Highlights of my work

April, 2024

Cem Tutum, Ph.D.

in/cem-c-tutum/ google.scholar github/cctutum

DTU Danmarks Tekniske Universitet — Process Modeling Group

Michigan State University — Computational Optimization and Innovation Lab

The University of Texas at Austin — Neural Networks Research Group

nnaisense — Industrial Automation

Relativity — Algorithms and Optimization & Additive Simulation

ICON — Strategic R&D

Overview

- ➢ My Background
  - ○ Short resume
    - ■ About me
    - ■ Academic experience
    - ■ Industrial experience
  - ○ Specialties
    - ■ Simulation: Multi-physics models
    - ■ Optimization: Sample efficient optimization
    - ■ Machine Learning: Robust decision making
    - ■ Process Monitoring: Spatio-temporal computing
    - ■ Spatial computing & Digital Twins
- ➢ Focus Project: Functional Generative Design
  - ○ Efficient design and validation cycle with ML and optimization

Background / Quick resume

➢ About me:

- I have comprehensive experience at the intersection of simulation and data-driven design, digital manufacturing, digital twins, scientific computing and visualization, machine learning and optimization.
- My passion lies in closing the loop between design and manufacturing to enable the creation of innovative products with desired functionalities.
- I develop centralized **digital twin** software platforms that serves as information hub, enabling cross-functional teams to access curated data relevant to their needs and facilitate a comprehensive evaluation of the manufacturing process.

Background / Quick resume

- Academic Experience:
  - **Technical University of Denmark,** Mechanical Engineering (2006-2013)
    - Ph.D., Postdoc, Assistant Professor in Process Modelling Group
    - Member of Topology Optimization Group
    - Multi-physics models of manufacturing processes, i.e., FSW, pultrusion, SLM, etc.
  - **Michigan State University,** Electrical and Computer Engineering (2013-2015)
    - Worked with Dr. Kalyanmoy Deb, a pioneer in *evolutionary multi-objective optimization*
    - Multi and Many-objective optimization (2-15 objectives, nonlinear constraints)
    - Surrogate-based optimization (Constrained Efficient Global Optimization)
  - **The University of Texas at Austin,** Computer Science (2015-*2020*)
    - Worked with Dr. Risto Miikkulainen, a pioneer in *neuroevolution (evolving neural networks)*
    - Assistant Professor of Practice, started *Computational Design Lab*
    - Research Scientist, Lifelong Learning Machines (L2M), DARPA
    - Evolutionary Decomposition for 3D Printing (Best Paper award, GECCO 2017)
    - Functional Generative Design (GECCO 2018)

Background / Quick resume

- ➢ Industrial Experience:
  - **FIGES, Inc.**, Turkey (2004-2005)
    - Lead optimization engineer
    - Consultancy for engineering design and simulation projects
  - **ROTAM** (Rotorcraft Design and Excellence Center), Turkey (2005-2006)
    - Lead Design Optimization Engineer in Fuselage Design Group
  - **NNAISENSE, Inc.**, Austin, TX (2019-*2020*)
    - Research Scientist in Intelligent Automation group
    - Developed ML models to predict failures by 88% accuracy in 3-axis laser cutting machine automation project for TRUMPF
    - Member of Monitoring-AI team working on in-situ defect detection in selective laser melting process for EOS

Background / Quick resume

➢ Industrial Experience (continued):

- **Relativity Space**, Long Beach, CA (2020-2022)
  - Senior Development Engineer in Algorithms and Optimization Group (2020-2022)
    - Led SBIR Phase-II proposal for NASA regarding in-situ process monitoring of wire-arc additive manufacturing process and served as project manager.
    - Developed centralized **digital twin** software platform that served as information hub, enabling cross-functional teams to access curated data relevant to their needs and conduct a holistic assessment of the manufacturing process.
    - Automated statistical analysis, anomaly detection, and defect-to-telemetry correlation to drive continuous improvement of computer simulations and process parameters.
  - Staff Data Science Engineer in Additive Simulation Group (2022-2022)
    - Led software integration of design and process simulation of rocket fuselage sections.
    - Processed large point clouds of scanned 3D printed parts to prepare high-fidelity Finite Element Models for buckling analysis.
    - Performed multi-objective structural optimization analysis to simultaneously improve buckling behavior and weight of rocket fuselage section utilizing parametric stiffener design.

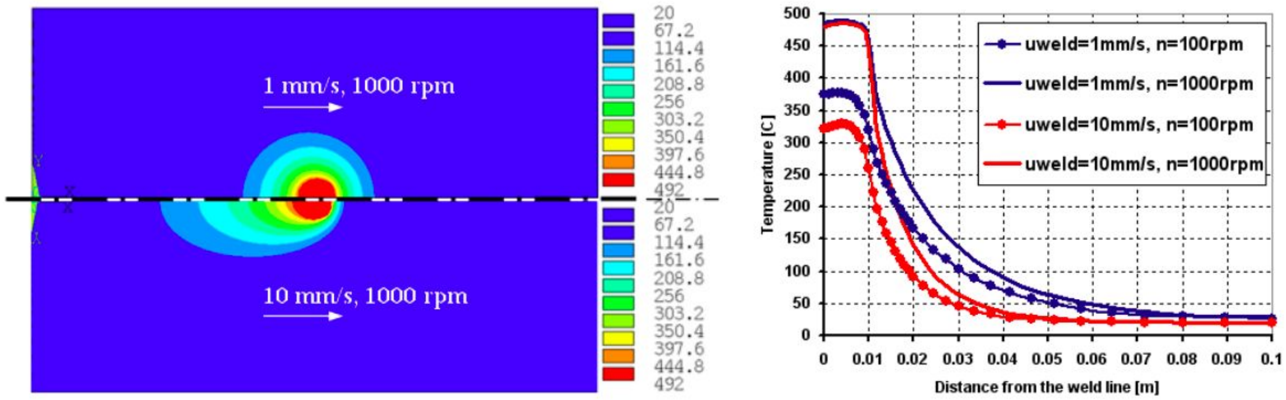
Background / Quick resume

- Industrial Experience (continued):
  - **ICON Technology**, Austin, TX (2022-2024)
    - Director of Computational Design Research in Strategic R&D Group
    - Built Digital Twins of 3D-printed buildings by integrating parametric design, process telemetry and automated product quality evaluation based on computer vision and point cloud processing.
    - Managed project for new computer vision pipeline with components ranging from image capture with multiple OAK-cameras and edge computing to cloud processing on AWS and dashboard tools.
    - Served as advisor for Space Team to better understand and control of laser processing of lunar regolith simulant using multi-physics simulations and machine learning.

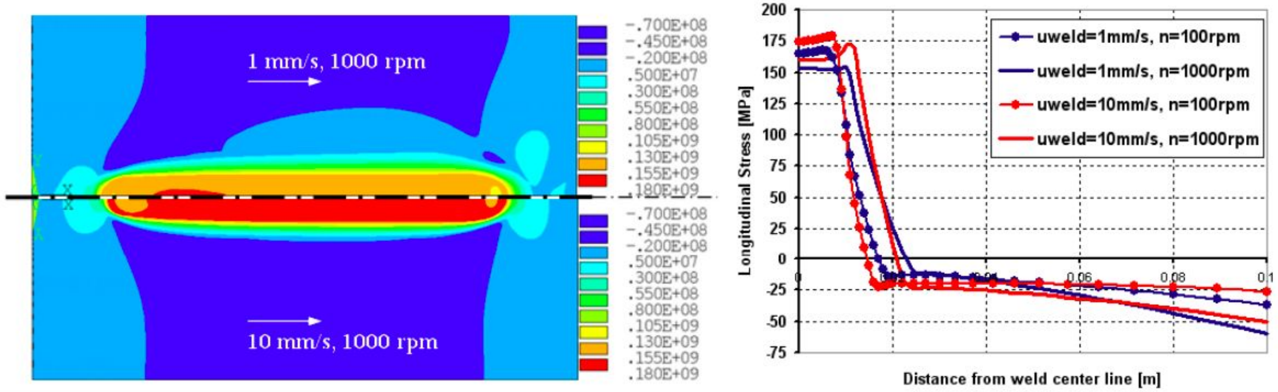
Specialties
Simulation

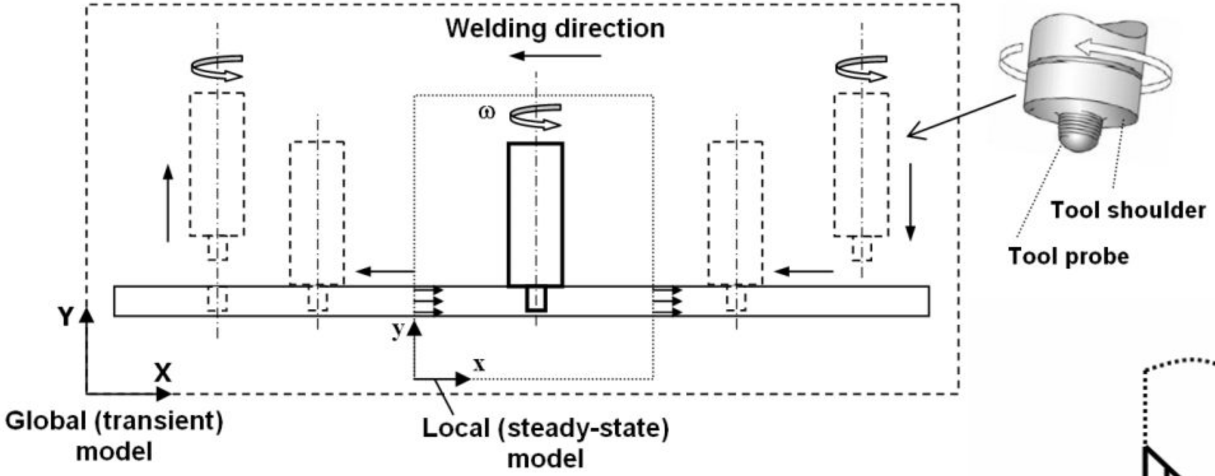
- Friction Stir Welding (TWI, 1991)
- Complex solid-state joining process
- High-strength aluminum alloys
- Somewhat lower residual stresses
- Heat generation via friction and mechanical defor.

Transient thermal model



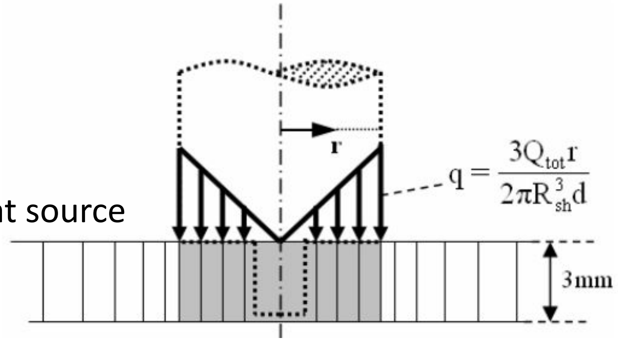
Transient thermo-mechanical model





Tutum and Hattel, 2010

Prescribed heat source model



Thermal-Pseudo-Mechanical Model

$$q(r,T) = \omega r \tau(T) = \left(\frac{n\ 2\pi}{60}\right) r \frac{\sigma_{yield}(T)}{\sqrt{3}},\quad for\ 0 \le r \le R_{shoulder}$$

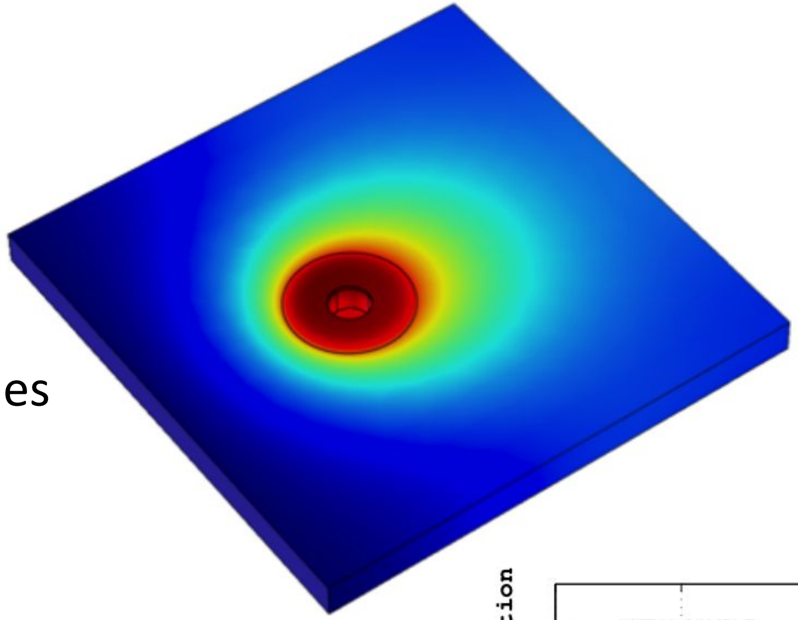
$$\sigma_{yield}(T) = \sigma_{yield,ref}\left(1 - \frac{T - T_{ref}}{T_{melt} - T_{ref}}\right)$$

Schmidt and Hattel, 2008

Developed fast and reliable thermal and residual stress models for optimization.

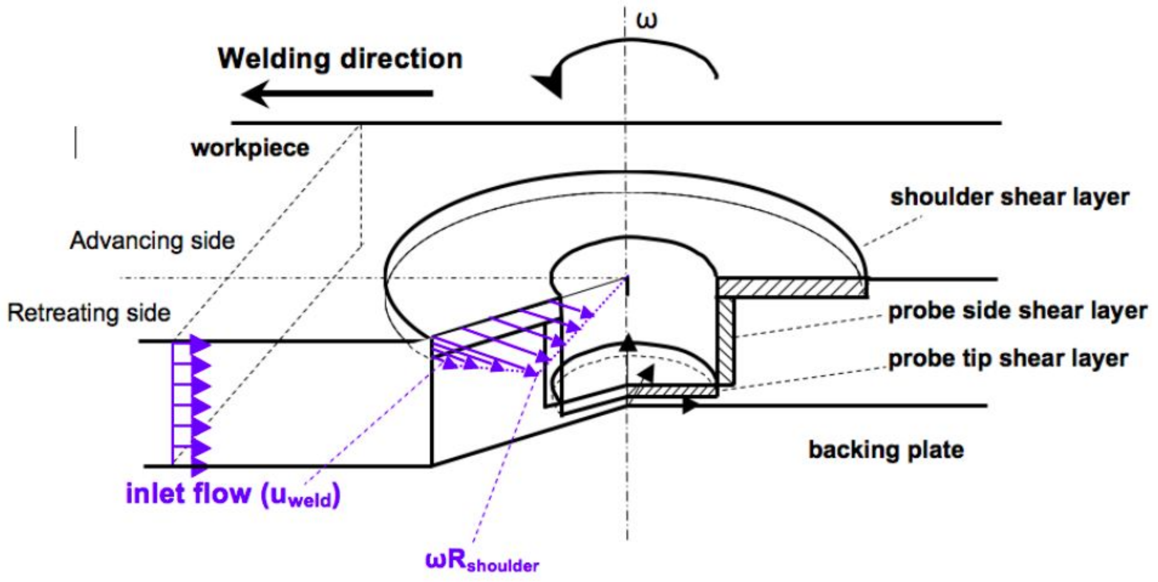
Specialties
Optimization

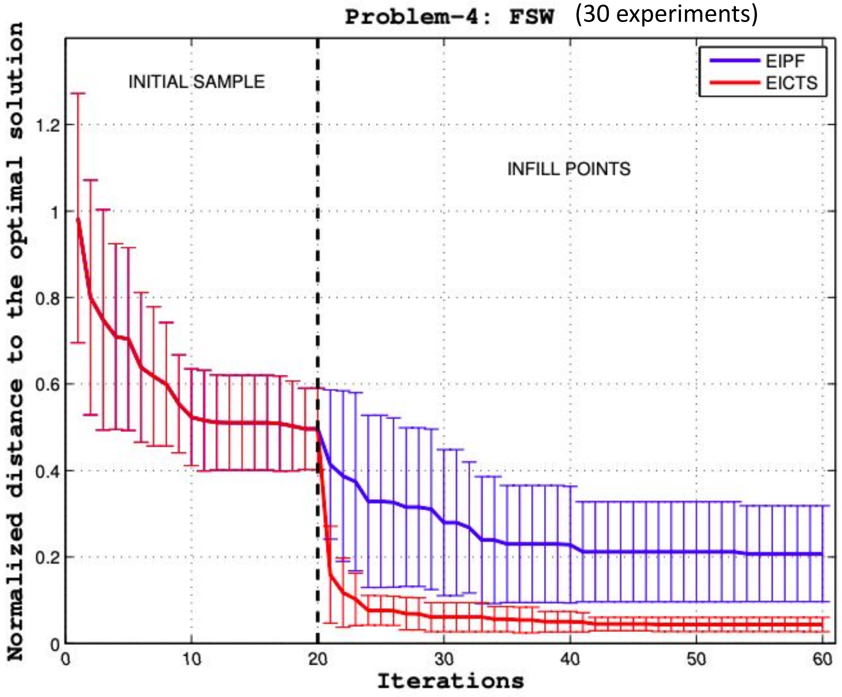
- Sample-efficient (constrained) optimization
- Control parameters: Tool design, Process variables
- Maximize production rate
- Constraints (i.e., hot and cold weld conditions)



