIA



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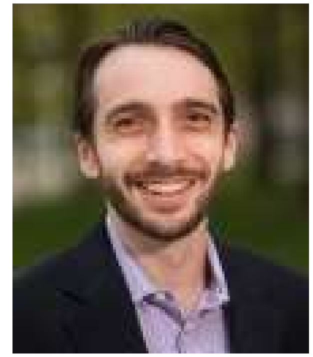

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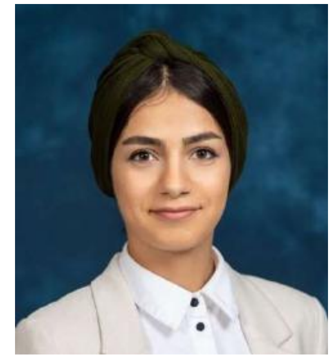

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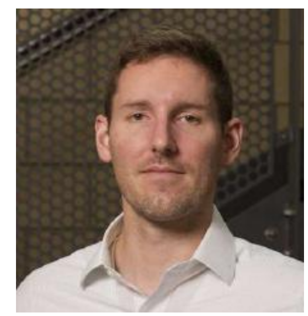


David Hoelzle
OSU

Outline

Basic Overview:
Learning in Manufacturing

Learning Case Study:

A. Challenges in additive manufacturing modeling and control
B. Learning applied to an additive manufacturing example

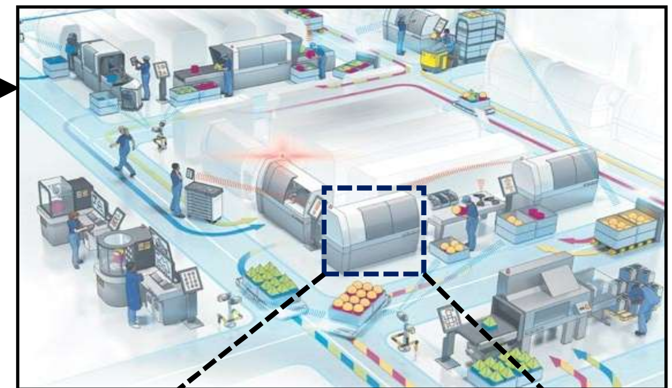
Open Opportunities for Learning + Control to Advance Manufacturing

Learning in Manufacturing

- Ability to derive a new understanding of a system using ***information*** from the ***system+***
- Applying the new knowledge towards an updated 'model/reference signal/control input/controller' to enhance system performance

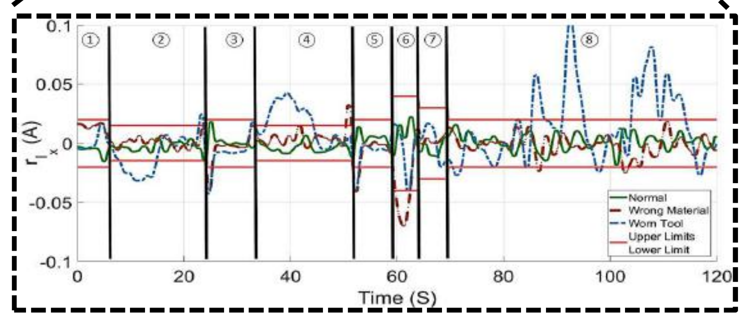
System+

- Resources
- Operators
- SMEs
- Supply chain
- Environment
- Other systems

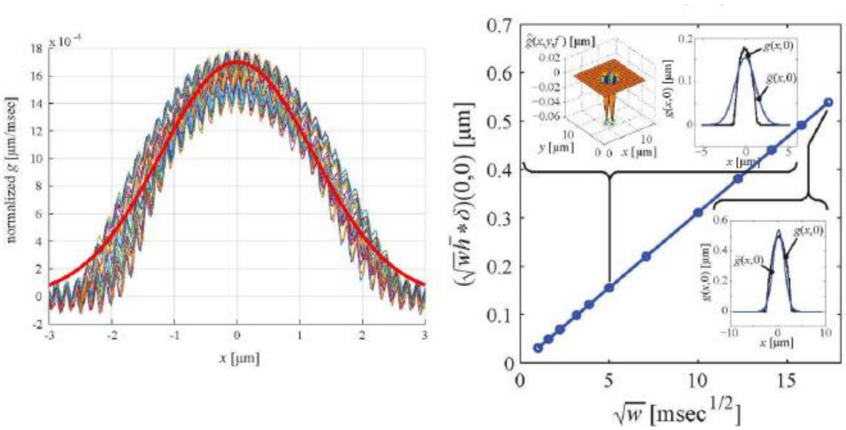


Information

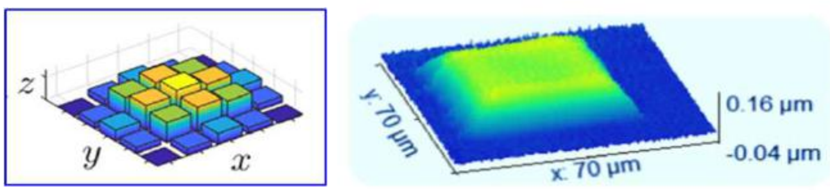
- Sensor data
- SME knowledge
- Physics-based models
- Historical data



Common methods of learning applied in manufacturing systems



Regression

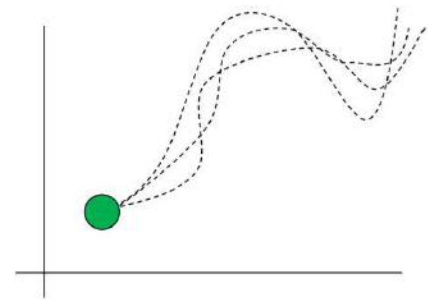


Convolutional Recurrent Neural Nets

Data-driven modeling

Iterative Learning Control (ILC)

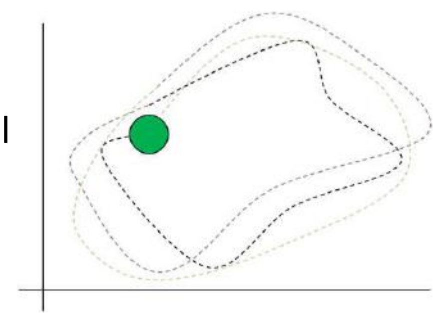
Batch process: Initial condition reset



Repetitive Control (RC)

Continuously-operated process:

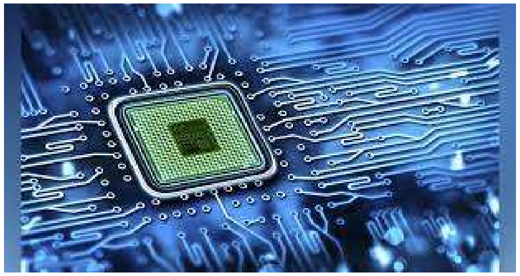
Initial condition is given by terminal condition at previous cycle

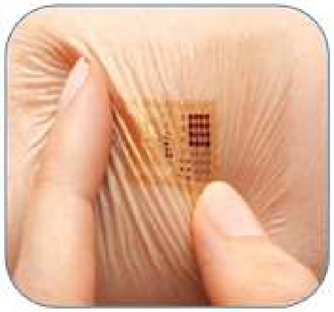


Repetitive and Adaptive Control Strategies

Needs for Intelligent Manufacturing – Control Challenges

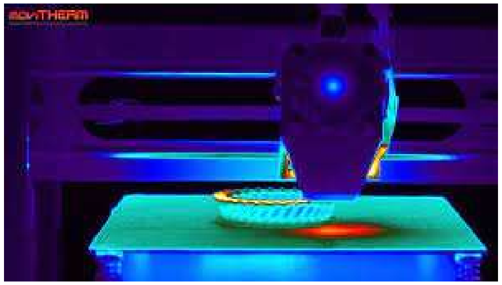
- **Flexible and agile responses:** disruptions, new products, customization
- **Advanced technology needs:** faster, higher-resolution, multi-material, multi-phase dynamics
- **Multiple domain dependencies:** spatial, temporal, material phase





Printed sensor tattoos

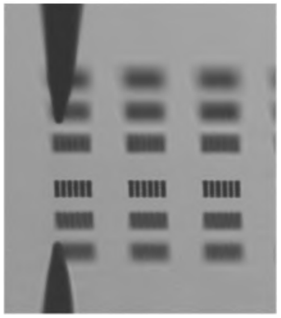
nicoledigiose.com

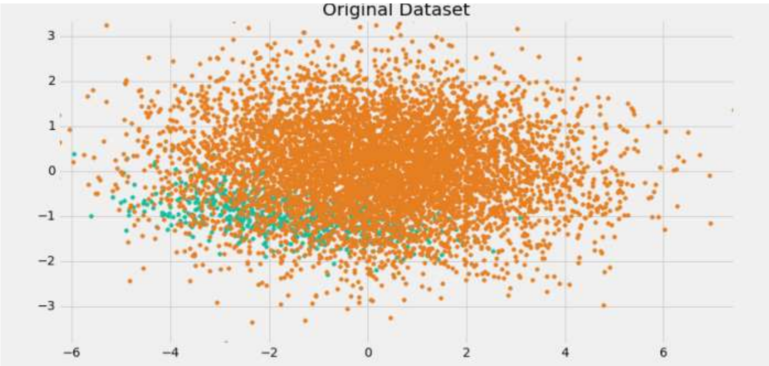


https://movitherm.com/

Learning within a Manufacturing Domain

Advantages	Challenges





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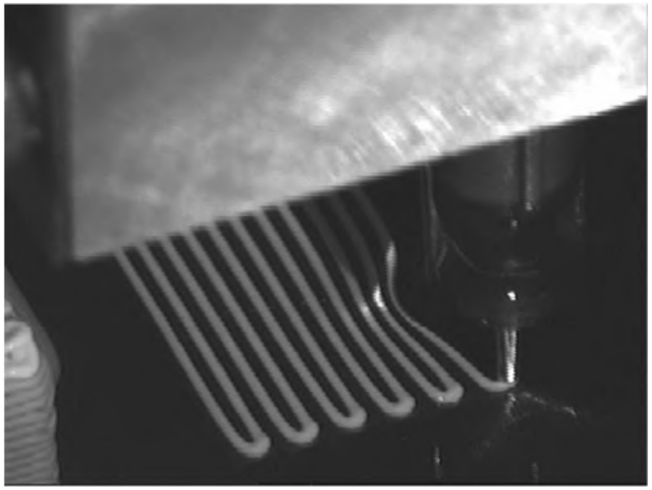
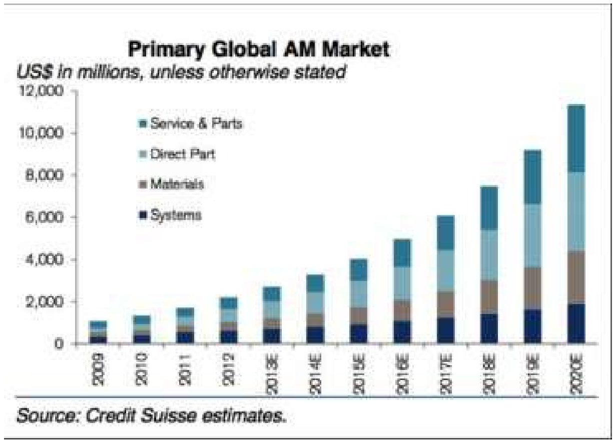
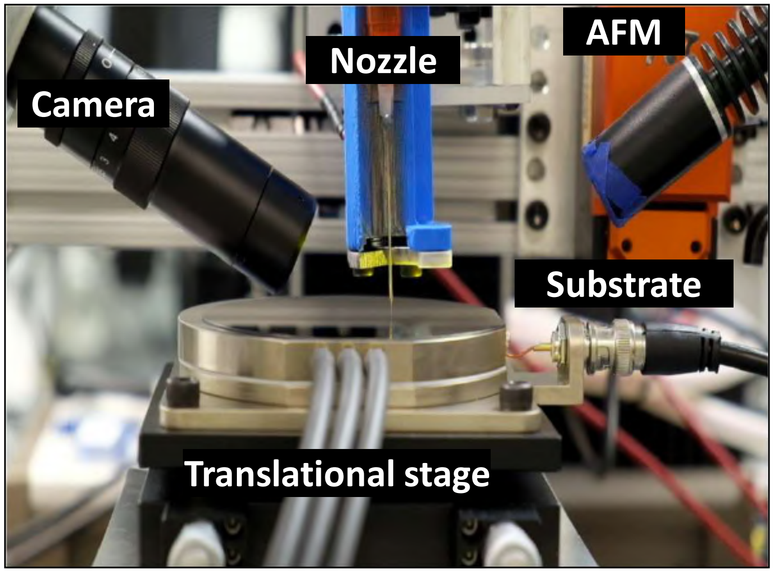
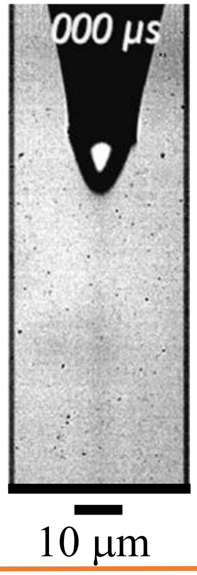


Extrusion Printing



Introduction – Electrohydrodynamic jet (e-jet) Printing

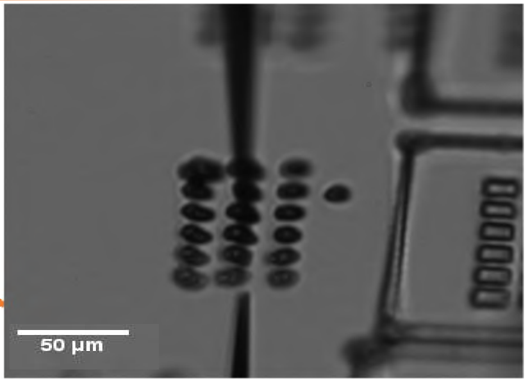


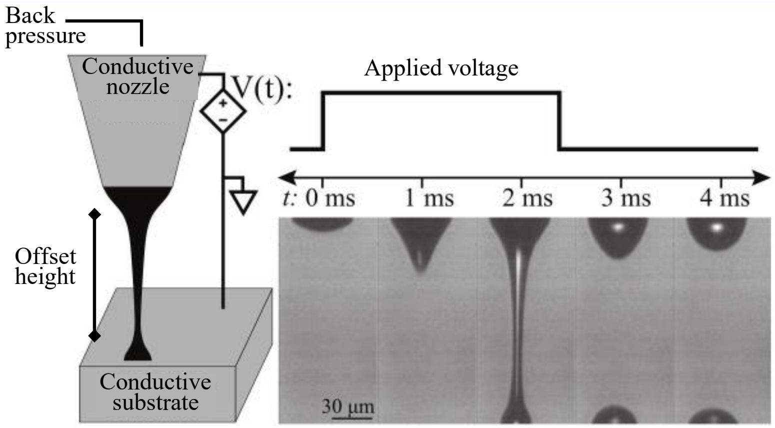


Advantages:

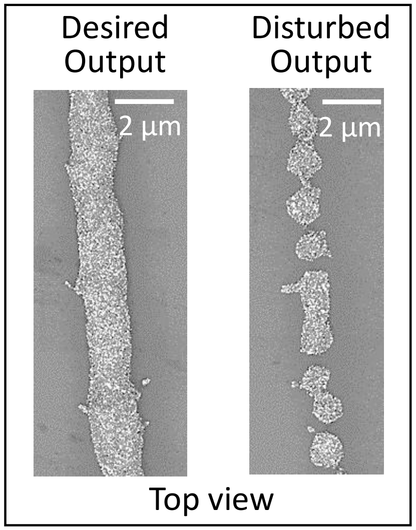
- Micro-Nano scale resolution
- Multi-material capability
- Non-planar substrates
- Enable complex designs
- Repeatable
- Fast
- Not expensive

How can learning and control lead to enhanced printing performance?



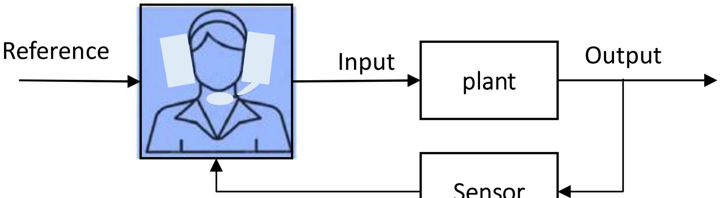


Spraying



Process / Design Parameters:

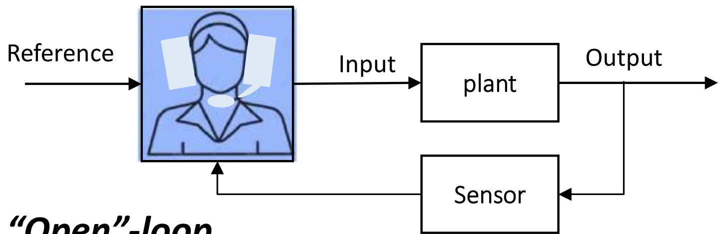
- Ink material / properties
- Substrate material / treatments
- Nozzle material
- Nozzle size / shape
- Offset height between nozzle/substrate
- Back pressure
- Applied voltage signal: DC, pulse - parameters
- Stage speed



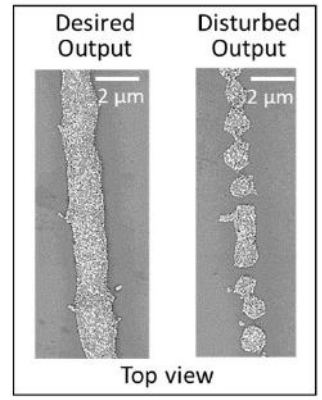
"Open"-loop

Manual process parameter tuning limits the speed and adoption of many additive manufacturing processes

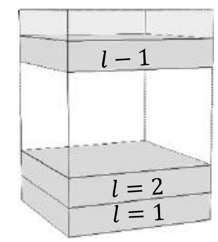
Challenges in Additive Manufacturing

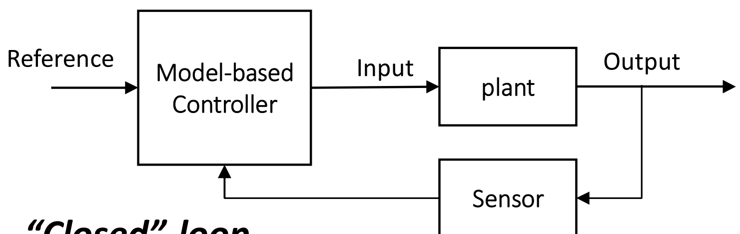


"Open"-loop

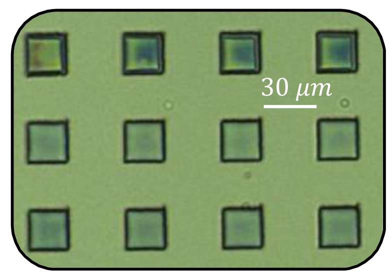


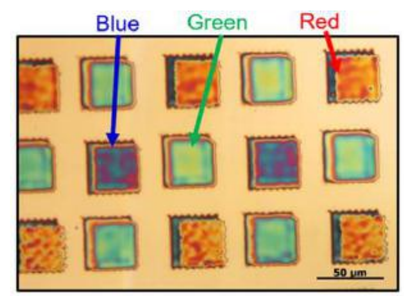
Tuned Output





"Closed"-loop

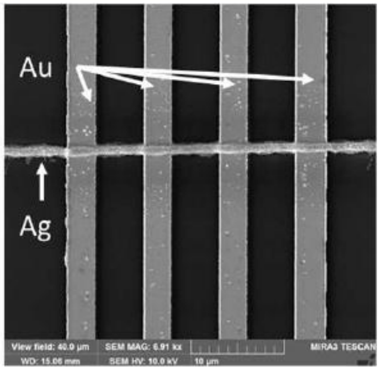


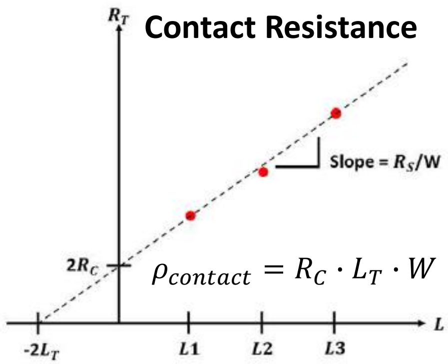


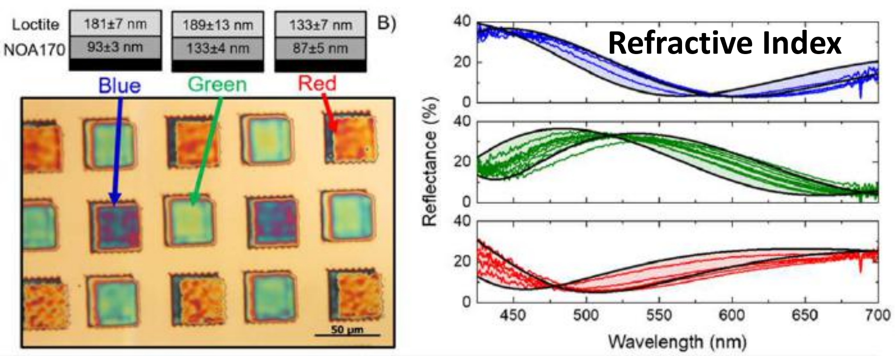
Controlled Output

Why is real-time feedback not a viable option for this process?

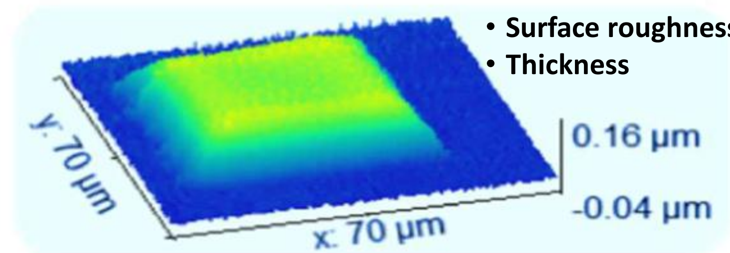
Challenges in Additive Manufacturing - Sensing



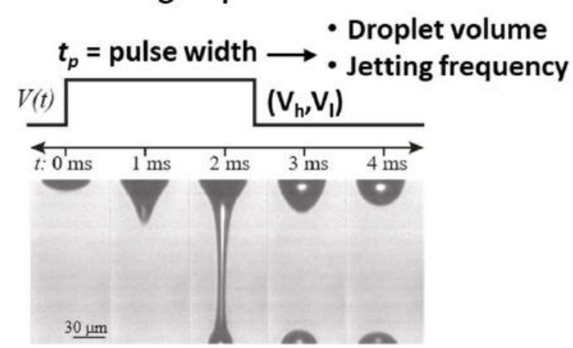




Atomic Force Microscope



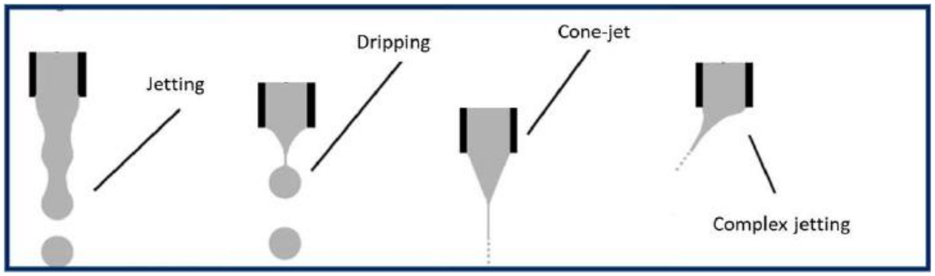
High-Speed Camera



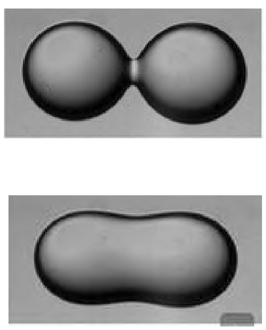
Indirect measurements with inferred behavioral responses

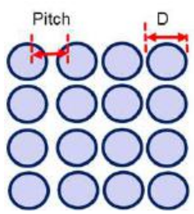
Fast temporal dynamics + high-resolution spatial dynamics

Critical dynamics are too fast or too small, while the true behaviors of interest cannot be monitored in real time