TPM heat source model:

$$q_{vol}(x, y, T) = \frac{\omega r(x, y)\sigma_{yield}(T)}{\sqrt{3}t_{SL}}$$





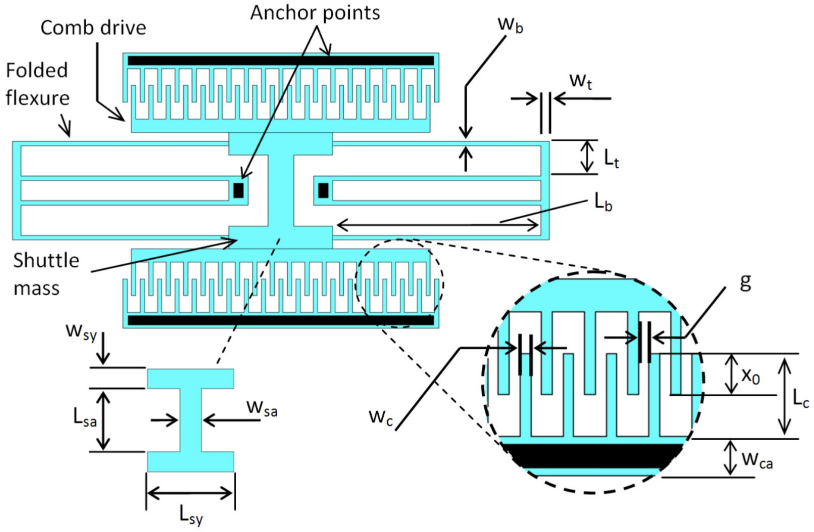
EICTS: Expected Improvement with Constraint Tournament Selection
EIPF: Expected Improvement with Probability of Feasibility

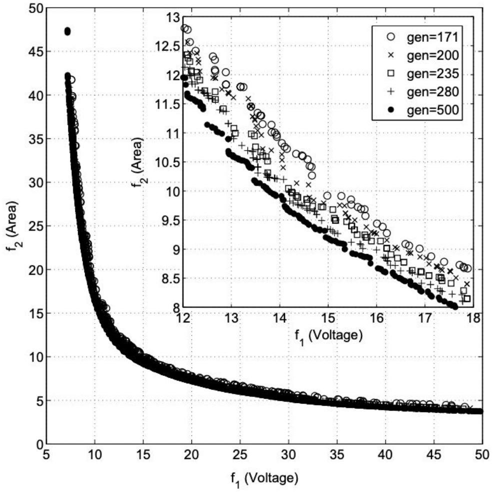
Tutum, et al., 2016

EICTS is 1.5-3.5x faster and more accurate than the state-of-the-art method (i.e., EIPF).

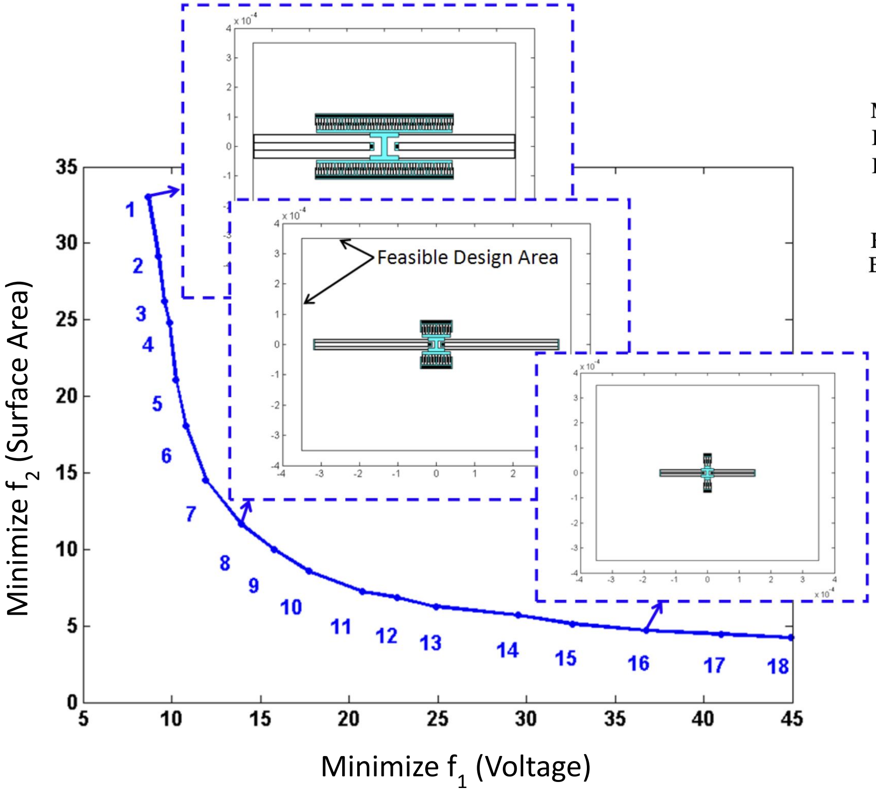
Specialties
Optimization

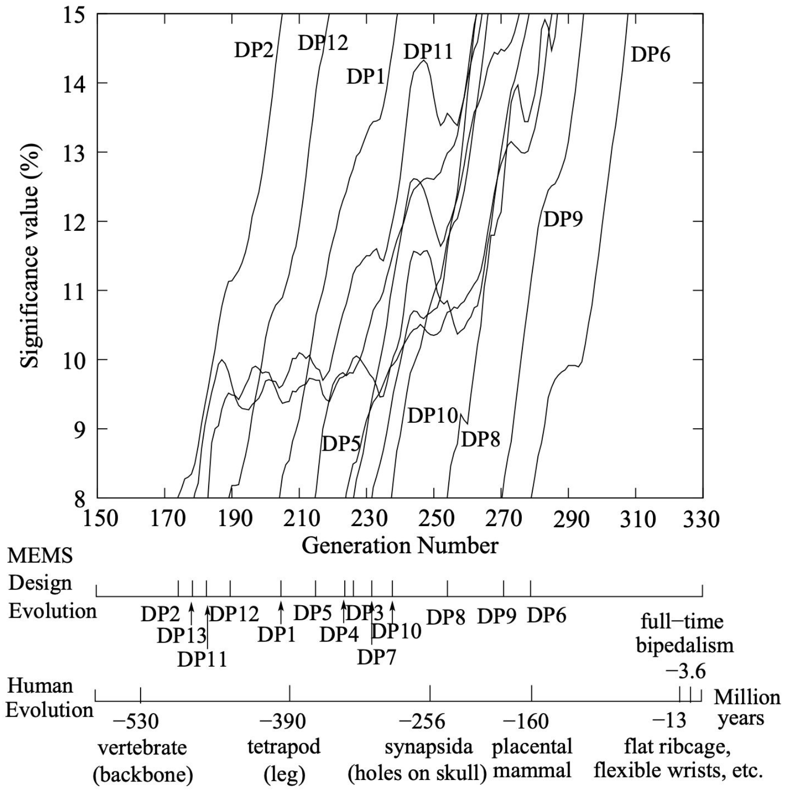
MEMS design





Progress of the Pareto Front





Temporal Evolution of Design Principles in Engineering Systems

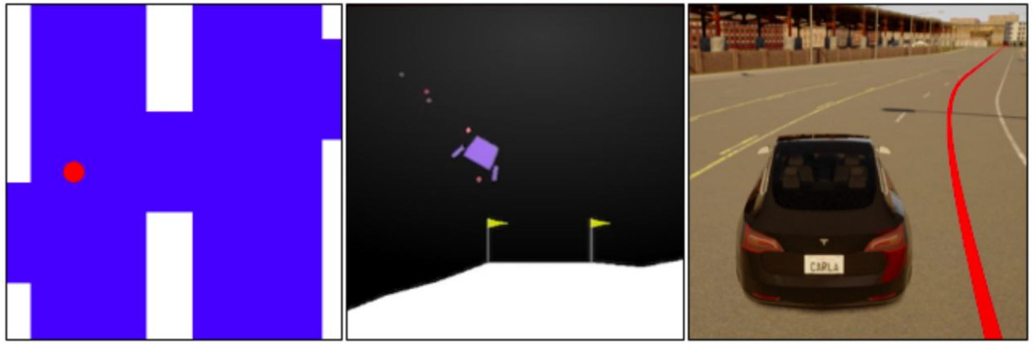
Tutum and Fan, GECCO 2011

Deb, Bandaru, Tutum, PPSN 2012

Multi-objective optimization provides rich information about tradeoffs in product design.

Specialties
Machine Learning

- Robust decision-making (DARPA project, L2M Program)



(a) Flappy Ball (b) Lunar Lander (c) CARLA

- Parametric changes in POMDP environments
- Better generalization performance is achieved for both interpolation and extrapolation, w.r.t. S-only and C-only models

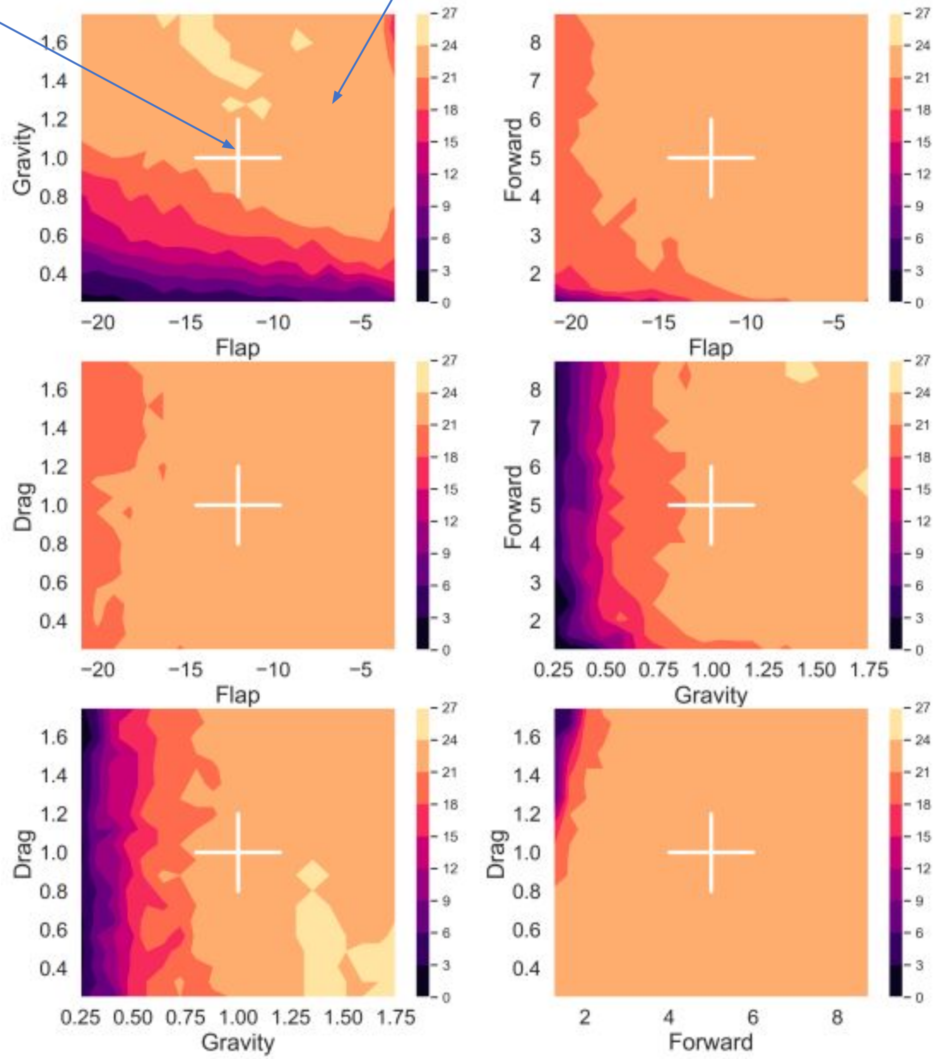
a. Limited training: Effects vary +/- 20% along one axis

b. Extensive testing: Effects vary +/- 70% in all axes at once

Tutum and Miikkulainen, ALIFE 2020
Tutum, et al., IEEE CoG 2021

Training

Impressive extrapolation capability



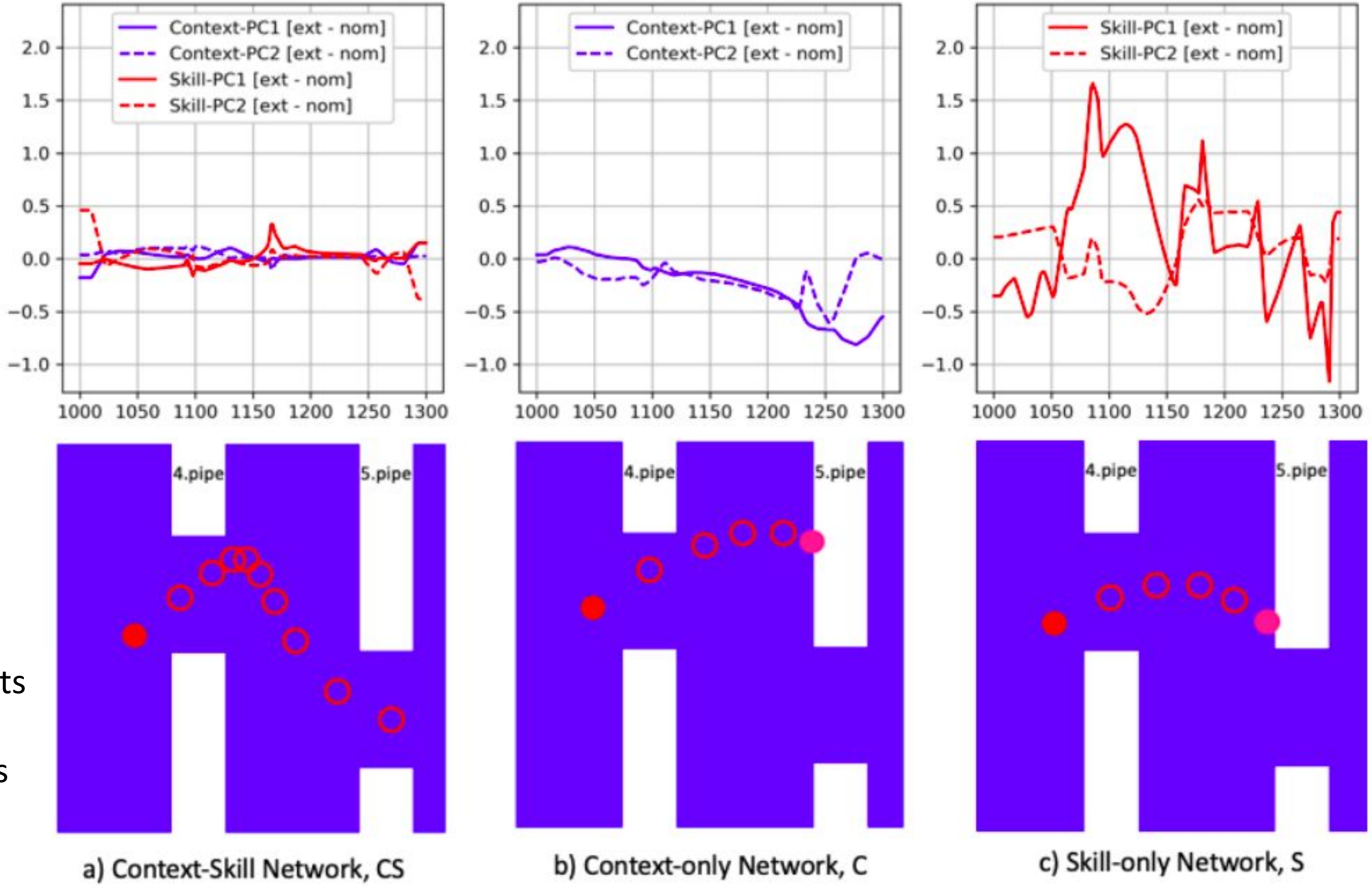
Context-Skill NN-model provides robust generalization capability before deployment.