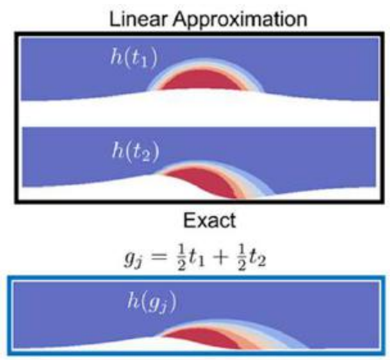


Jetting Dynamics



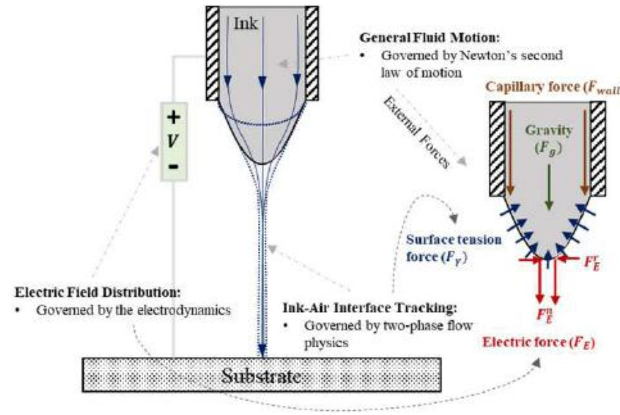


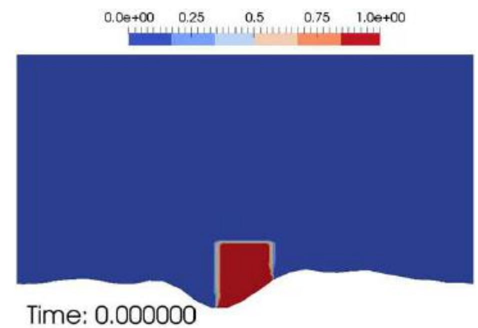
Droplet merging



Droplet impingement

Multimodality





Multiphysics

Governing physics are complex and often difficult to write as a simple ODE

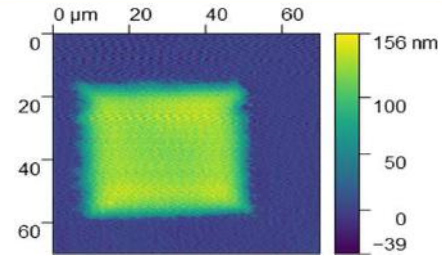
Challenges in Additive Manufacturing - Control

Design Parameters
- Droplet volume
- Jetting frequency
- Droplet merging
- Droplet impingement

Controller

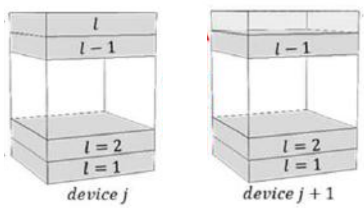
- t_p = pulse width
- P = pitch

Offline



Sensing

Online



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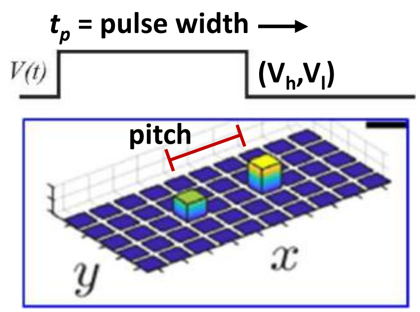
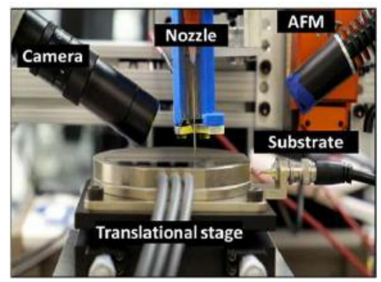
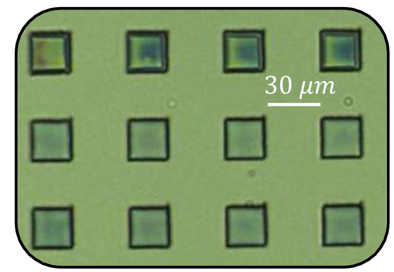


Control Input



Plant



Output

Control challenges:
- High-speed temporal dynamics
- High-resolution spatial dynamics
- No real-time sensing
- Unmodelled dynamics

Dynamics are not conducive to real-time feedback control.
Could leverage repetitive behaviors to control iteratively.

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Opportunities to Use Learning in Additive Manufacturing - Control

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- Droplet volume
- Jetting frequency
- Droplet merging
- Droplet impingement

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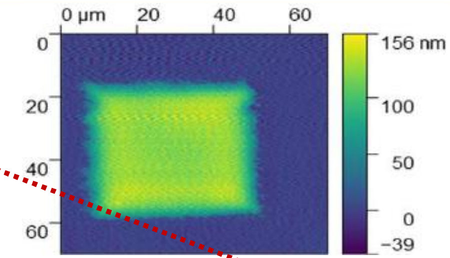
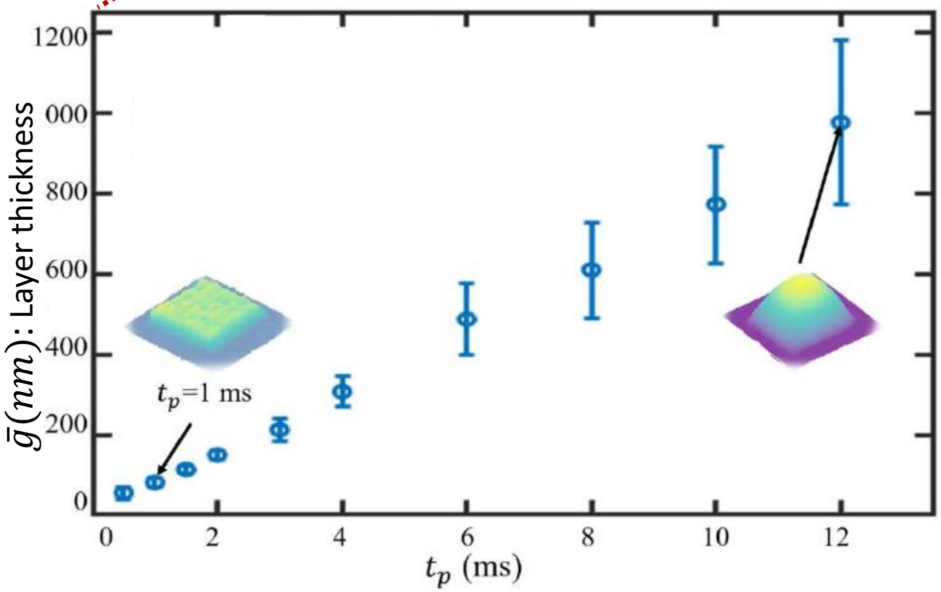
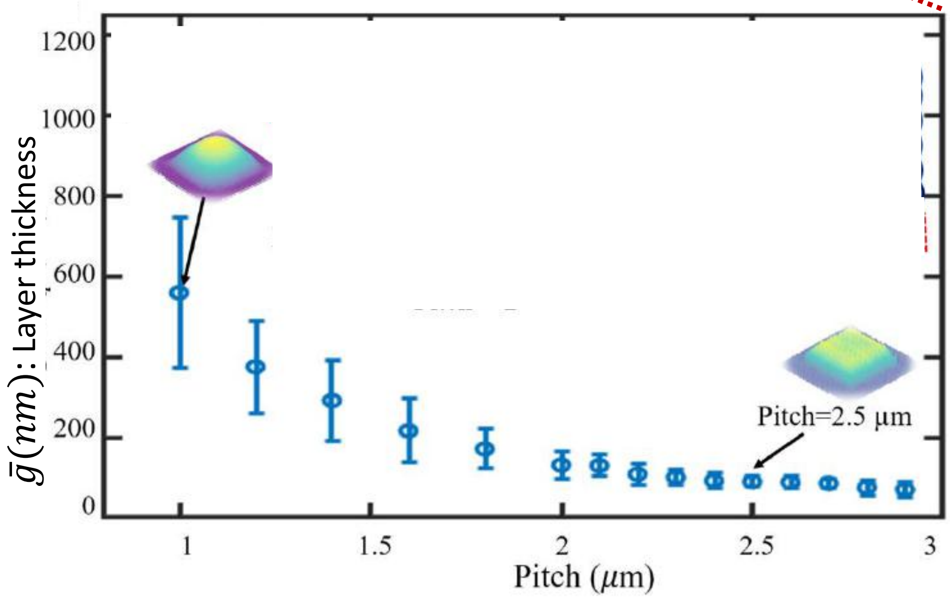


Sensing

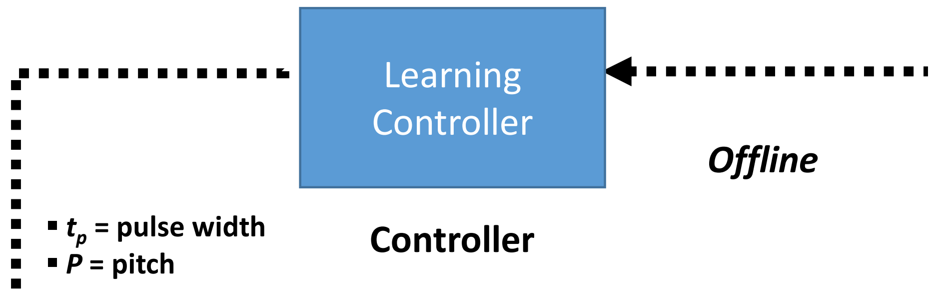


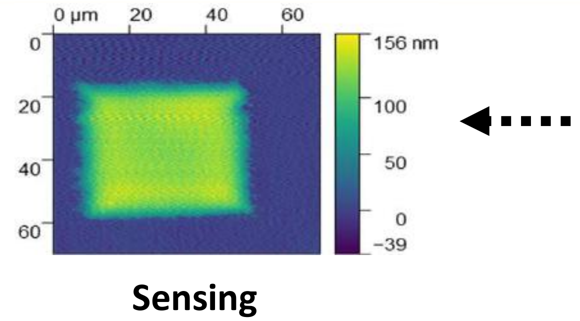


Afkhami Z, et al. *Adv. Mat. Tech.*, 2020;5(10):2000386.

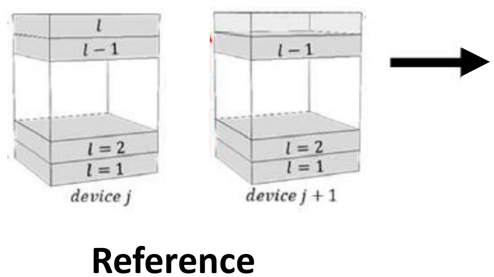
Opportunities to Use Learning in Additive Manufacturing - Control

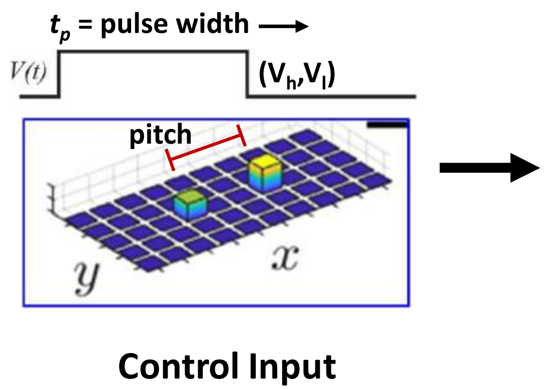
<u>**Design Parameters**</u>
- Droplet volume
- Jetting frequency
- Droplet merging
- Droplet impingement

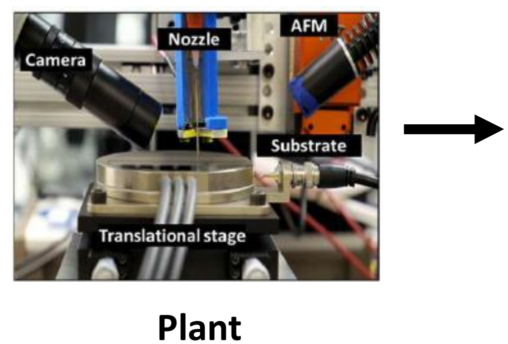


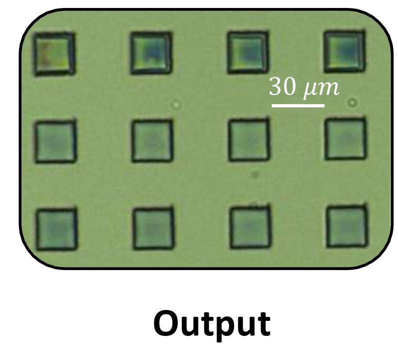


Online





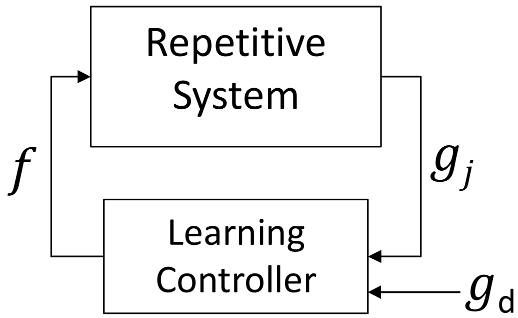




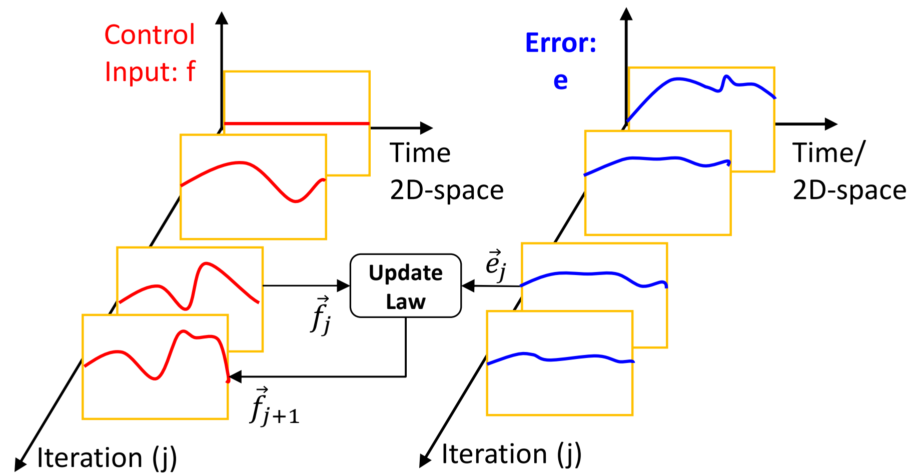
Goals:
- Autonomous regulation of product quality
- Automatic data validation and processing

Inner loop – Iterative Learning Control for process regulation

Introduction to Iterative Learning Control (ILC):



- Repetitive systems
- Reject repetitive disturbance
- Robust to model uncertainty
- Use past input and error signals



j : Iteration number

f_j: Input

g_j: output

g_d: Reference

e_j: Error

L_f: Input filter

L_e: Error filter

First order ILC (FO-ILC):

$$\underbrace{f_{j+1}}_{\text{Next iteration input}} = \underbrace{L_f f_j}_{\text{Current iteration input}} + \underbrace{L_e e_j}_{\text{Current iteration error}}$$

$$e_j = gd - g_j$$

Higher order ILC (HO-ILC):

Order of ILC

$$\vec{f}_{j+1} = \underbrace{\sum_{i=0}^{\boxed{N}} L_{f_i} f_{j-i} + L_{e_i} e_{j-i}}_{\text{Multiple past iterations}}$$

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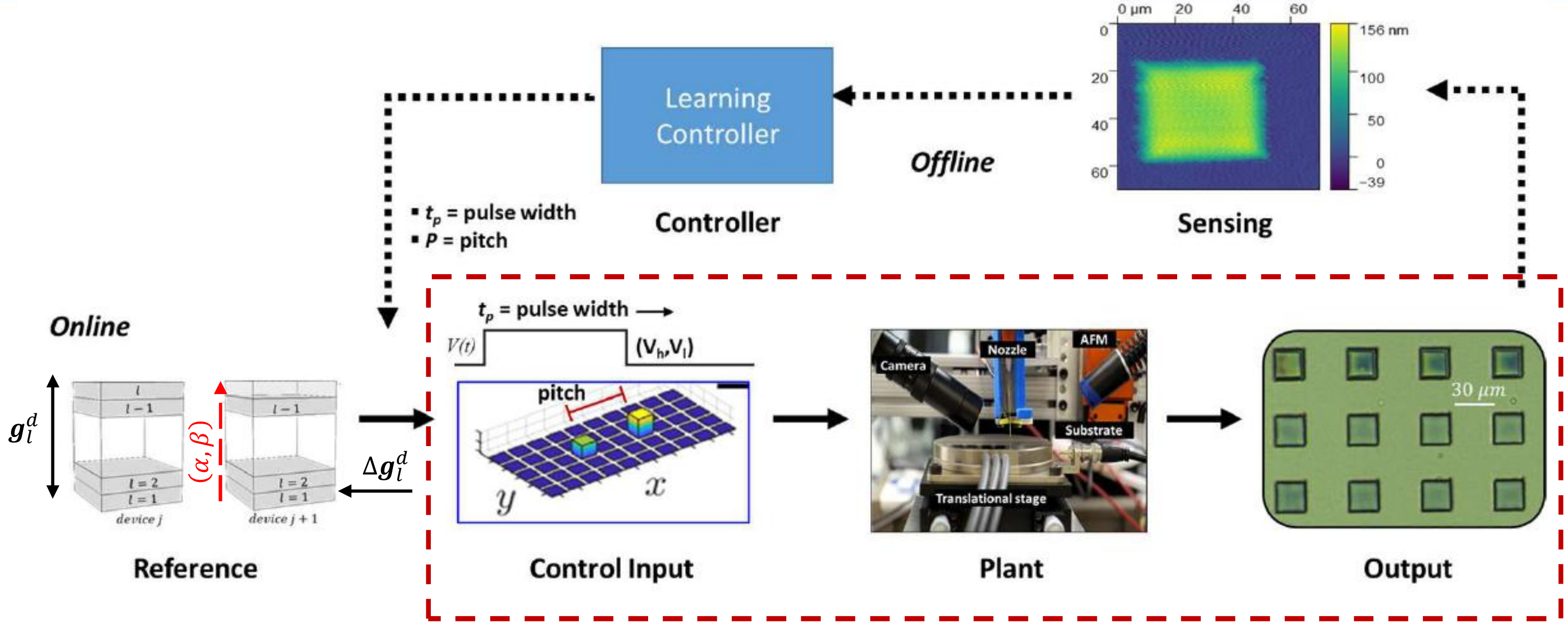
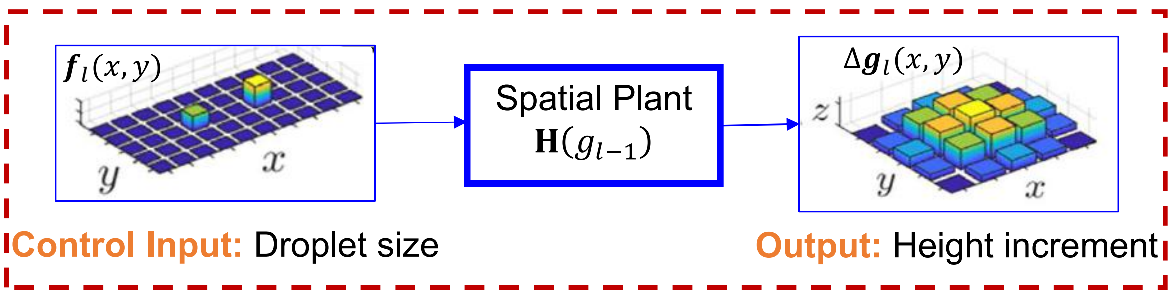
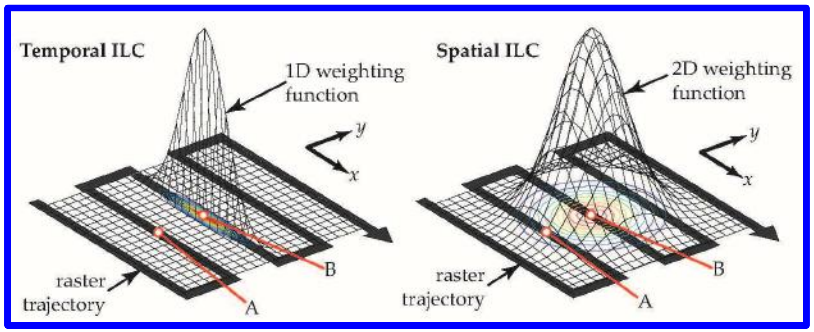


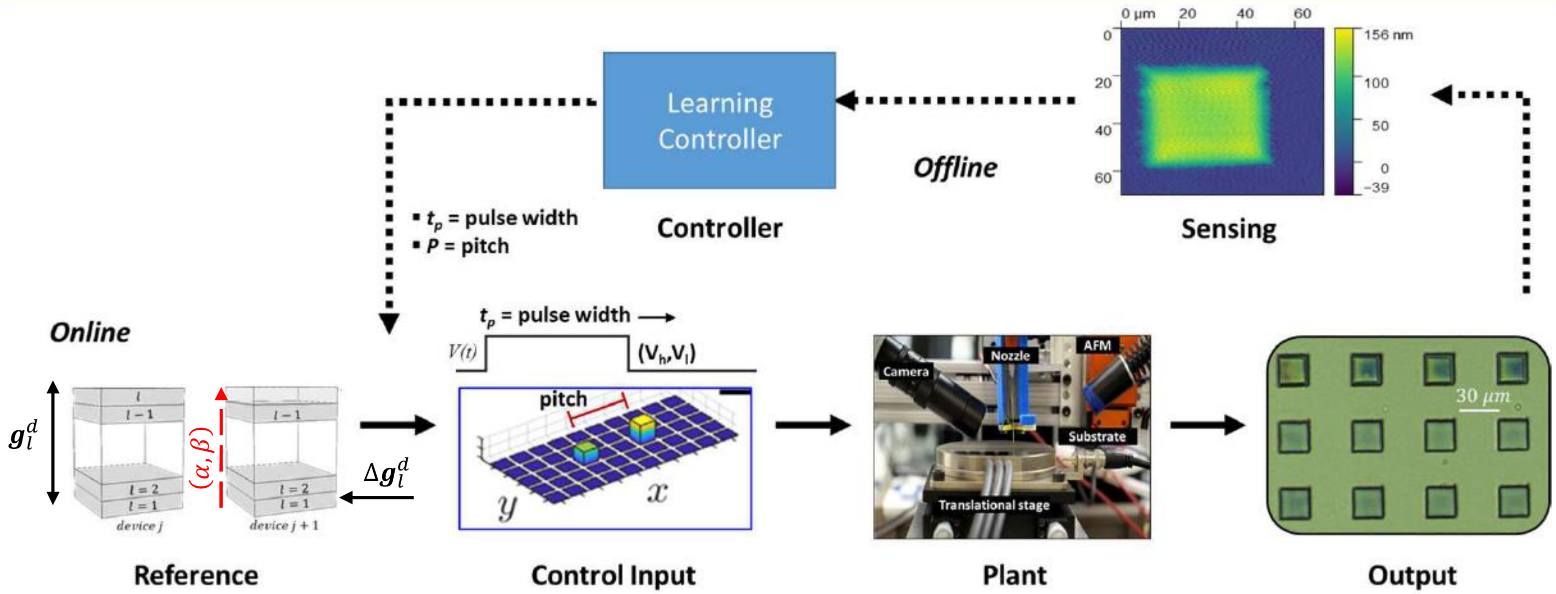




Spatial Plant: 2D Impulse Function

Hoelzle and Barton, IEEE TCST, 2016.

Spatial Iterative Learning Control (SILC)

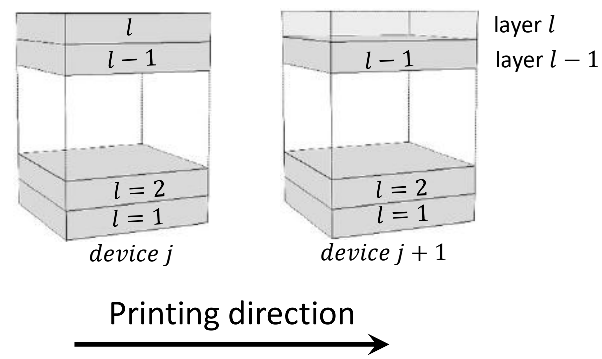


Performance Objectives:

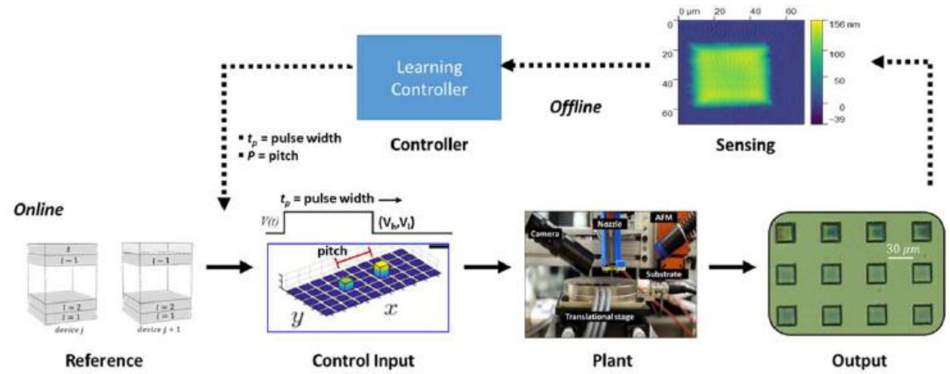
- Total error ($\boldsymbol{e}_{l,j}$) decreases over layers (l): $\vec{e}_{l,j} = g_l^d - \vec{g}_{l,j}$
- Incremental error $\Delta \boldsymbol{e}_{l,j}$ decreases over layers (l) & devices (j)

$$\Delta\vec{e}_{l,j} \triangleq \quad \Delta\vec{g}_l^d - \Delta\vec{g}_{l,j} = \Delta\vec{e}_l + \alpha_1\Delta\vec{e}_{l-1} + \cdots + \alpha_N\Delta\vec{e}_{l-N}$$