Specialties
Machine Learning

Change in C and S modules during generalization

Network	PC	MSD	STD
CS	Context-PC1	0.004	±0.058
	Context-PC2	0.003	±0.039
	Skill-PC1	0.007	±0.082
	Skill-PC2	0.018	±0.133
C	Context-PC1	0.139	±0.282
	Context-PC2	0.061	±0.147
S	Skill-PC1	0.414	±0.600
	Skill-PC2	0.088	±0.286

- Differences between the Principle Components of the Context and Skill module outputs between the nominal and generalization tasks differ little in CS-model. Therefore, controller does not get confused in an anomaly case.



Contrasting the generalization ability of CS, C-only, and S-only networks

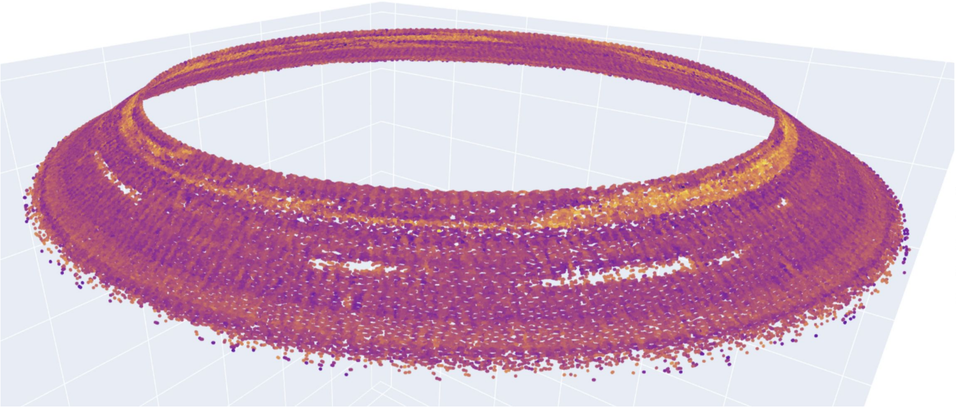
Context-Skill NN-model provides robust generalization capability before deployment.

Specialties

Process Monitoring & Defect Analysis

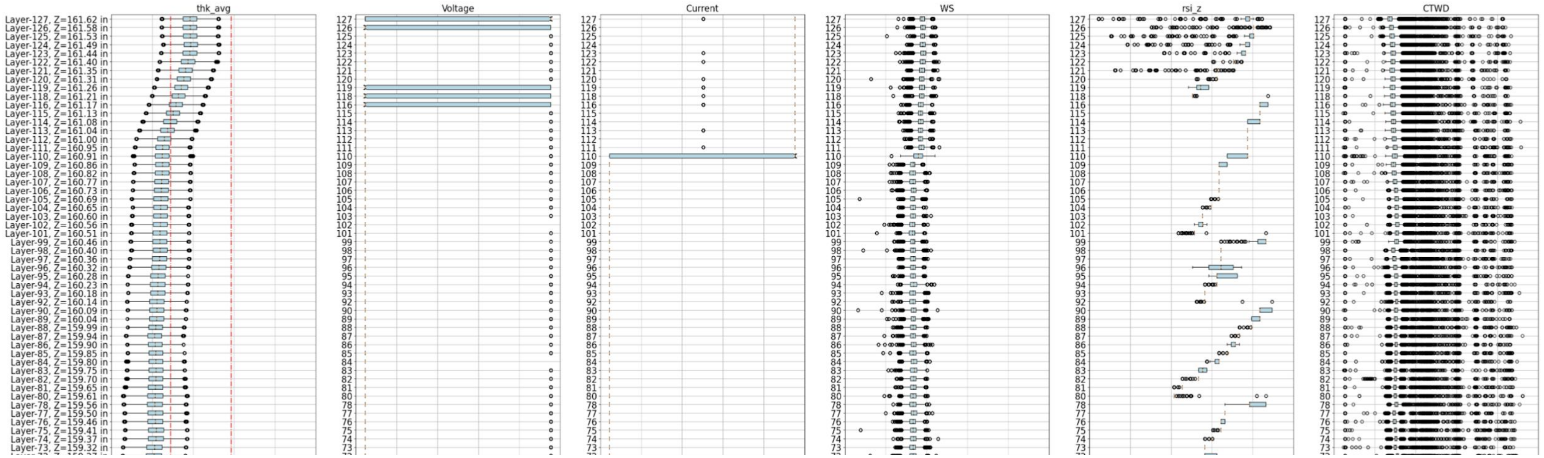
<u>Process data:</u>

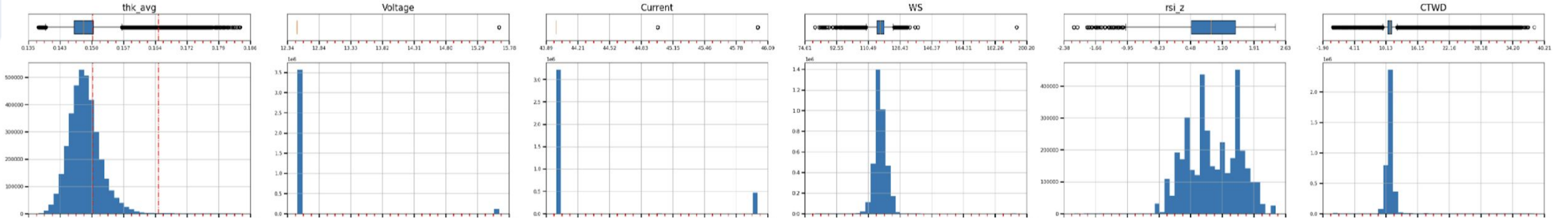
Robot nozzle pozition-X, Y, Z
Weld-job, Layer
Voltage, Current
Wire Feed Speed
End effector-z control
Contact tip to part distance
Temperature, Humidity
Shielding gas flow
Wall thickness (min, max, average), etc.



Wall thickness point cloud (from lasers)

Layer-wise Boxplots





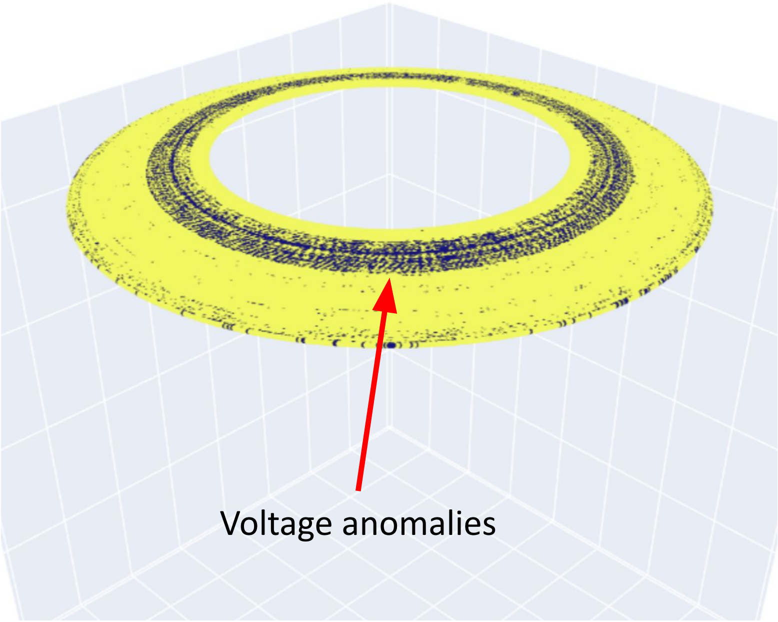
Weld-job Summary (Histogram)

Telemetry is mapped on to spatial (3D) coordinates and supported by statistical summary.

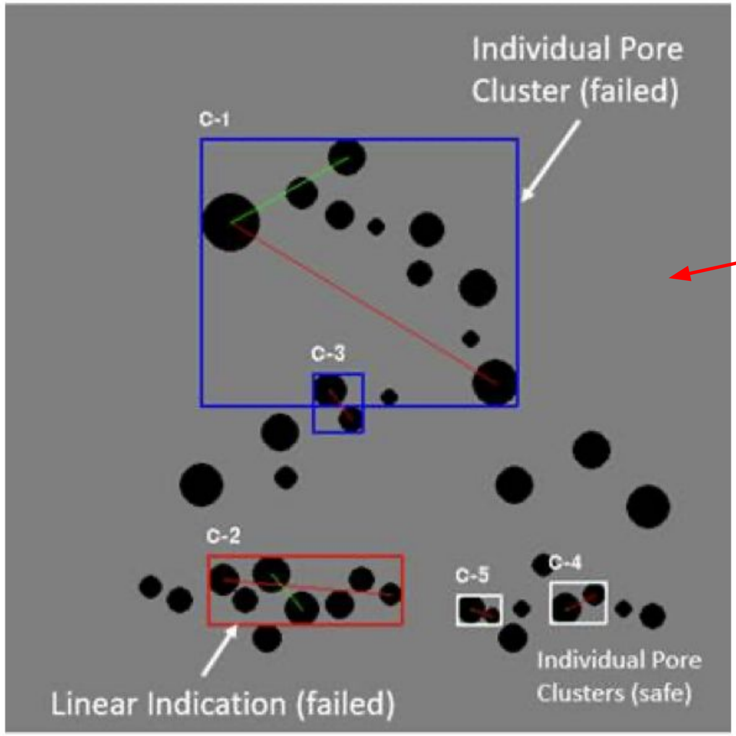
Specialties

Process Monitoring & Defect Analysis

(Relativity Space)



Additional metadata is viewed when you hover your mouse on the point cloud (including technician's reports, manual parameter changes, etc.)



Class-R failure criterion (Patent pending)

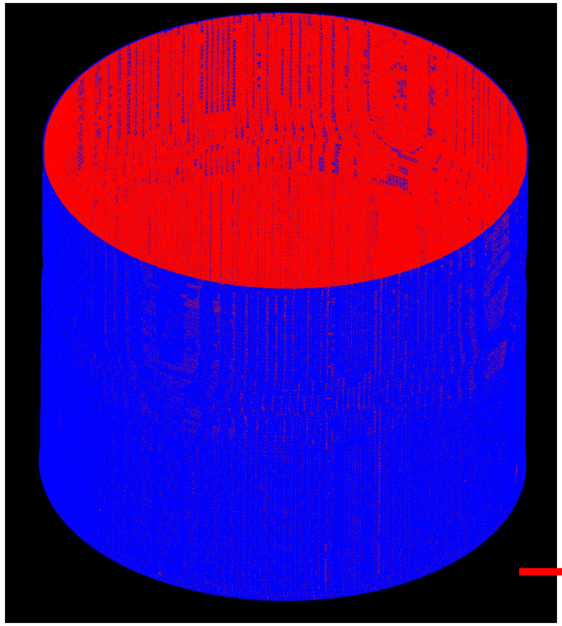
This clustering analysis is done on preprocessed RT-images

Anomalies in telemetry spatially detected. Failure criteria for distribution and size of porosities, as detected in X-Ray images, developed for additively manufactured rocket structures.

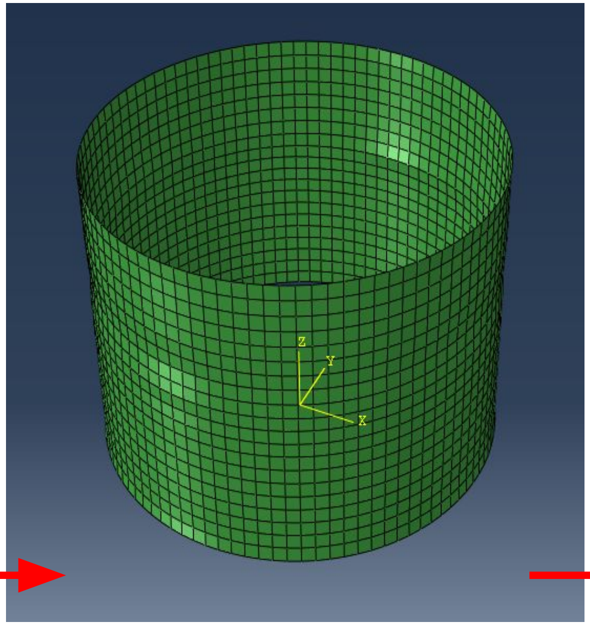
Specialties

Processing Large Point Clouds

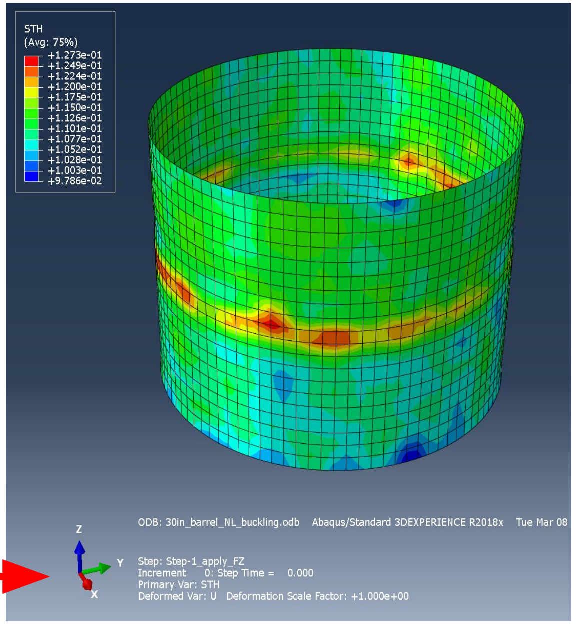
(Relativity Space)



Test print (18M points)
Red: Inner Dia., Blue: Outer Dia.