Number of layers: $\alpha_i = \dfrac{\alpha}{i} < 1,$



Controller Design:
Norm Optimal SILC Cost Function:



$$\Im_{SILC} = \underbrace{\left\|\vec{e}^{\,w}_{l,j+1}\right\|^2_{q.\mathbf{I}}}_{\text{Performance tracking}} + \underbrace{\left\|\vec{f}_{l,j+1}\right\|^2_{s.\mathbf{I}}}_{\text{Robustness to model uncertainty}} + \underbrace{\left\|\vec{f}_{l,j+1} - \vec{f}_{l,j+1}\right\|^2_{r.\mathbf{I}}}_{\text{Convergence rate and noise attenuation over j}} + \sum_{i=1}^{N=L-1} \underbrace{\beta_i \left\|\vec{f}_{l,j+1} - \vec{f}_{l-i,j+1}\right\|^2_{r.\mathbf{I}}}_{\text{Convergence rate and noise attenuation over } l}$$

$$\Delta\vec{e}_{l,j} \triangleq \quad \Delta\vec{g}^{\,d}_{l} - \Delta\vec{g}_{l,j} = \Delta\vec{e}_{l} + \alpha_1 \Delta\vec{e}_{l-1} + \cdots + \alpha_N \Delta\vec{e}_{l-N}$$

Number of layers: $\alpha_i = \dfrac{\alpha}{i} < 1, \quad \beta_i = \dfrac{\beta}{i} < 1$

Solve:

$$\frac{\partial \Im_{SILC}}{\partial \vec{f}_{l,j+1}} = 0$$

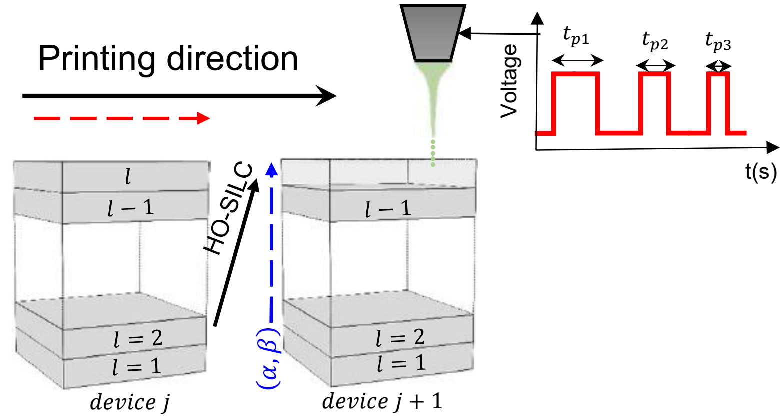
Learning Filters:

$$\mathbf{L}_f(q, s, r, \alpha, \beta)$$
$$\mathbf{L}_e(q, s, r, \alpha, \beta)$$

Spatial Iterative Learning Control (SILC)

Controller Design:
SILC Update Law:

$$\vec{f}_{l,j+1} = \underbrace{\mathbf{T}^{h}_{l-1,j}\ \vec{f}_{l,j}}_{\text{Horizontal learning}} + \underbrace{\mathbf{T}^{v1}_{l-2,j}\ \vec{f}_{l-1,j+1} + \cdots + \mathbf{T}^{vN}_{l-N-1,j}\ \vec{f}_{l-N,j+1}}_{\text{Vertical learning}} + \left(\mathbf{L}^{h}_{e} + \sum_{i=1}^{N=L-1} \mathbf{L}^{vi}_{e}\right)\Delta\vec{g}^{d}_{l}$$



$$\begin{cases} \mathbf{T}^{h}_{l,j} = \mathbf{L}^{h}_{f} - \mathbf{L}^{h}_{e}\mathbf{H}_{l,j} & \text{Horizontal CL-plant matrix} \\ \mathbf{T}^{vi}_{l,j} = \mathbf{L}^{vi}_{f} - \mathbf{L}^{vi}_{e}\mathbf{H}_{l,j} & \text{Vertical CL-plant matrix} \end{cases}$$

Convert higher order to first order for analysis

$$\vec{Z}_{l} = \begin{bmatrix} \vec{f}_{l} \\ \vdots \\ \vec{f}_{2} \\ \vec{f}_{1} \end{bmatrix}$$

FO-ILC update law:

$$\vec{Z}_{l,j+1} = \mathbf{F}_{l,j}\vec{Z}_{l,j} + \vec{R}_{r} \quad \rightarrow \mathbf{F}_{l,j} = \mathcal{F}(\mathbf{T}^{h}_{l,j}, \mathbf{T}^{vi}_{l,j})$$

F is high dimensional

Spatial Iterative Learning Control (SILC)

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Controller Design:
Stability Analysis:

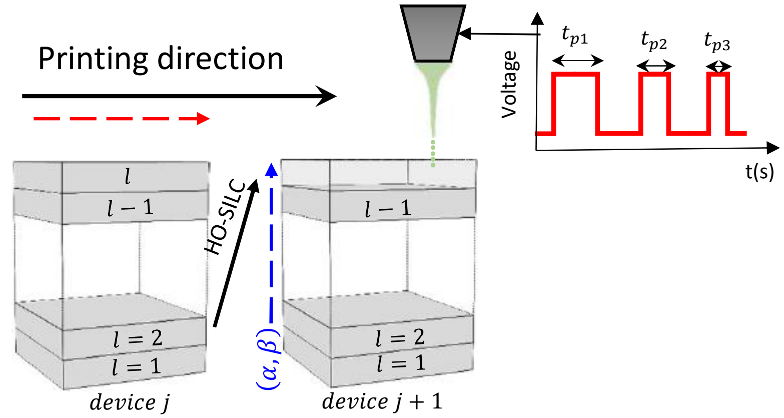
FO-ILC update law: $\vec{Z}_{l,j+1} = \mathbf{F}_{l,j}\vec{Z}_{l,j} + \vec{R}_r$ $\qquad \mathbf{F}_{l,j} = \mathcal{F}(\mathbf{T}^{h}_{l,j}, \mathbf{T}^{vi}_{l,j})$

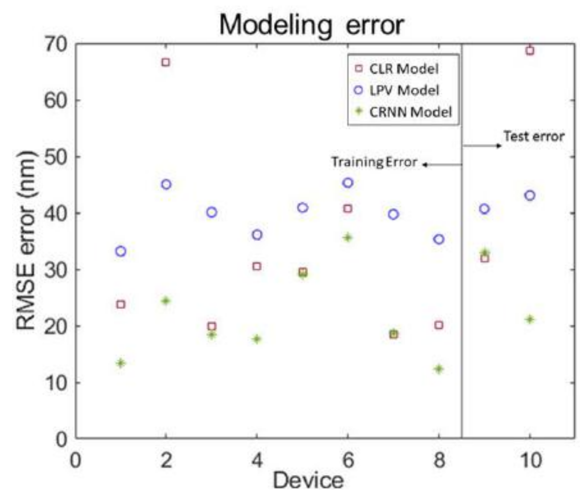
Goal: **Asymptotic stability:** $\rho(\mathbf{F}_0) < 1$

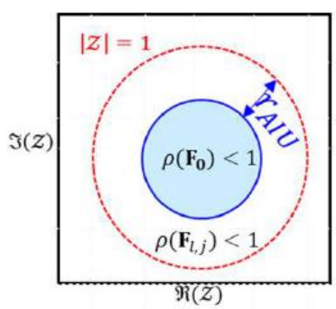
- Estimate the robustness radius ($\|\Delta\mathbf{H}_{l,j}\| < r_{AIU}$) such that the iteration varying SILC update law remains stable ($\|\mathbf{F}_{l,j}\| < 1$)
- How do we design r_{AIU} to ensure robustness?

$$\mathbf{H}_{l,j} = \underbrace{\mathbf{H}_0}_{\text{Nominal plant}} + \underbrace{\Delta\mathbf{H}_{l,j}}_{\text{Model uncertainty}} \qquad \mathbf{F}_{l,j} = \underbrace{\mathbf{F}_0}_{\text{Nominal}} + \Delta\mathbf{F}_{l,j}\,(\Delta\mathbf{H}_{l,j}) \qquad \|\Delta\mathbf{H}_{l,j}\| < \overset{\text{design}}{\boxed{r_{AIU}}}$$

Robustness radius design: $r_{AIU}(\underbrace{q, s, r}_{\text{SILC}}, \underbrace{\alpha, \beta}_{\text{HO-SILC}})$







Z Afkhami, et al. TCST, (2022).
Afkhami, Hoelzle, Barton, (2022). *IFAC-PapersOnLine*
Pannier et al. 2019
E. Balta, et al. TCST 2021.

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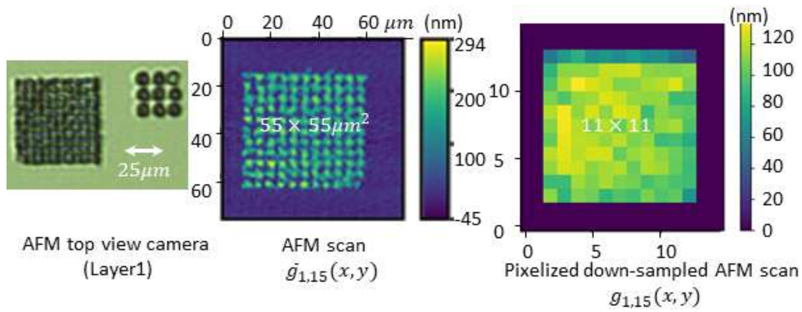
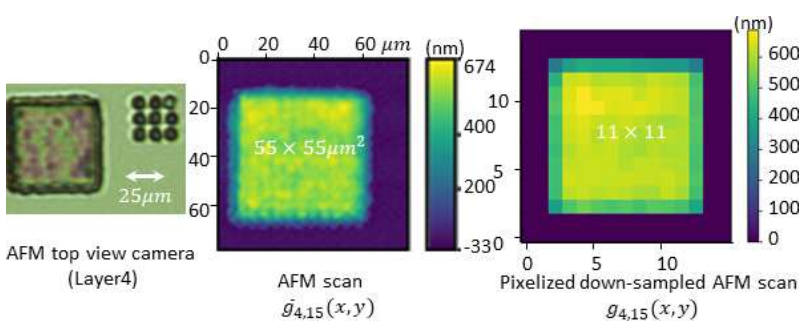
Controller Performance:

HO-SILC Experimental Results

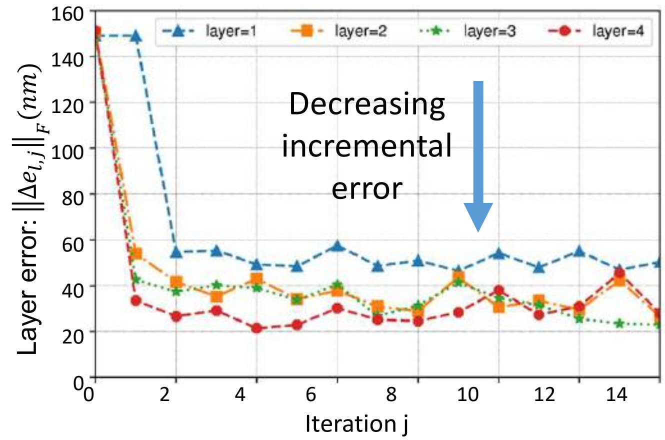
Layer=1

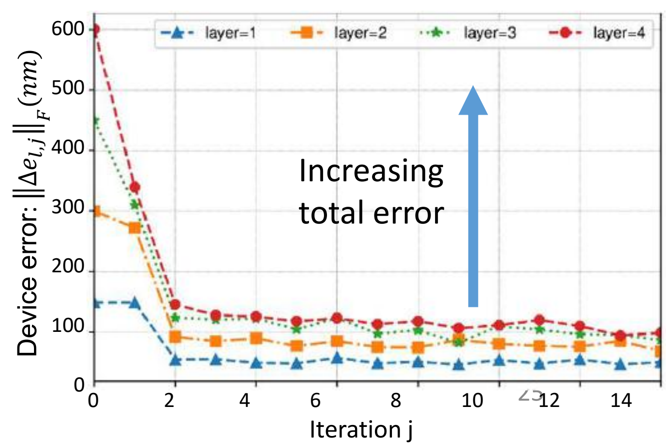


Layer=4



HO-SILC Errors

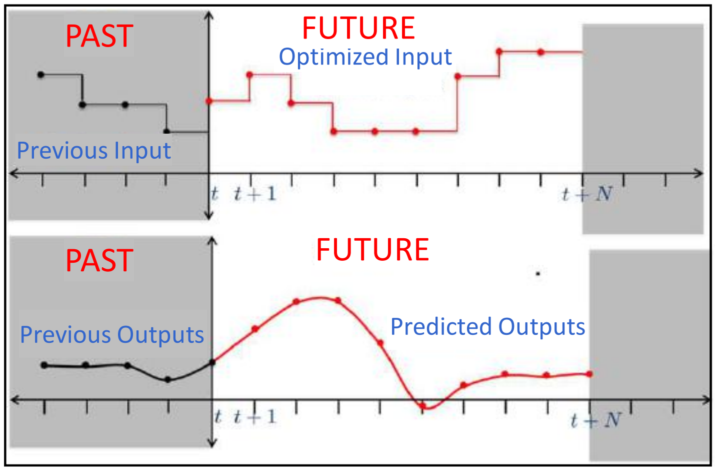




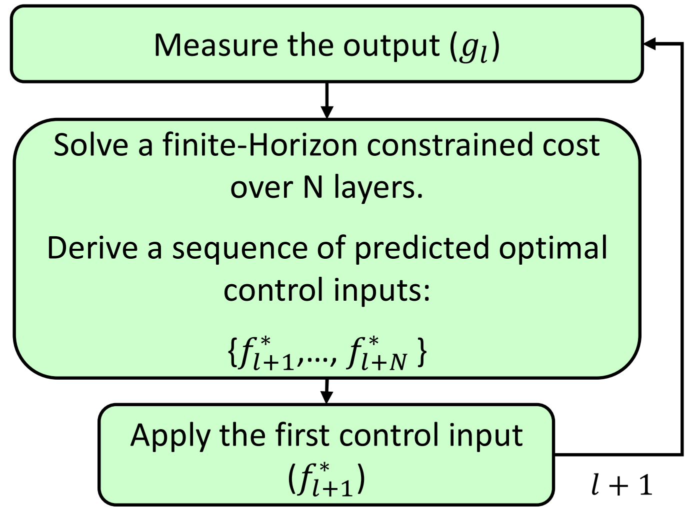
Can we do anything to address the increasing errors?

Z Afkhami, et al. TCST, (2022).
Afkhami, Hoelzle, Barton, (2022). *IFAC-PapersOnLine*

Model Predictive Control (MPC)



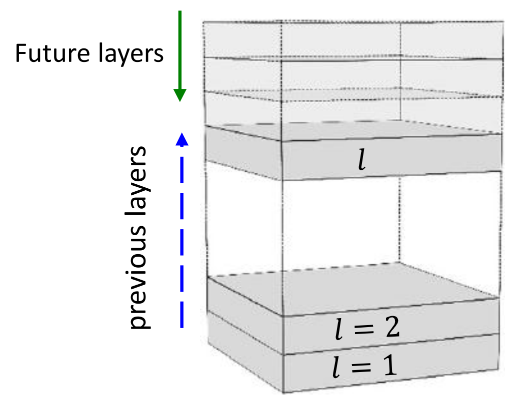
Modified figure from EECI19-M22 course by S. Di Cairano and I. Kolmanovsky



Leverage MPC to enhance robustness

Goal:

- Learn from previous layers using SILC design
- Predict future layer deposition errors using MPC design
- Predict the optimal input signal of multiple layers ahead ($\vec{f}_{l+1}$, …, $\vec{f}_{l+N}$)
- At each printing pass, only the input signal of the first layer, $\vec{f}_{l+1}$, is considered



Z Afkhami, et al. TCST, (2022).
Afkhami, Hoelzle, Barton, (2022). *IFAC-PapersOnLine*

SILC-MPC Framework:

SILC cost function:

$$\Im_{SILC} = \underbrace{\|\vec{e}_{l+1}\|^2_{Q_{e1}} + \|\Delta\vec{e}_{l+1}\|^2_{Q_{\Delta e}}}_{\text{Performance tracking}} + \underbrace{\left\|\vec{f}_{l+1}\right\|^2_{S1}}_{\text{Robustness to model uncertainty}} + \underbrace{\left\|(\vec{f}_{l+1} - \vec{f}_{l})\right\|^2_{R1}}_{\text{Convergence rate and noise attenuation}}$$

MPC cost function:

$$\Im_{MPC} = \underbrace{P_N\|\vec{e}_{l+N}\|^2_{I}}_{\substack{\text{Terminal cost} \\ \text{Improves stability properties}}} + \underbrace{\sum_{i=2}^{N}\|\vec{e}_{l+i}\|^2_{Q_{e_i}} + \left\|\vec{f}_{l+i}\right\|^2_{S_i} + \left\|(\vec{f}_{l+i+1} - \vec{f}_{l+i})\right\|^2_{R_i}}_{\text{Model predictive horizon}} \qquad s.t.\ \vec{0} < \vec{f}_{l+i} < \vec{F}$$

SILC-MPC cost function:

$$\Im_{SILC-MPC} = \Im_{SILC} + \Im_{MPC}$$

$s.t.\ \vec{0} < \vec{f} < \vec{F}_{\max}$ Bounded control signal

$$S = \begin{bmatrix} S_1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & S_N \end{bmatrix}$$

$$R = \begin{bmatrix} R_1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & R_N \end{bmatrix}$$

$$Q = \begin{bmatrix} Q_{\Delta e} & & & 0 \\ & Q_{e1} & & \\ & & \ddots & \\ 0 & & & Q_{e_N} + P_N I \end{bmatrix}$$

Design matrices

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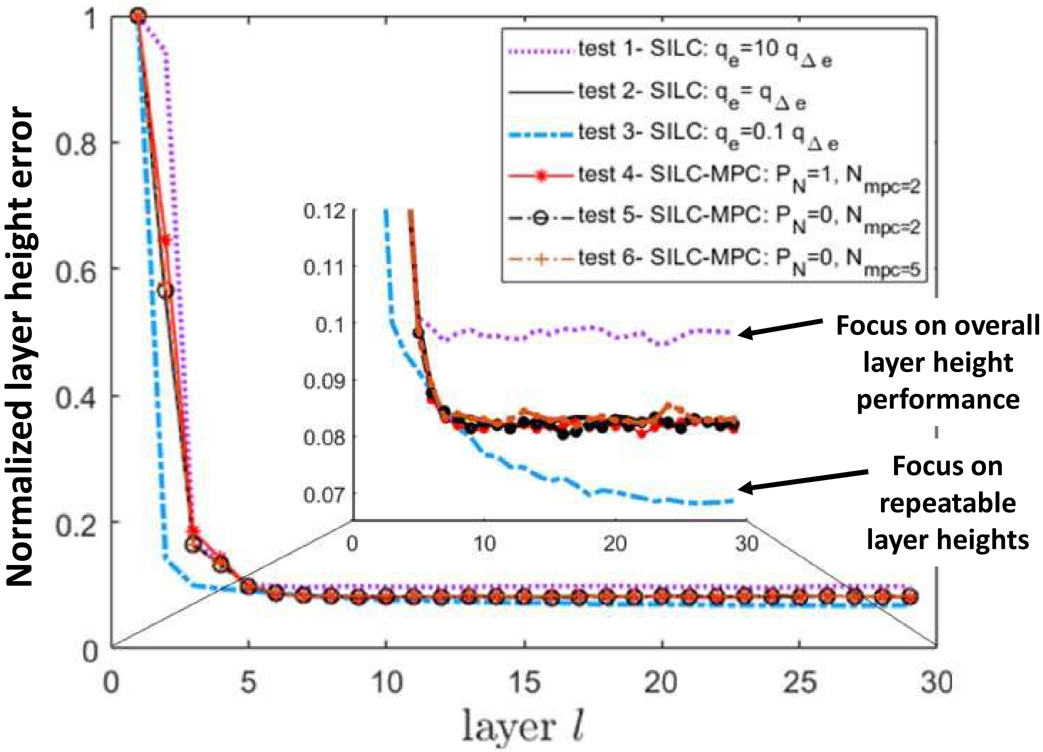
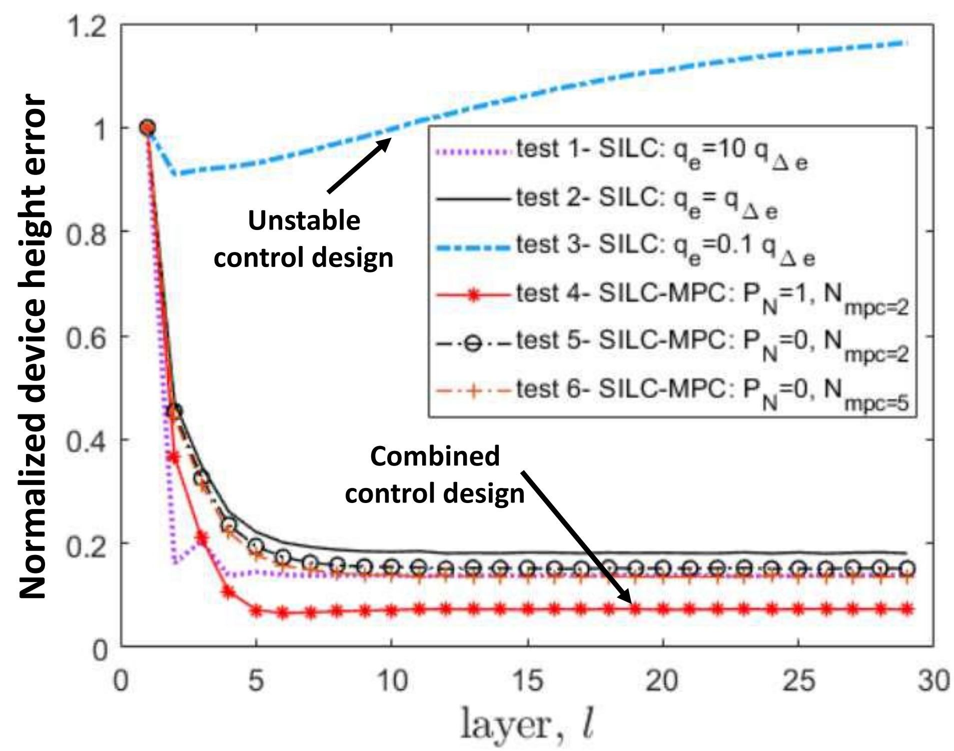
Intelligent. control. innovation.





Forward prediction and iterative learning control leads to optimal performance

Outline

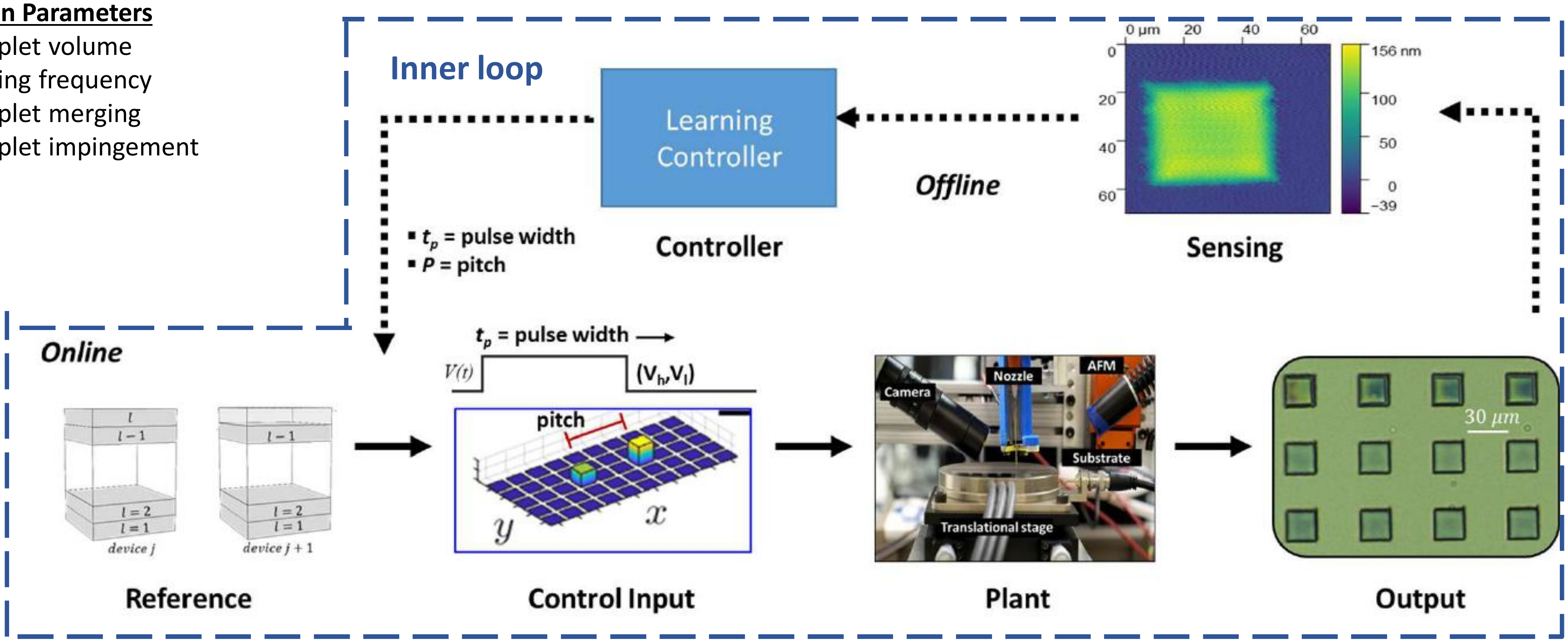
Basic Overview:
Learning in Manufacturing