Mid-surface (shell) model in ABAQUS
(with true thicknesses)

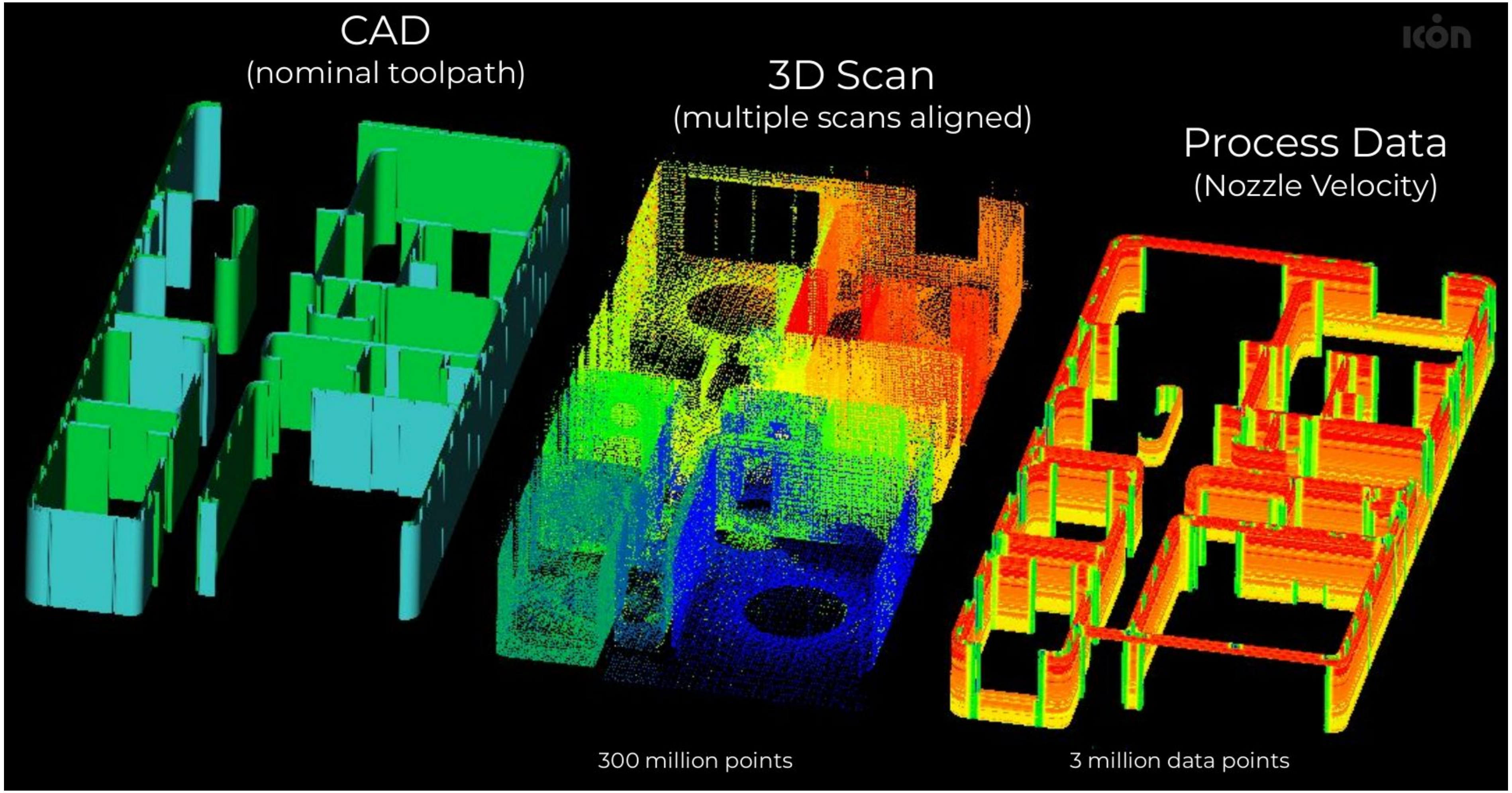


Buckling analysis in ABAQUS

High-fidelity buckling model is developed by updating nominal shell model with processed 3D scan data.

Specialties
Digital Twin & Spatial Computing
(ICON Technology)

3D-printed house



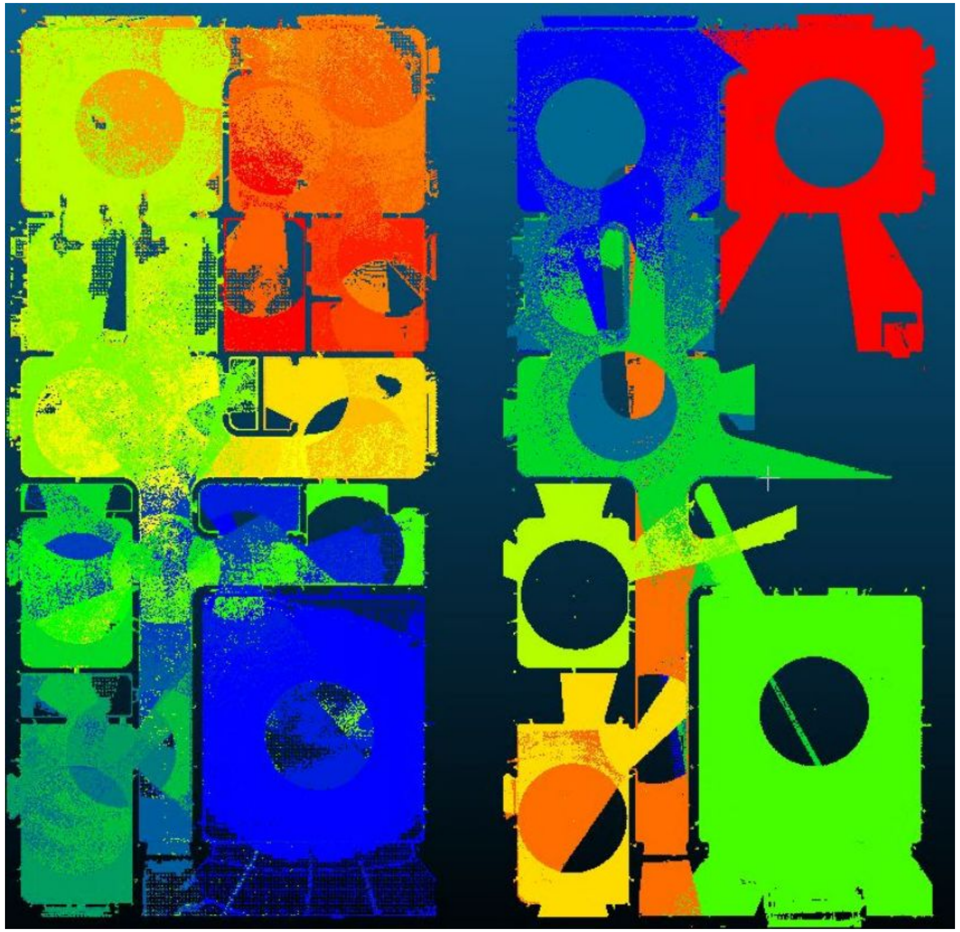
Digital Twin is built by fusing design, process-telemetry and product quality (3D scan, CV) for causal analysis and design for additive manufacturing.

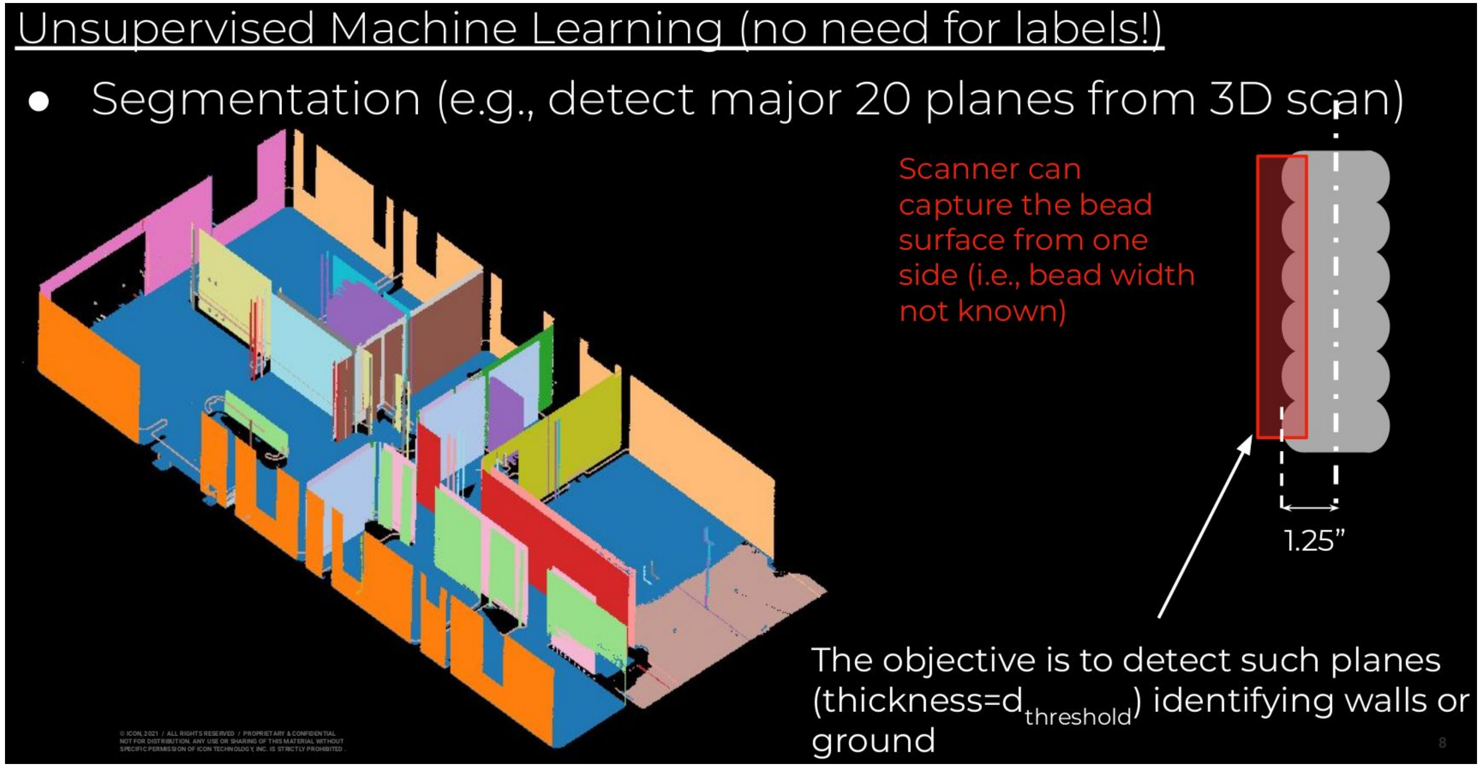
Specialties

Digital Twin & Spatial Computing (ICON Technology)

Low resolution, high number of scans
(25 x 12 million points)

HIgh resolution, low number of scans
(8 x 60 million points)



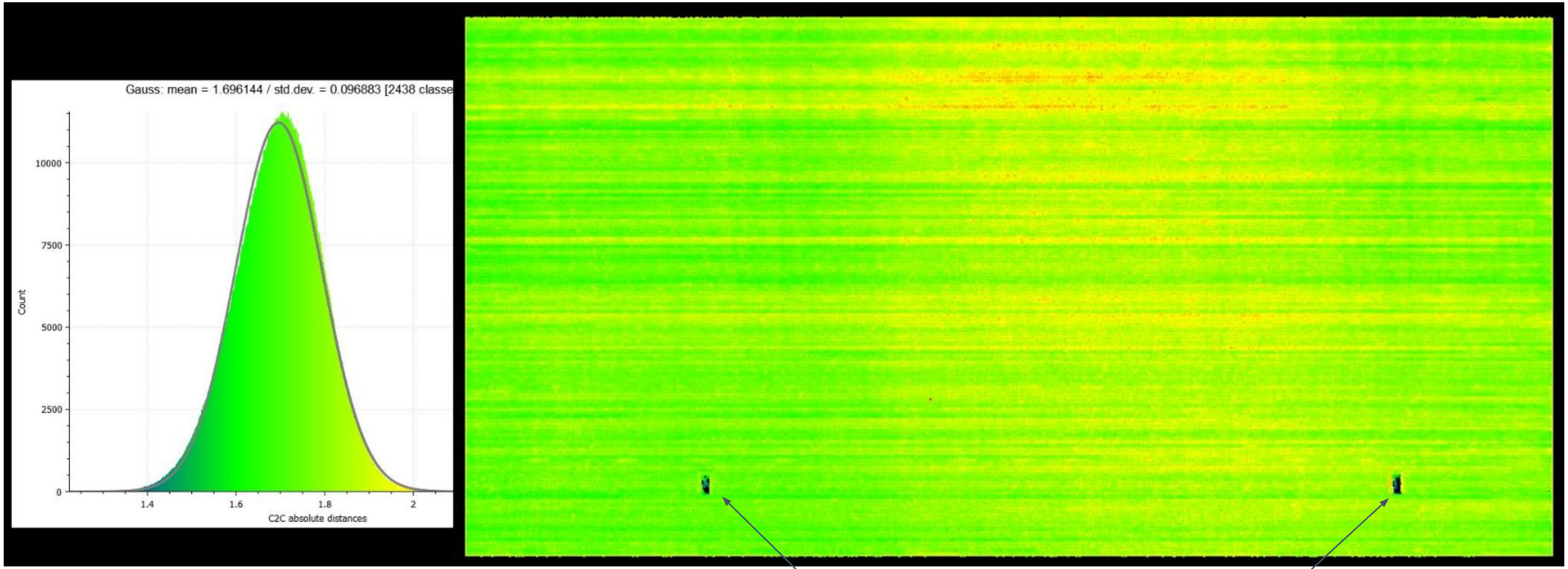


3D Object detection developed to segment the point clouds into walls, ground and outliers for each detected plane.

Specialties

Digital Twin & Spatial Computing (ICON Technology)

Heatmap on the right shows the deviation of 3D-printed wall surface from ideal plane together with mean and standard deviation (left).