Learning Case Study:
A. Challenges in additive manufacturing modeling and control
B. Learning applied to an additive manufacturing example

Open Opportunities for Learning + Control to Advance Manufacturing

Opportunities to Use Learning in Additive Manufacturing - AI

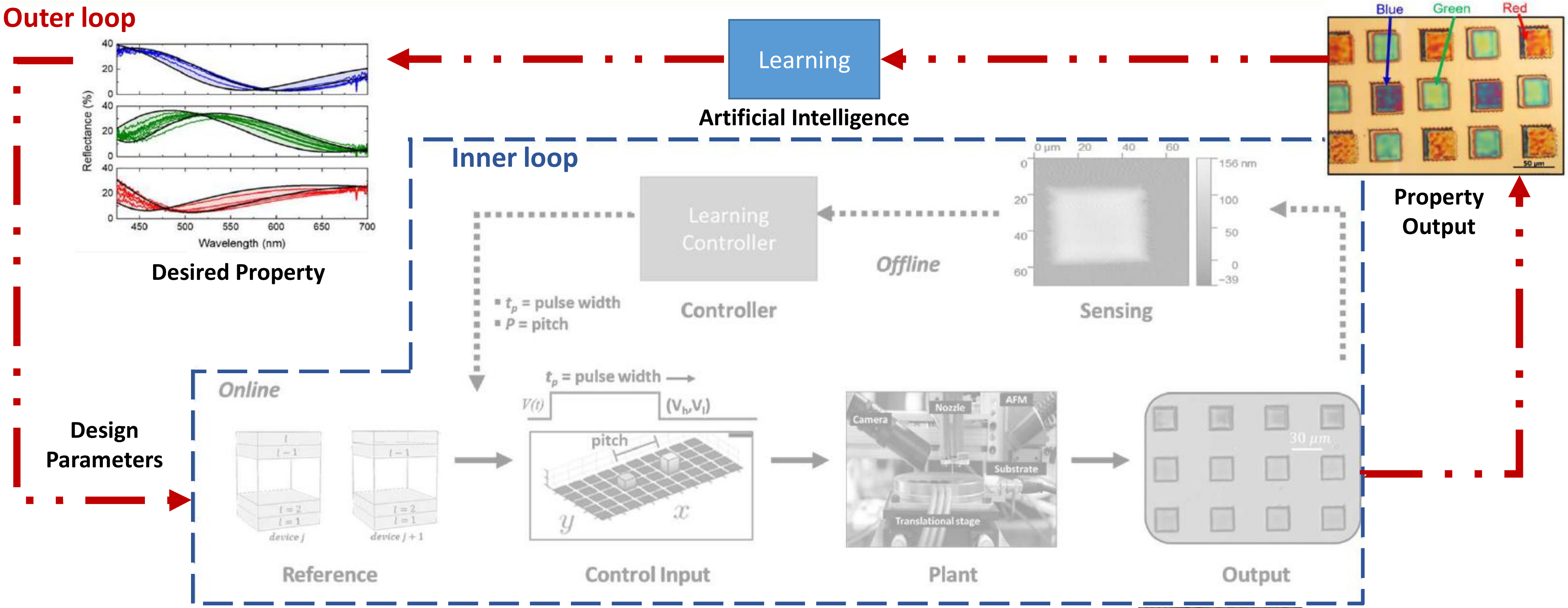
<u>**Design Parameters**</u>
- Droplet volume
- Jetting frequency
- Droplet merging
- Droplet impingement



Goals:
- Autonomous regulation of product quality
- Automatic data validation and processing

Inner loop – Iterative Learning Control for process regulation

Opportunities to Use Learning in Additive Manufacturing - AI

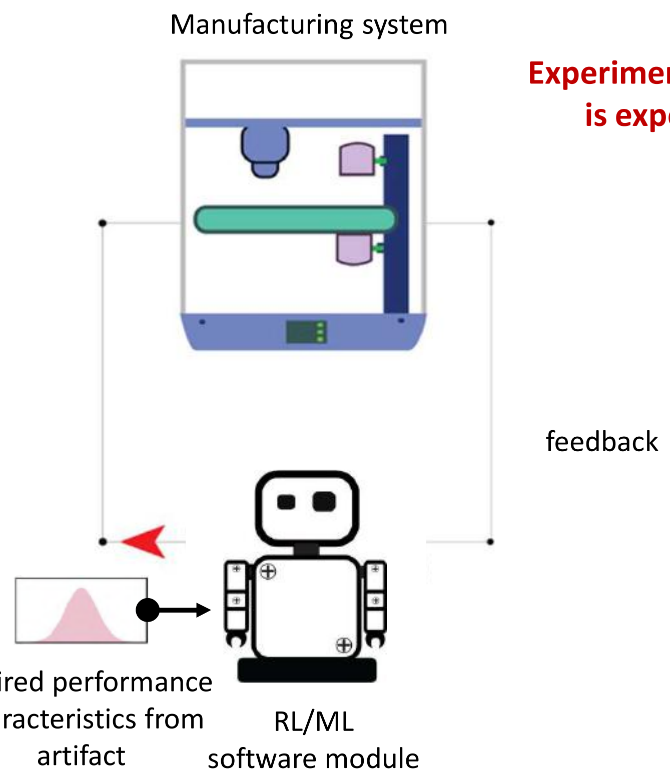


Goals: • Automatic identification of process-structure-property relationships

Outer loop – Reinforcement Learning for process-structure-property relationships

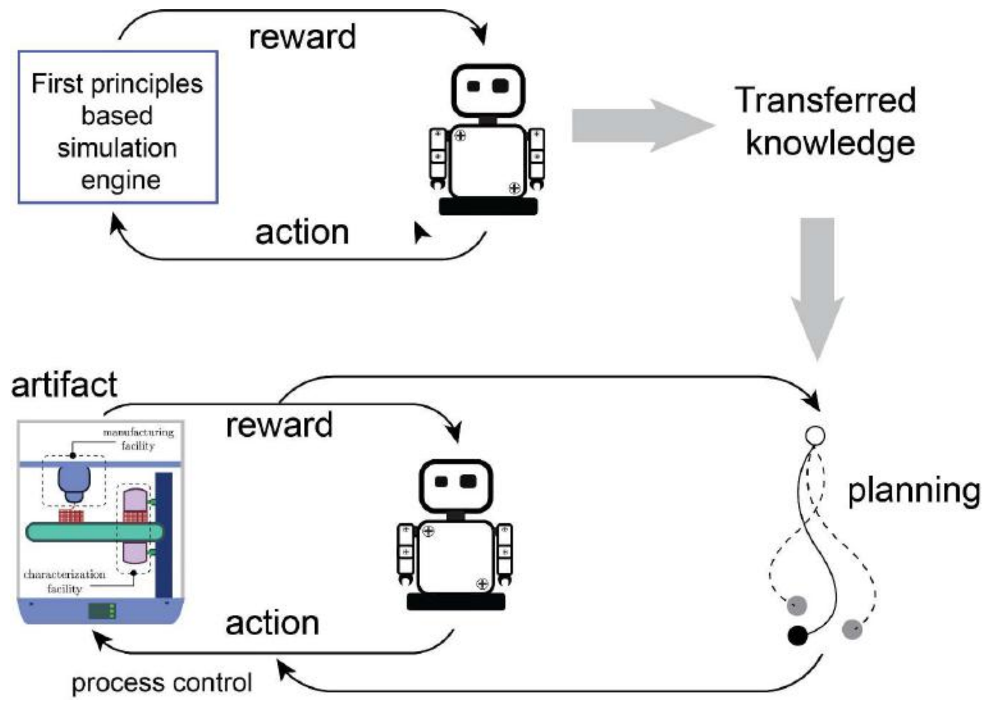
Collaboration with Prof. David Hoelzle's group at Ohio State University

Opportunities to Use Learning in Additive Manufacturing - AI



Experimental testing is expensive!

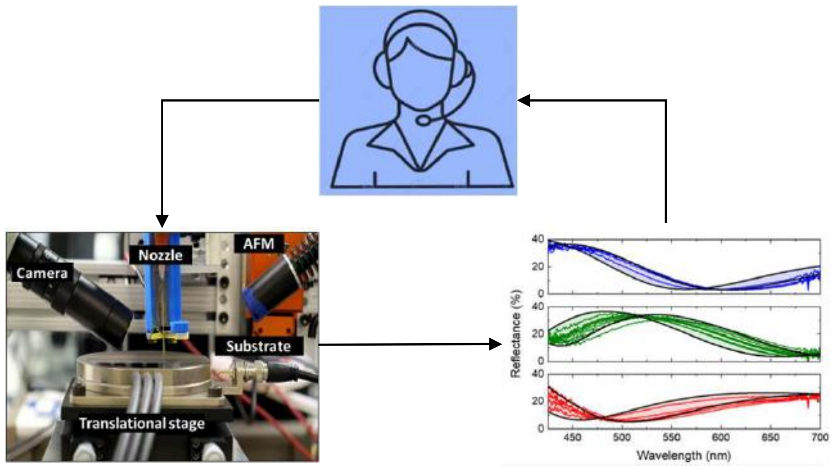
Reinforcement Learning



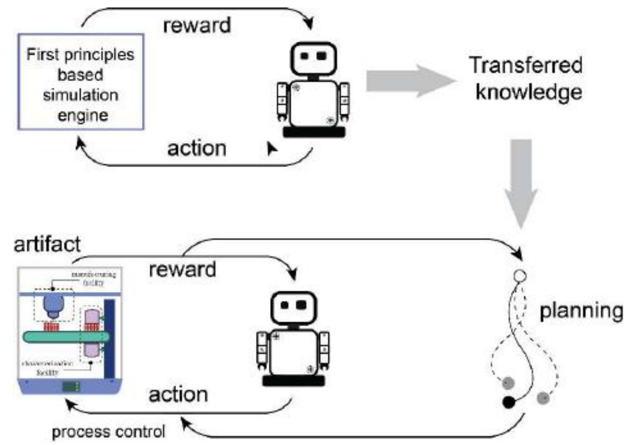
Transfer learning framework in the context of RL for manufacturing decision making

Md Ferdous Alam, Max Shtein, Kira Barton & David J. Hoelzle, American Control Conference (ACC), 2021 and 2022.
Md Ferdous Alam, Max Shtein, Kira Barton & David J. Hoelzle, IEEE Control Systems Letters (L-CSS)

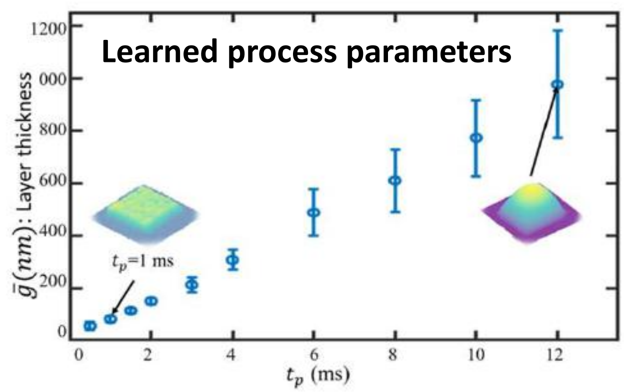
Reinforcement Learning for Process-Structure-Property Relationship



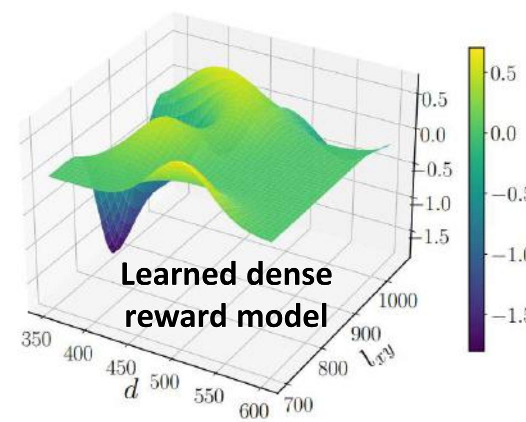
Brute force learning – [Months]