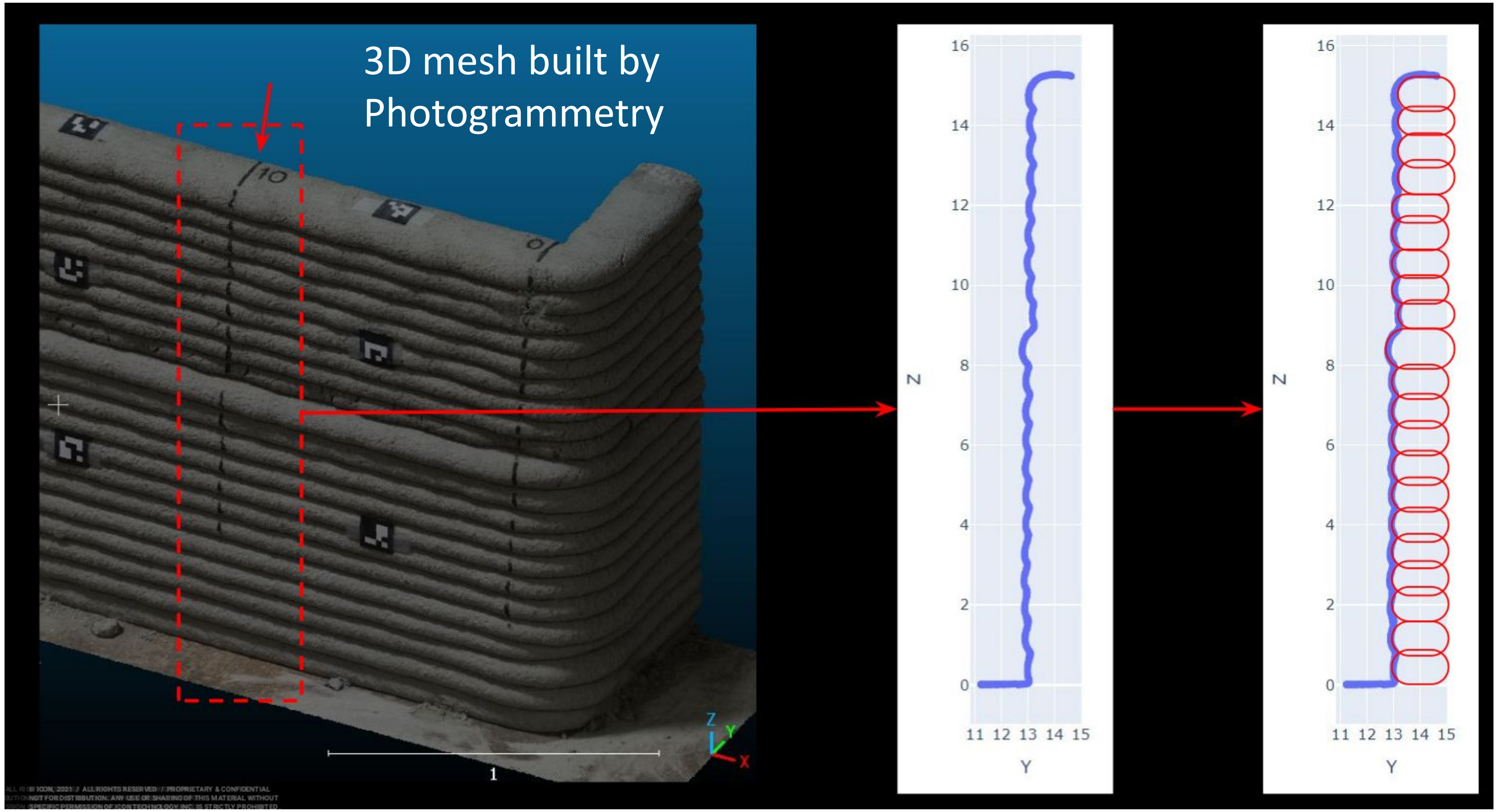


Electrical boxes in the wall

Product quality assessment for each 3D-printed wall is automated by statistical analysis of the point clouds.

Specialties

Digital Twin & Spatial Computing (ICON Technology)

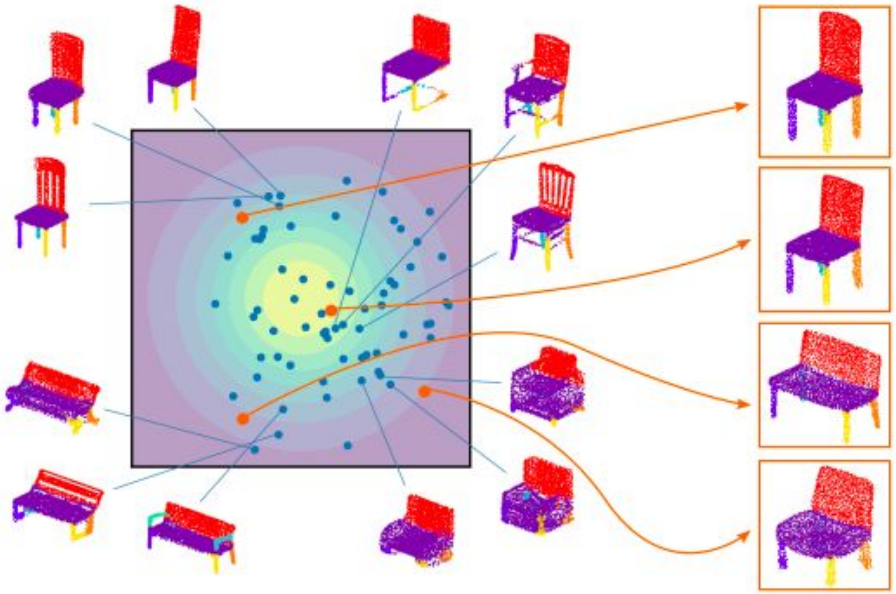


Estimation of bead profiles from 3D point cloud obtained by photogrammetry

Photogrammetry is used to build 3D mesh from 2D images (with April tags). Bead profiles are computed by processing each slice from 3D-point clouds.

Focus Project: Functional Generative Design
Motivation

- ML has contributed to major success stories across industries.
- Mostly supervised learning (labeled data), i.e., computer vision, medical diag., NLP, etc.
- Limited interest in unsupervised learning, though generative models gained popularity in 2D image or 3D shape generation.

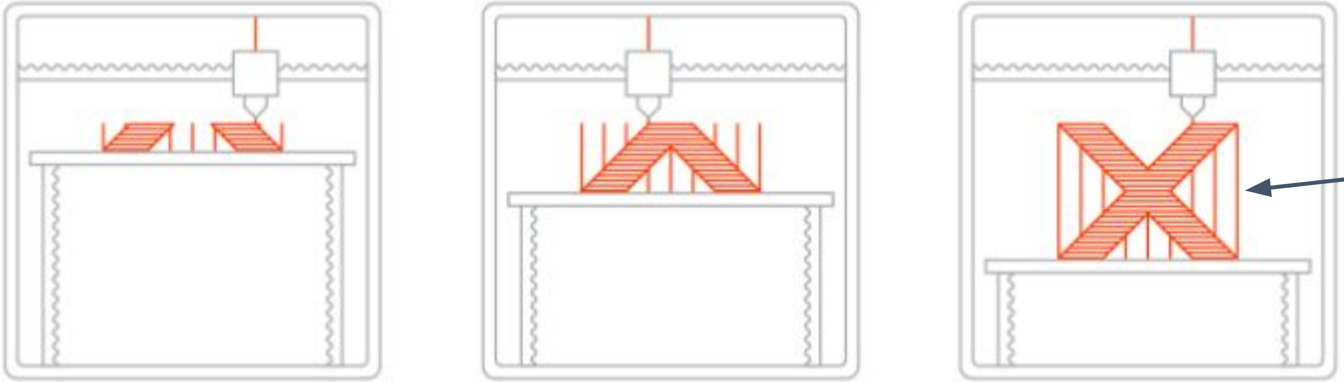


Nash, C. and Williams, K.I., 2017

Focus Project: Functional Generative Design

Motivation

Question: How can we design <u>functional</u> parts for <u>3D printing</u>?



Printed supports

Fused Deposition Modeling Process

requires post-processing

- Takes time/effort to remove
- Produces waste material
- Leaves excess plastic behind
- Damage object during removal

Focus Project: Functional Generative Design
Motivation

- Examples for 3D printed non-functional parts

Focus Project: Functional Generative Design

Motivation

- We can decompose parts to minimize the use of supports

3D Printed parts with supports

Decomposed objects

Yu, E., et al., 2017 (**Best Paper Award**)

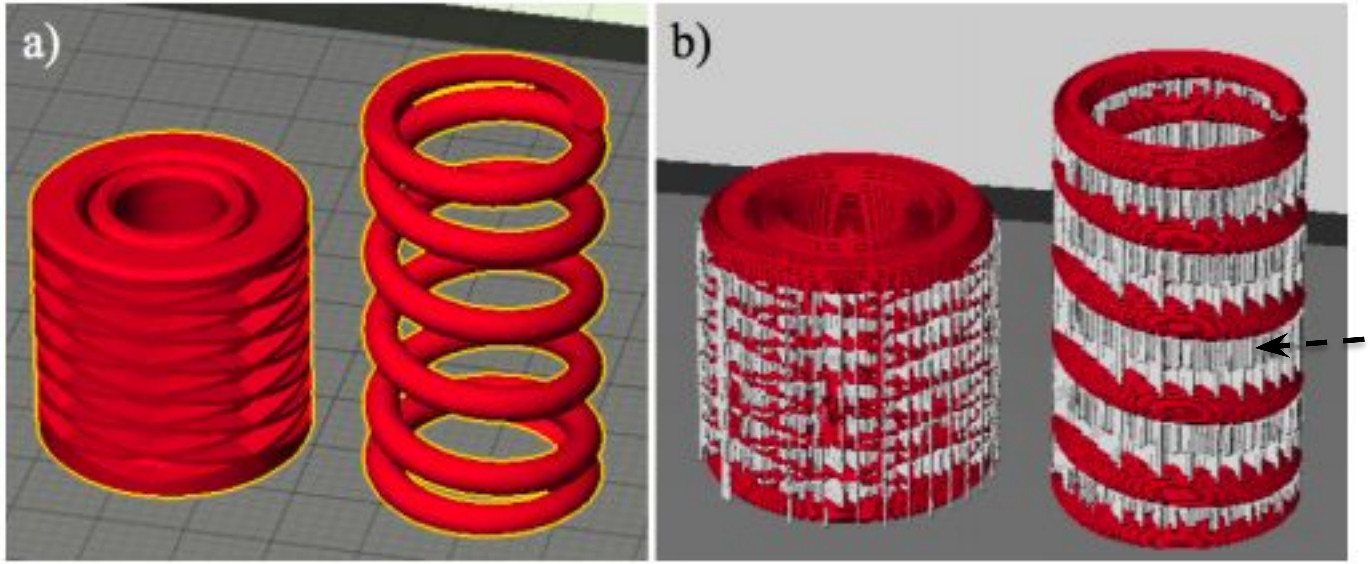
Focus Project: Functional Generative Design

Motivation

- **PROBLEM-1:** Functional (i.e., load carrying) parts cannot be decomposed

Spring designs

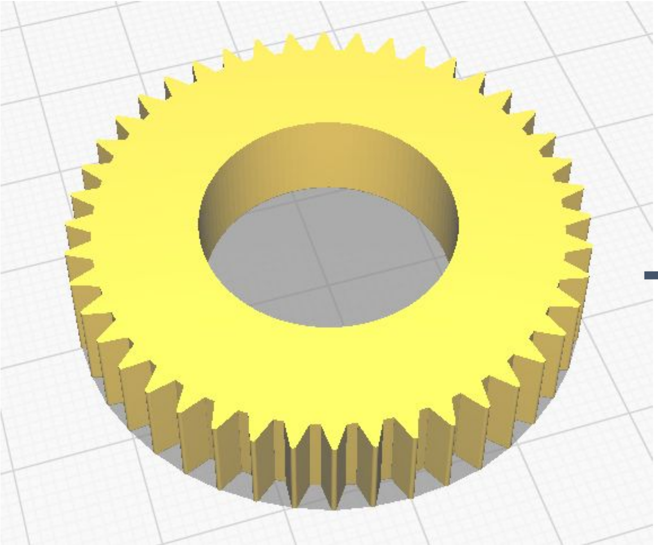
Sliced springs



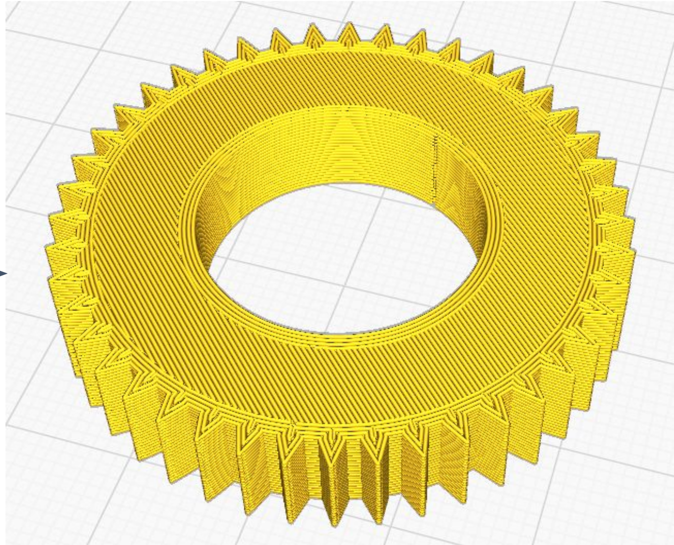
Supports
(Grey)

Focus Project: Functional Generative Design
Motivation

- **PROBLEM-2:** Limited resolution in 3D printing



Slicing
(Output: GCODE)



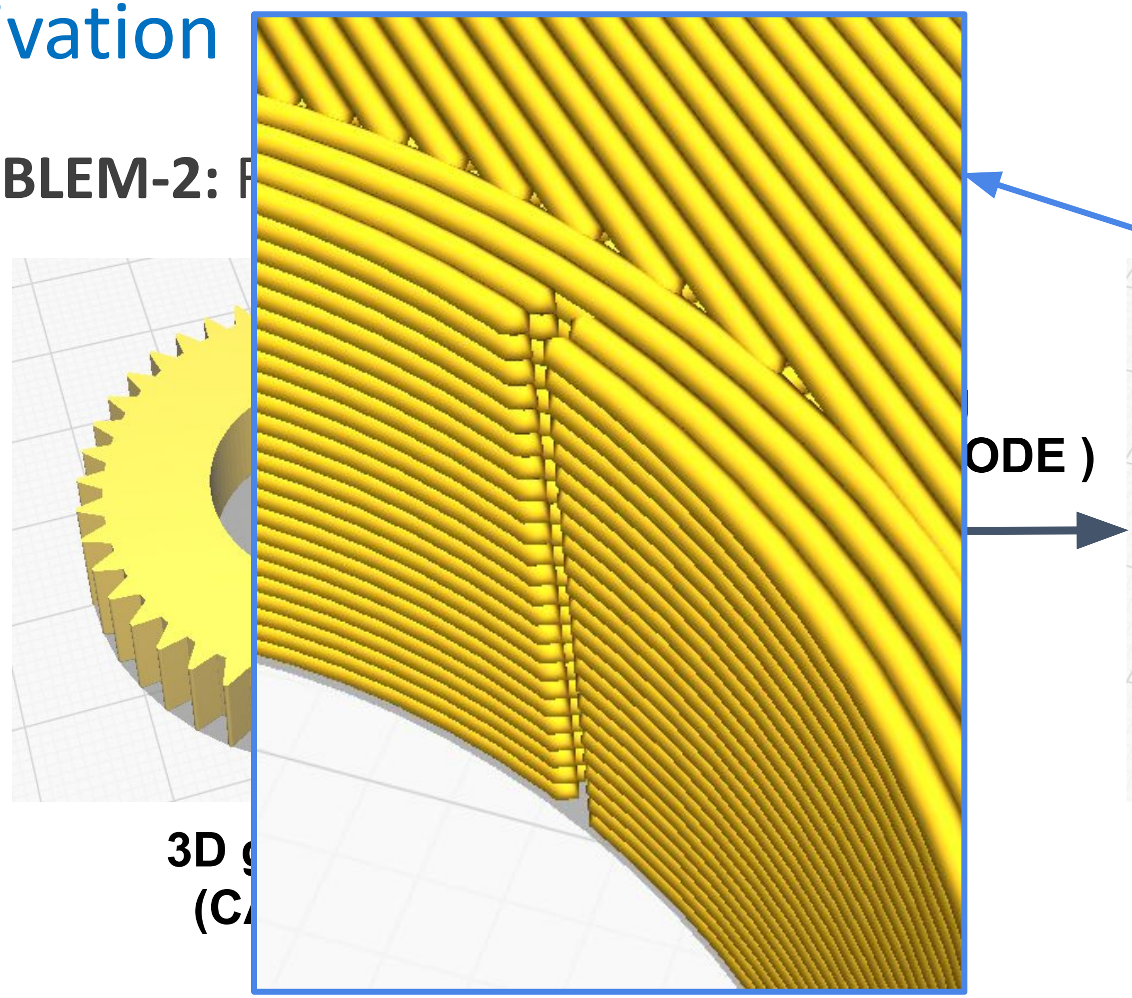
3D gear design
(CAD model)

3D Printing model
(Discrete model)

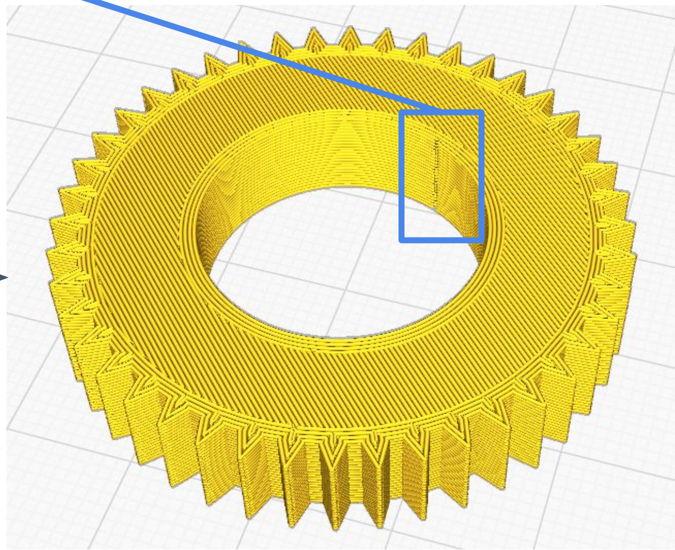
Focus Project: Functional Generative Design

Motivation

- **PROBLEM-2: F**



3D g
(CA

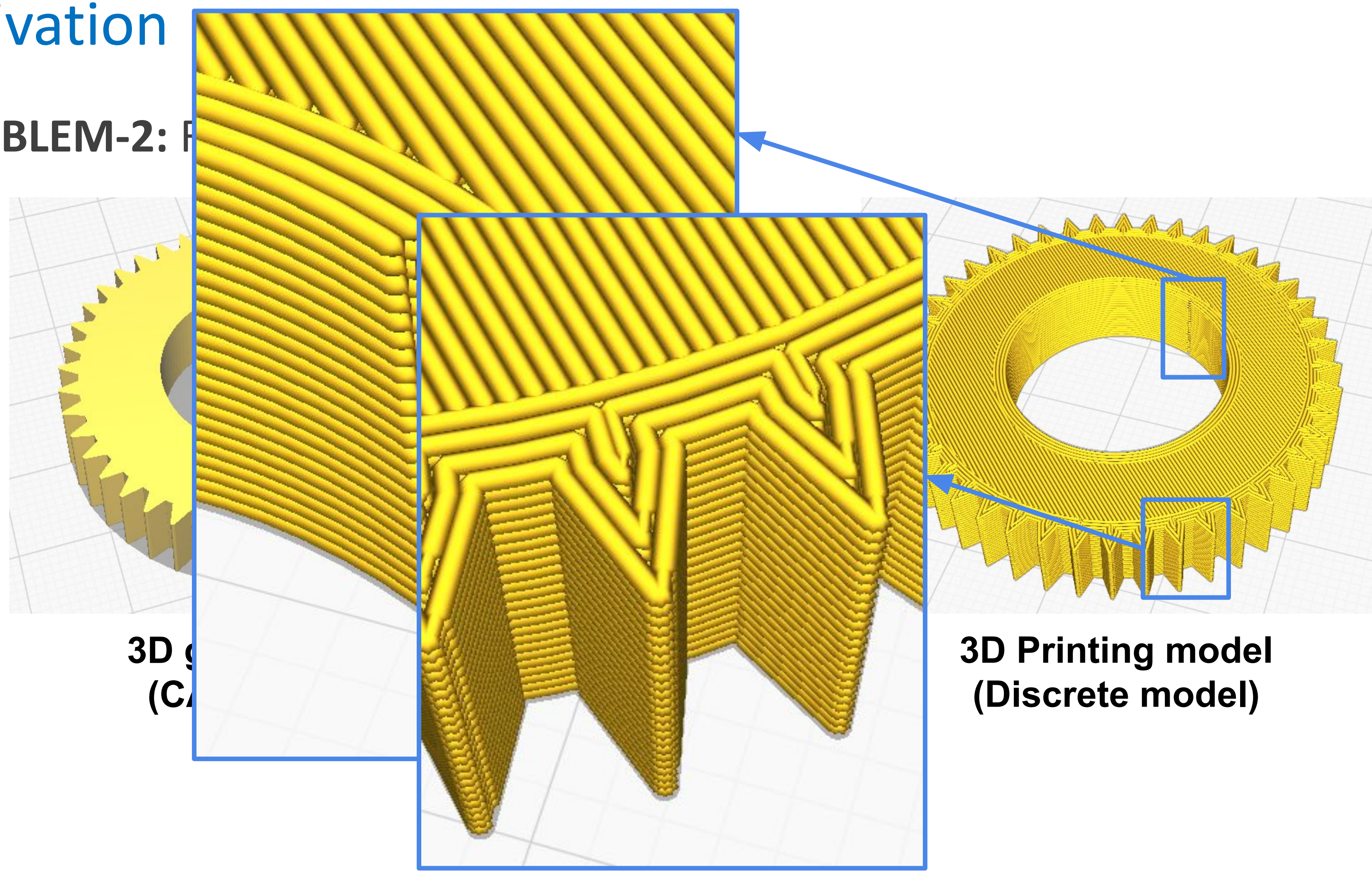


3D Printing model
(Discrete model)

Focus Project: Functional Generative Design

Motivation

- **PROBLEM-2: F**



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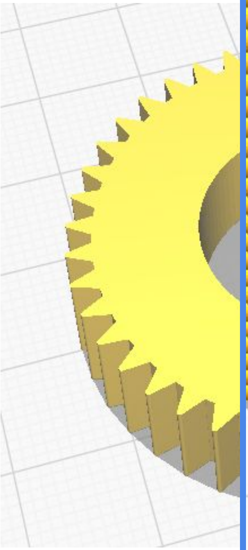
3D Printing model
(Discrete model)

Focus Project: Functional Generative Design

Motivation

- **PROBLEM-2: F**



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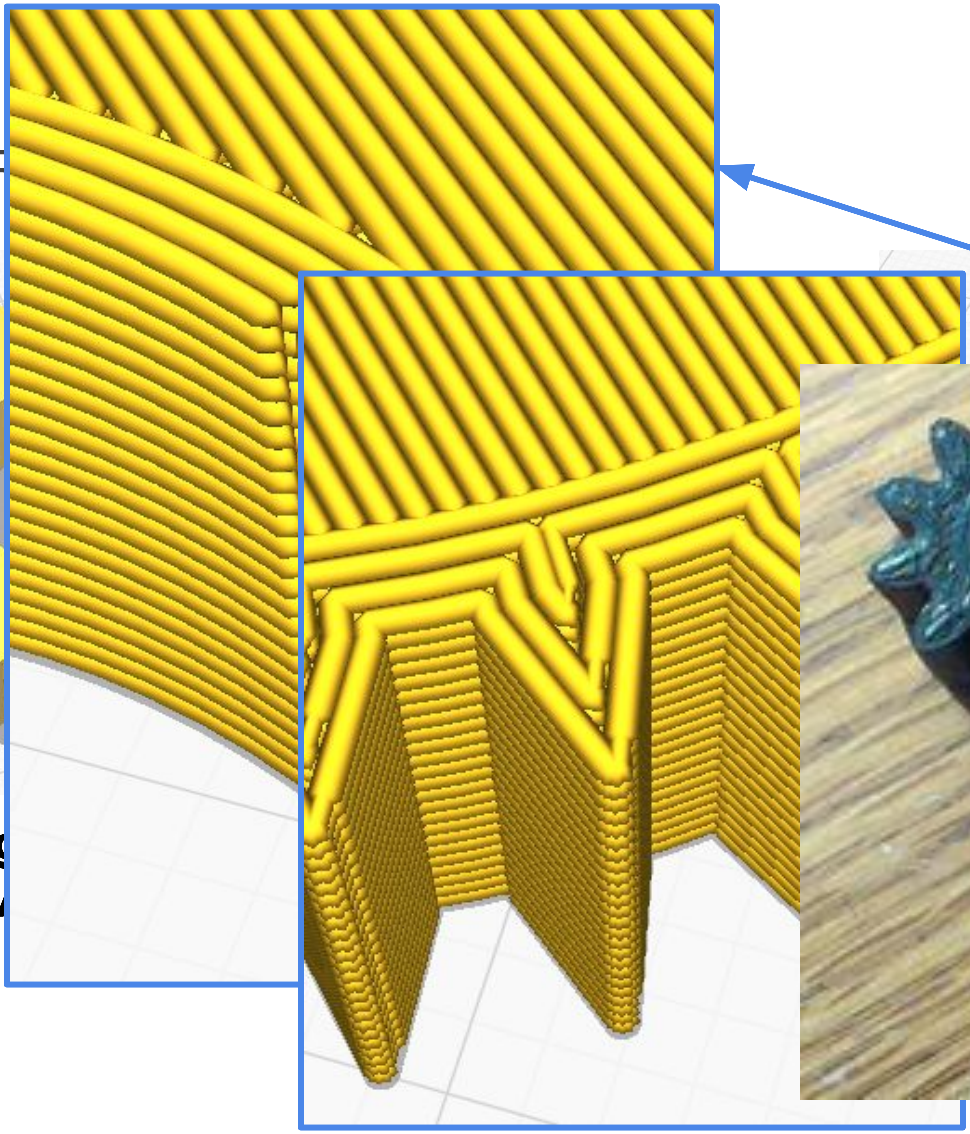
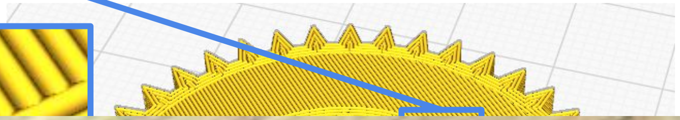
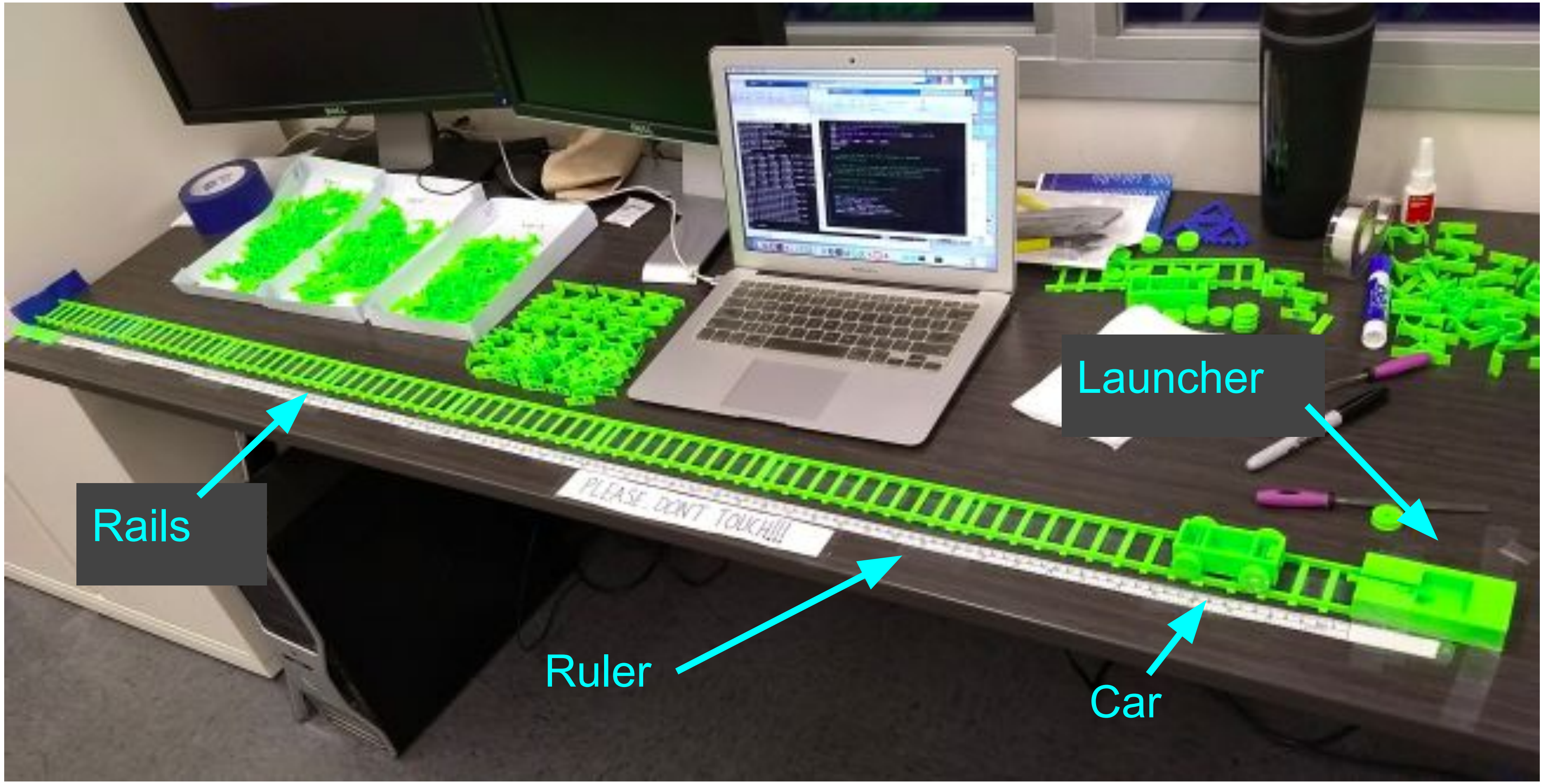