Automated learning – [Hours]



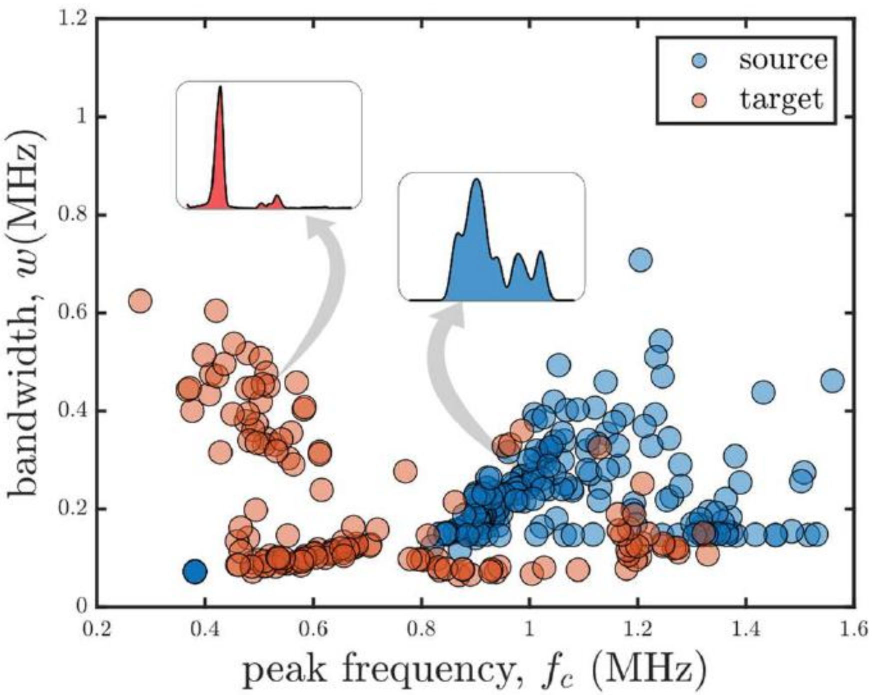
Human derived process-structure-property relationship



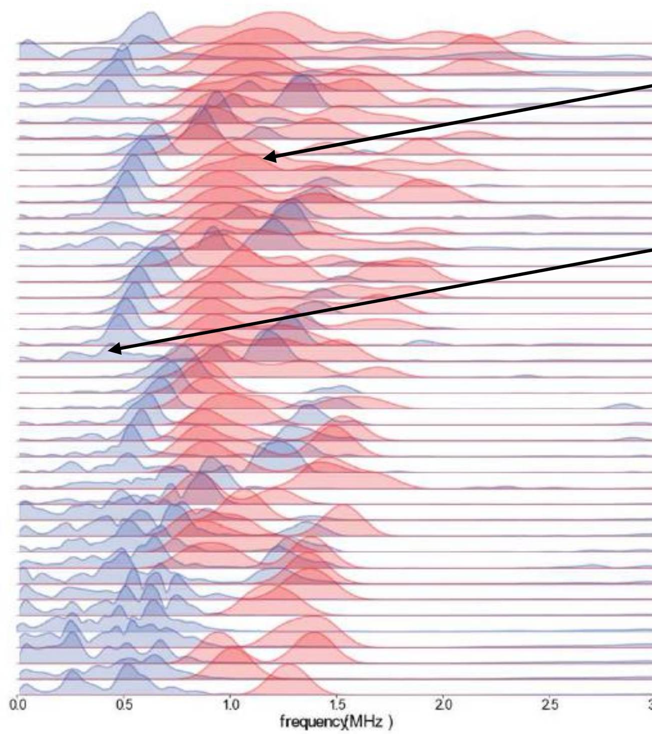
RL derived process-structure-property relationship

Why is implementing Machine learning a challenge in manufacturing systems

Distribution of features changes from simulation model to manufactured artifact



Output characteristics of an artifact change from simulation to manufactured artifact

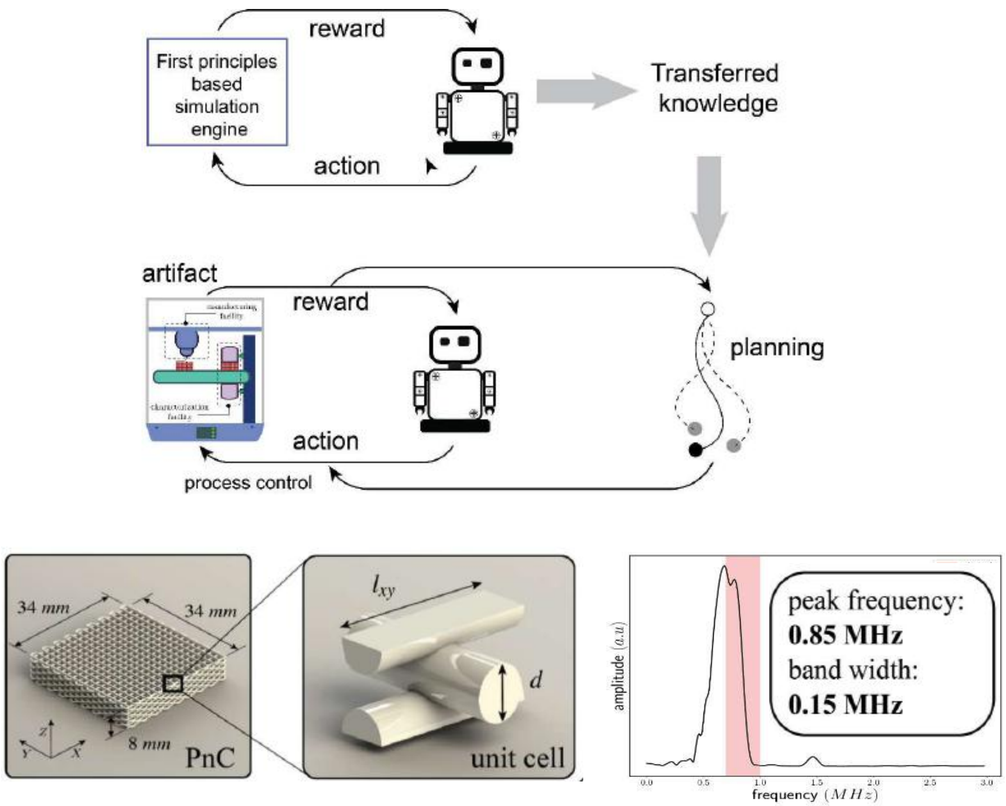


Spectral response from FEM simulations

Spectral response from manufactured artifacts

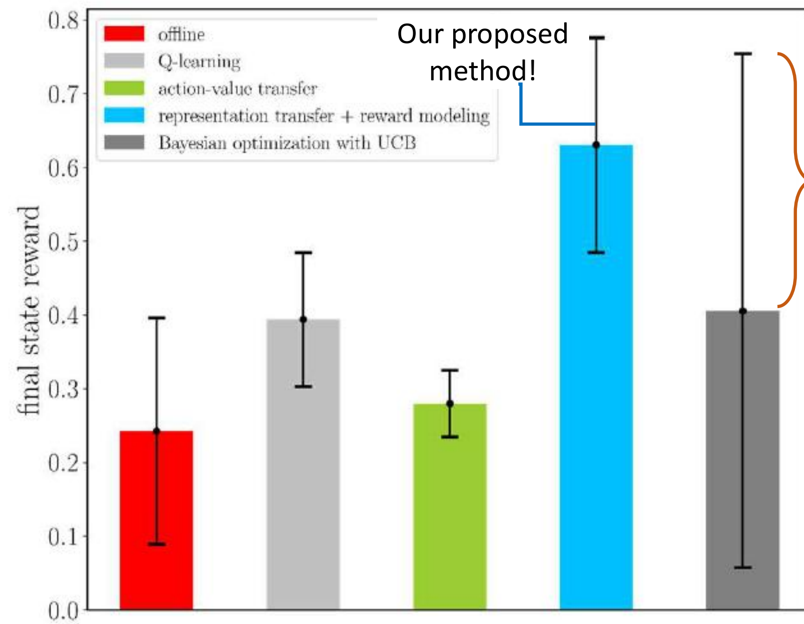
Need a learning strategy that can handle model uncertainty

How do other transfer learning strategies perform?



Representation transfer with probabilistic reward modeling

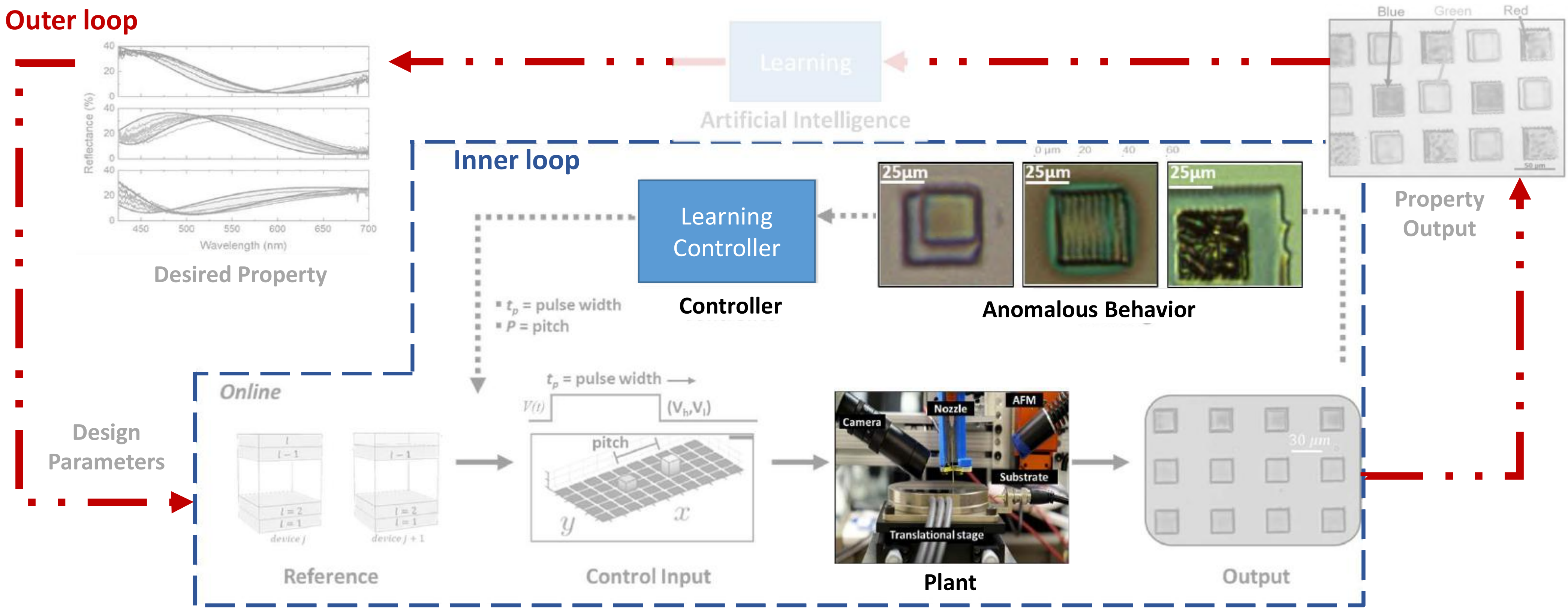
Bayesian optimization fails due to manufacturing defects for complex geometry artifacts



Reward obtained from final artifact

Md Ferdous Alam, Max Shtein, Kira Barton & David J. Hoelzle, IEEE Control Systems Letters (L-CSS)
"Reinforcement Learning Enabled Autonomous Manufacturing Using Transfer Learning and Probabilistic Reward Modeling", ThCT04.3

Opportunities to Use Learning in Additive Manufacturing - AI



Applications of Learning:

- Control design
- Functional device design
- Model identification and updating
- Anomaly detection and classification
- In situ quality control

Open Control Questions:

- Performance and robustness guarantees for combined ML + Learning Control mtds.
- Robustness requirements for automatic model updating
- Uncertainties associated with manufacturing defects

Thank you for your attention!

CCTA 2023

- Bridgetown, Barbados
- Venue: Hilton Barbados
- Date: 16-18 August, 2023
- Papers due: Jan. 31, 2023
- https://ieeeccta.org/

Conference on Control Technology and Applications

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WHERE DISCOVERIES BEGIN

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- Rockwell Automation
- General Motors
- National Institute of Standards and Technology (NIST)
- Applied Dynamics International
- Boeing

Research collaborators:
- University of Michigan
- Ohio State University
- University of Illinois
- Air Force Research Lab
- Army Research Lab

All the students that have contributed to this research!

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Thank You!