Focus Project: Functional Generative Design
Motivation

- Car-Launcher Mechanism – as a proof-of-concept

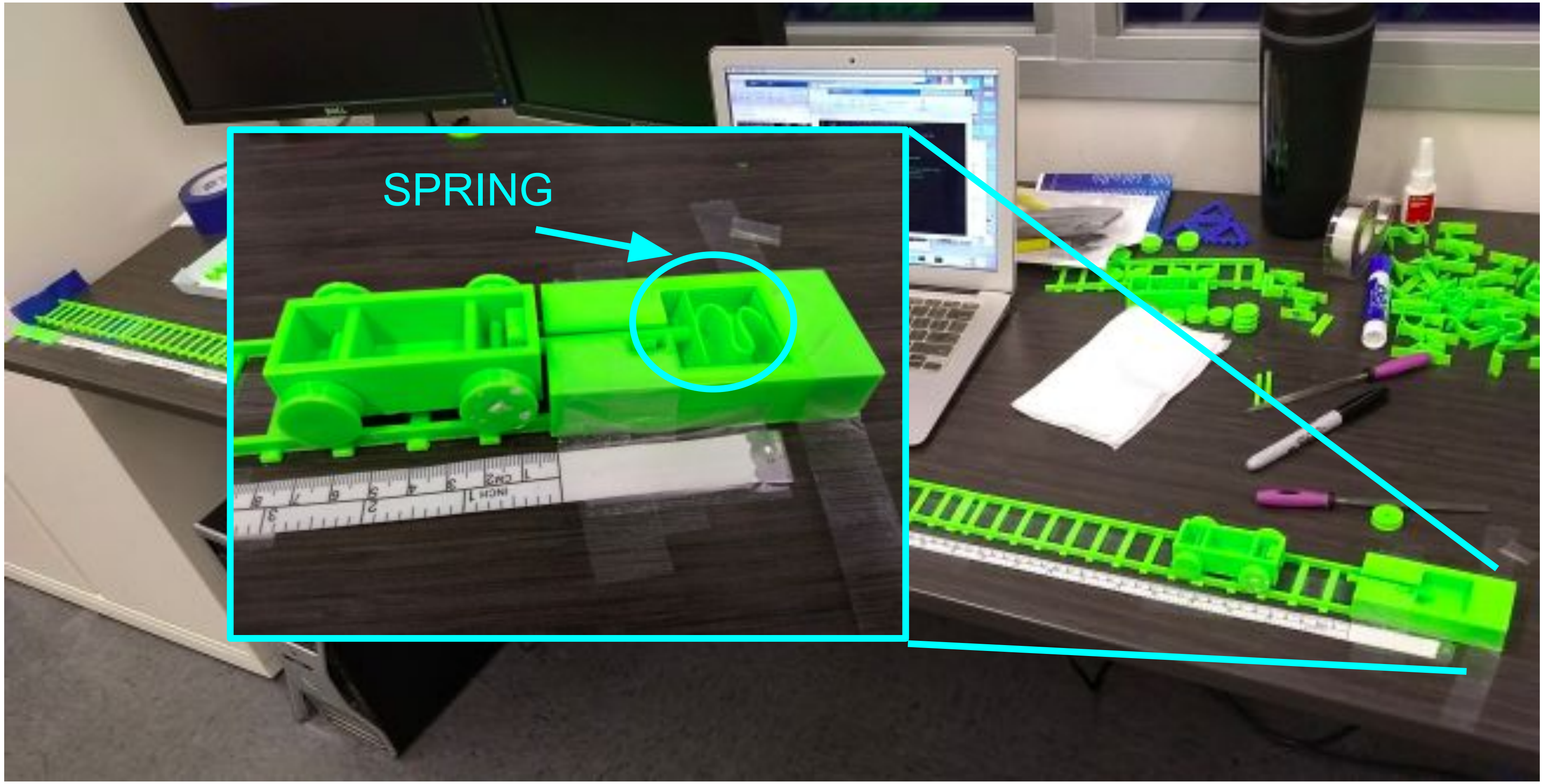


Tutum, et.al., 2018

Focus Project: Functional Generative Design

Motivation

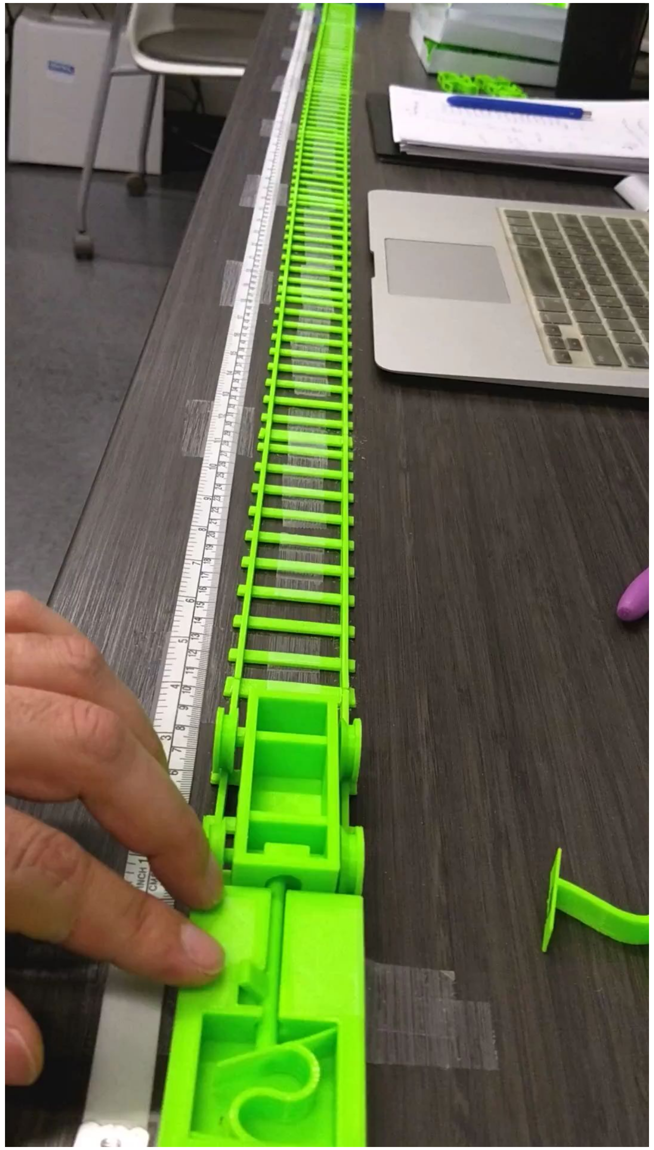
- Car-Launcher Mechanism – as a proof-of-concept



Focus Project: Functional Generative Design

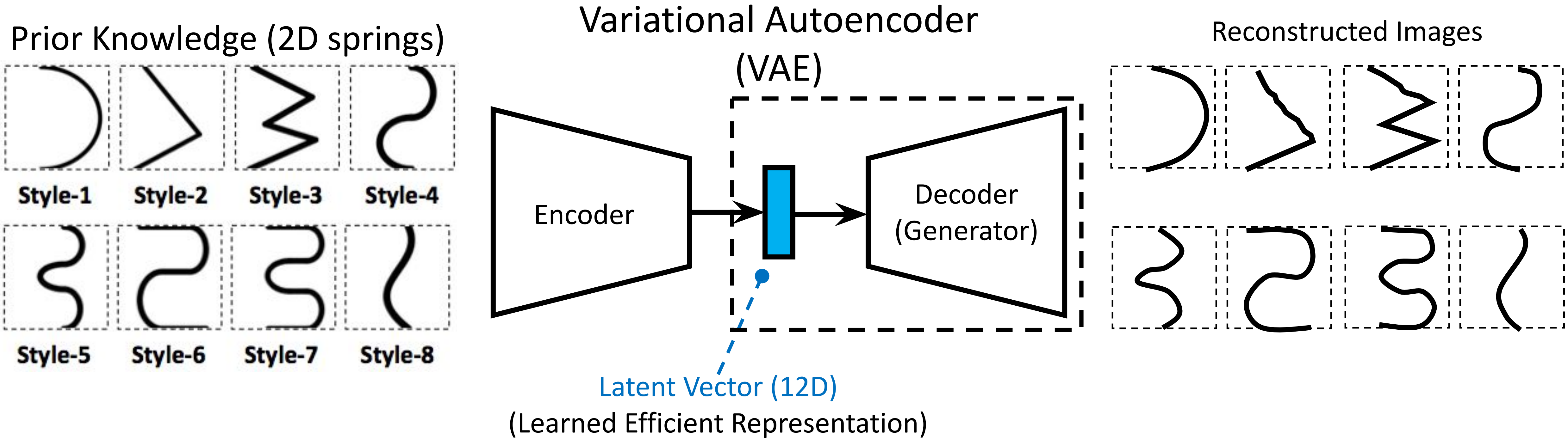
Motivation

- Car-Launcher Mechanism – as a proof-of-concept
  (Video)
- The goal is to design a spring to propel the car to a distance of 75 cm in a consistent way (i.e., 10 times in a row)



Focus Project: Functional Generative Design

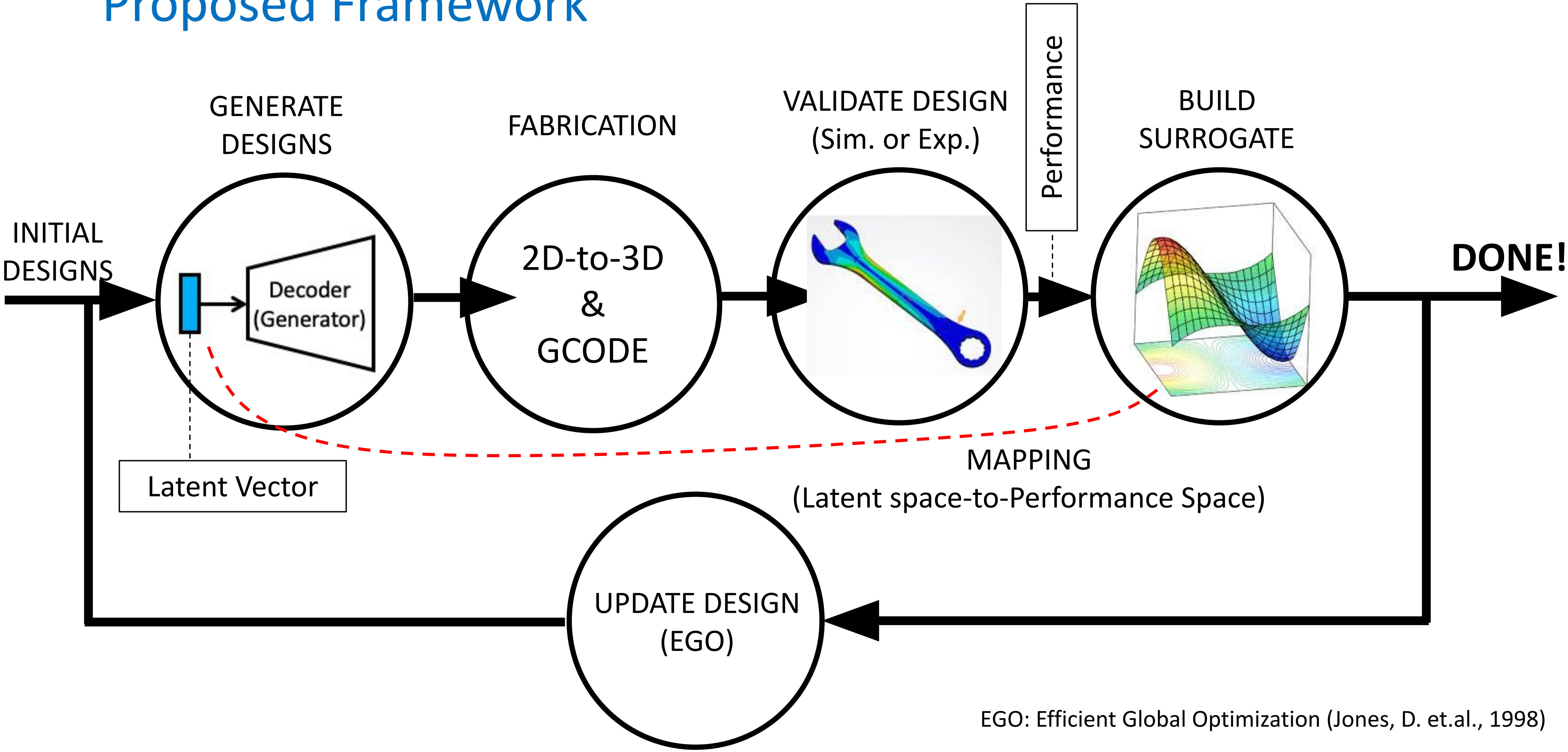
Proposed Framework



VAE: Variational Autoencoder (Kingma and Welling, 2014)

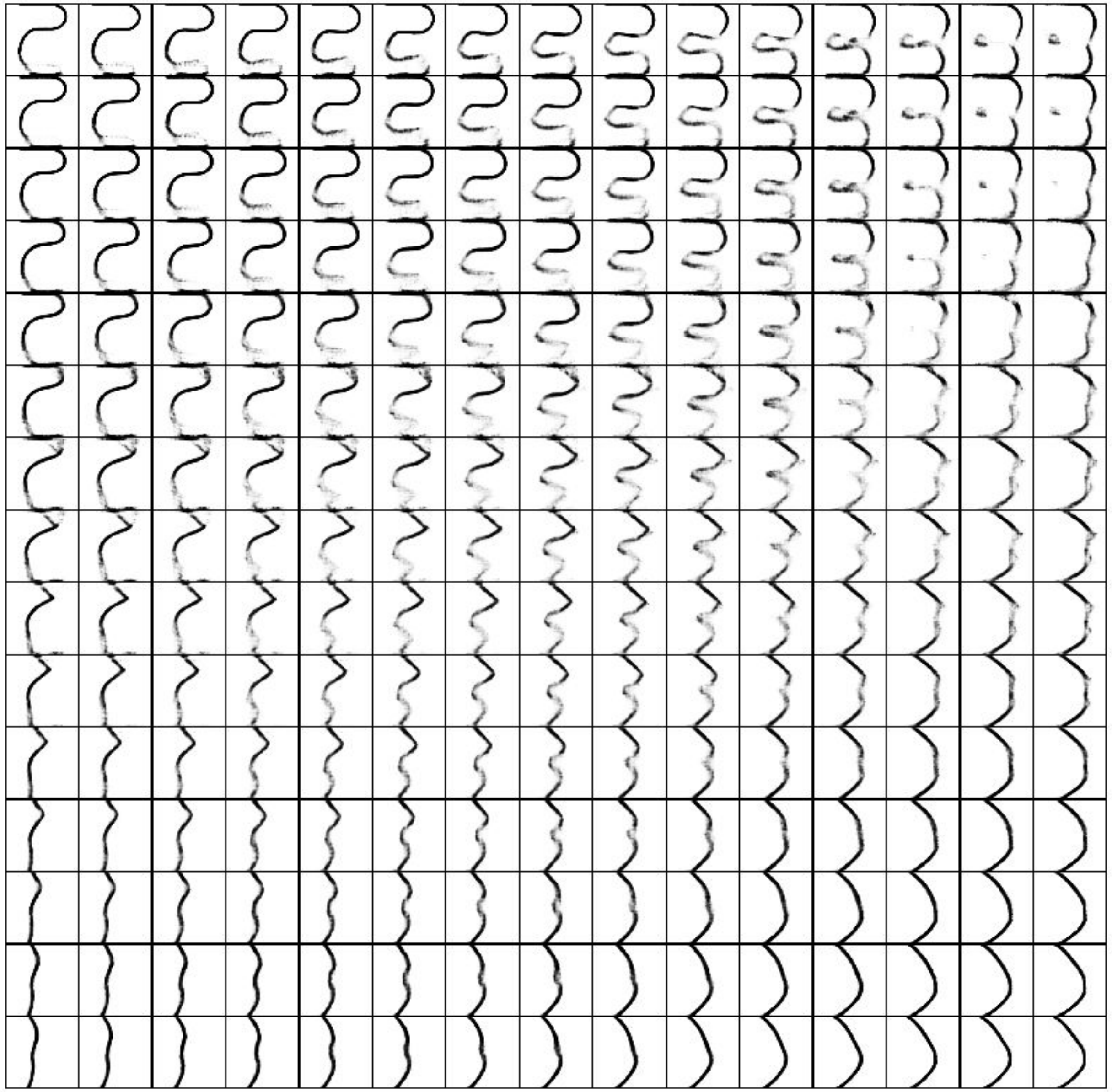
Focus Project: Functional Generative Design

Proposed Framework



EGO: Efficient Global Optimization (Jones, D. et.al., 1998)

Focus Project: Functional Generative Design

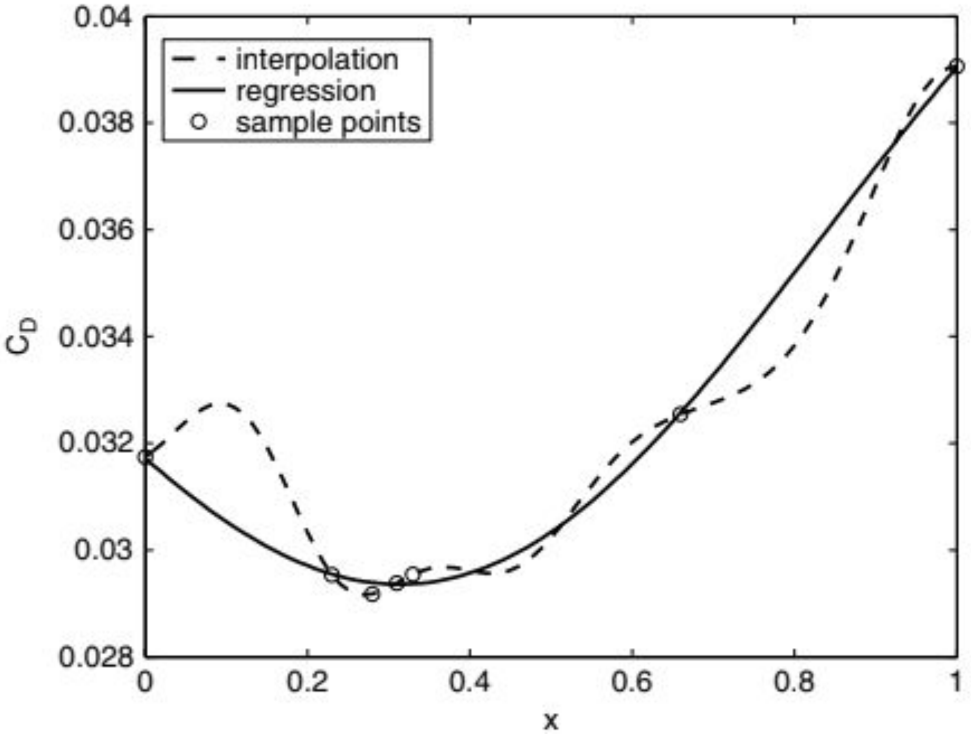


Interpolation in latent variable space

Focus Project: Functional Generative Design

Build Surrogate – Noisy (Regression) Kriging

- Kriging ⟶ surrogate (e.g., function approximator, response surface model)
- Interpolation vs. <u>Regression</u>



Correlation between two points:

$$cor\left[y(\mathbf{x}^{(i)}), y(\mathbf{x}^{(j)})\right] = \prod_{k=1}^{d} exp\left(-\theta_k \left|\mathbf{x}_k^{(i)} - \mathbf{x}_k^{(j)}\right|^2\right)$$

Prediction at new point x*:

$$\hat{y}(\mathbf{x}^*) = \hat{\mu} + \mathbf{r}^T(\mathbf{R} + \lambda\mathbf{I})^{-1}(\mathbf{y} - \mathbf{1}\hat{\mu})$$

Predicted error (for EGO):

$$\hat{s_{ri}}^2(\mathbf{x}^*) = \hat{\sigma_{ri}}^2\left[1 - \mathbf{r}^T\mathbf{R}^{-1}\mathbf{r} + \frac{1 - \mathbf{1}^T\mathbf{R}^{-1}\mathbf{r}}{\mathbf{1}^T\mathbf{R}^{-1}\mathbf{1}}\right]$$

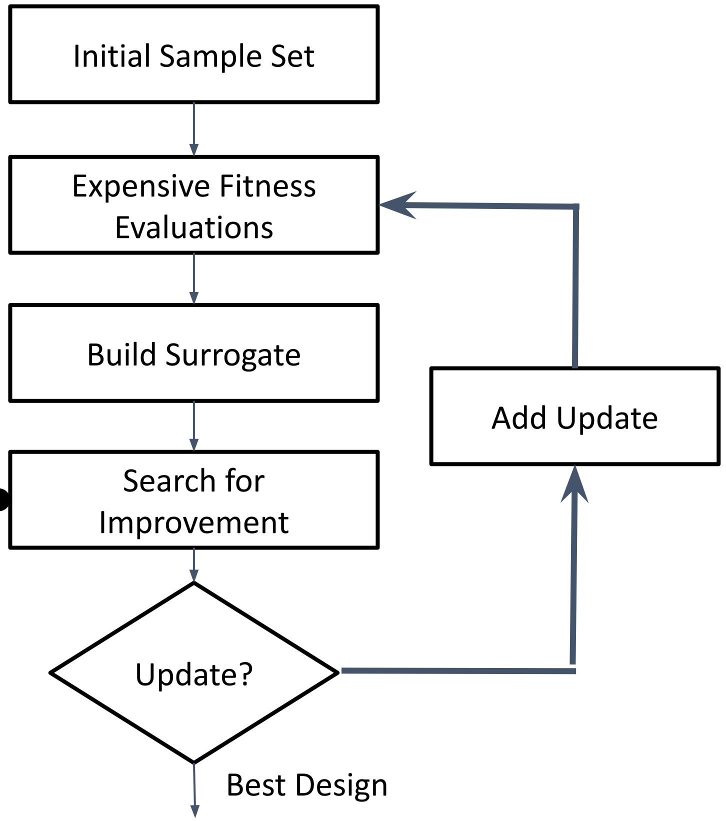
Kriging (Krige, D., et.al., 1951)

Focus Project: Functional Generative Design

Efficient Global Optimization (EGO)

- Sequential Model-based Optimizer or Active Learner
- Iteratively updating the surrogate model with promising infill points which maximize <u>Expected Improvement</u> criterion

$$E[I(\mathbf{x})] = (y_{best} - \hat{y}(\mathbf{x}))\Phi\left(\frac{y_{best} - \hat{y}(\mathbf{x})}{\hat{s}(\mathbf{x})}\right) + \hat{s}(\mathbf{x})\phi\left(\frac{y_{best} - \hat{y}(\mathbf{x})}{\hat{s}(\mathbf{x})}\right)$$



Focus Project: Functional Generative Design
Efficient Global Optimization (EGO)

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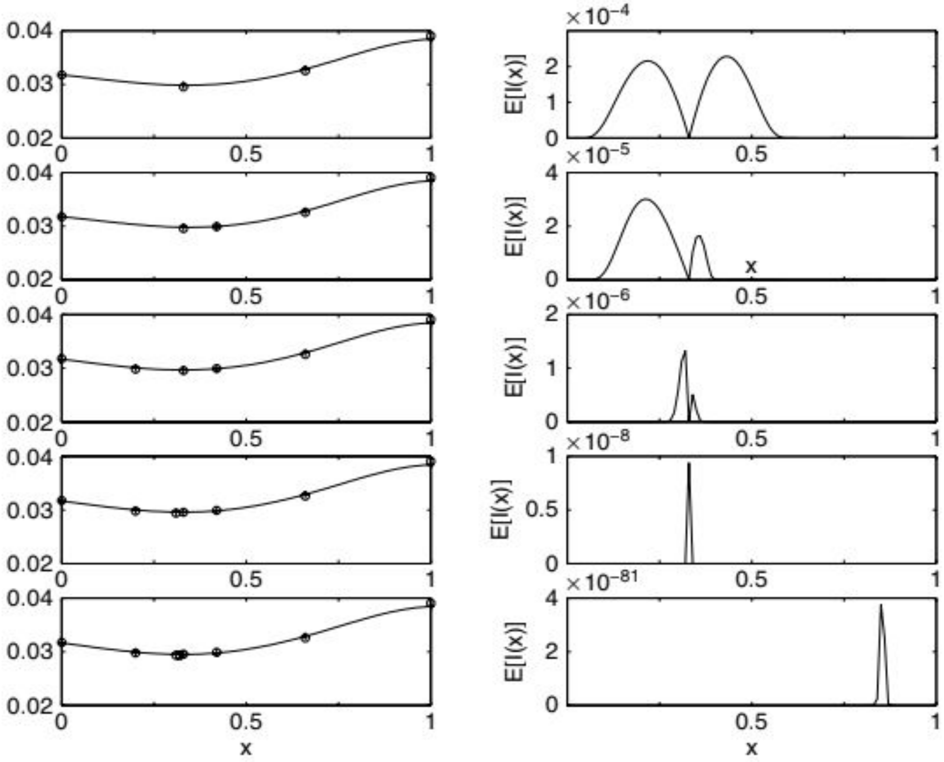
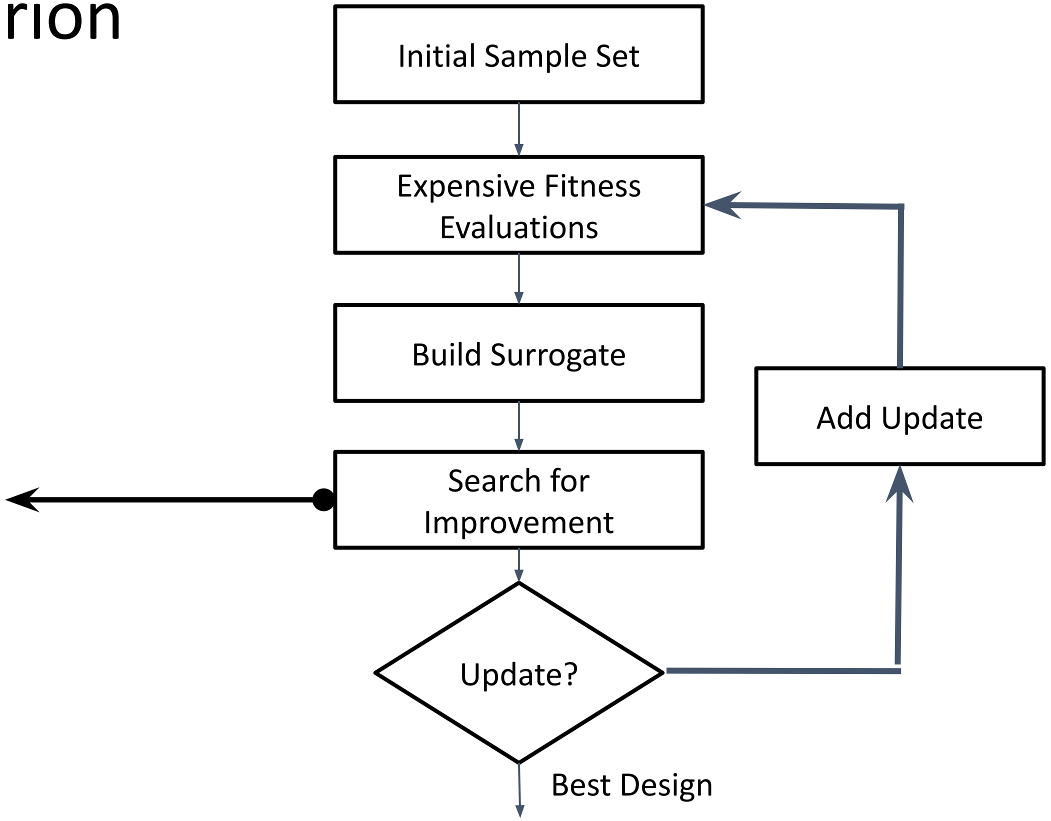


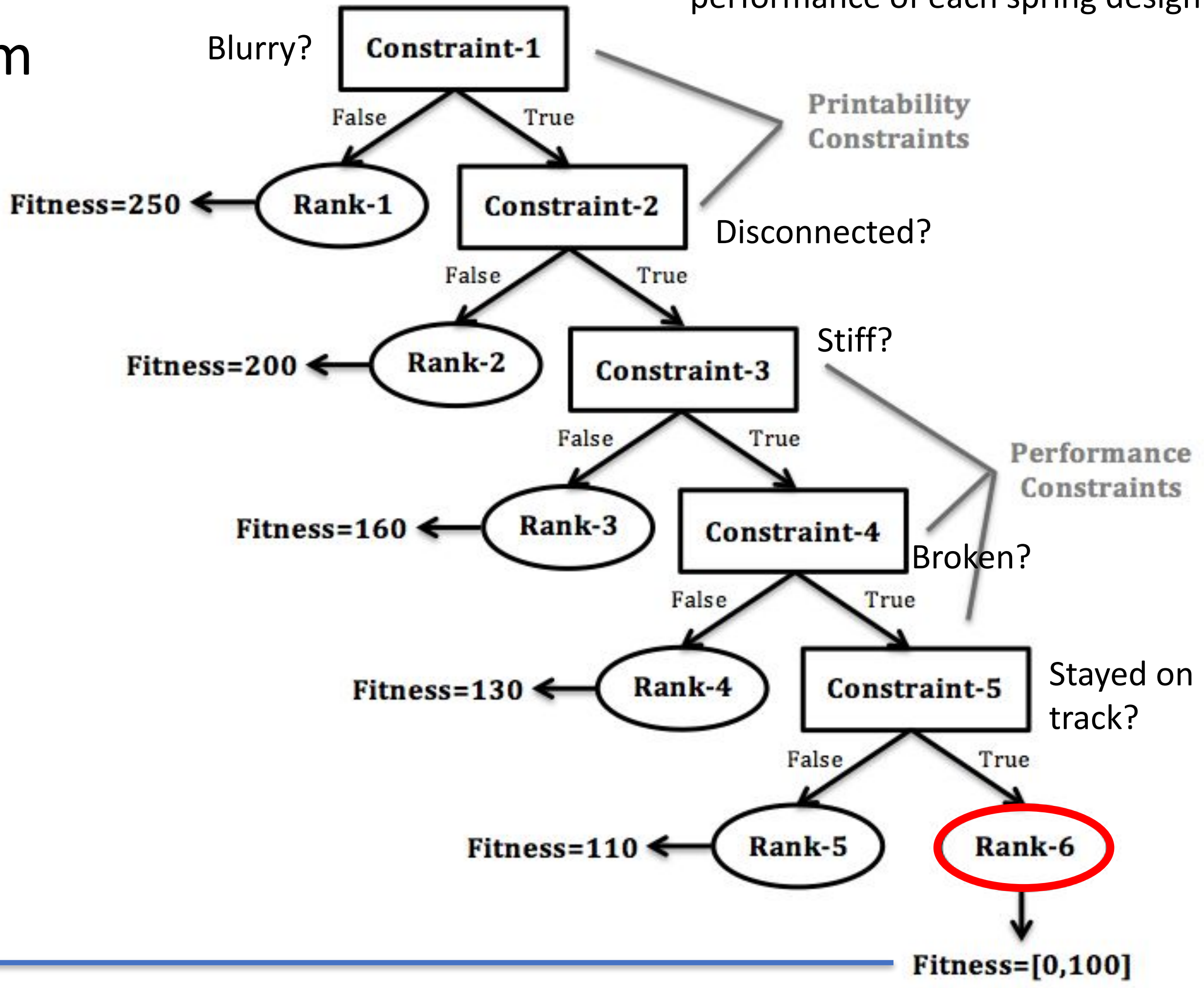


Focus Project: Functional Generative Design

Constraint Handling and rGA

- rGA $\longrightarrow$ real parameter Genetic Algorithm
- Operators:
  - Tournament Selection,
  - α-Blend Xover,
  - Gaussian Mutation
- Its roles:
  - Tuning Kriging hyperparameters
  - Maximizing EI in EGO
- $$f(x) = \sum_{i=1}^{n_{exp}} MSE_i = \frac{1}{10} \sum_{i=1}^{10} |d_i - 75|^2,$$

Tree structure for ranking the performance of each spring design



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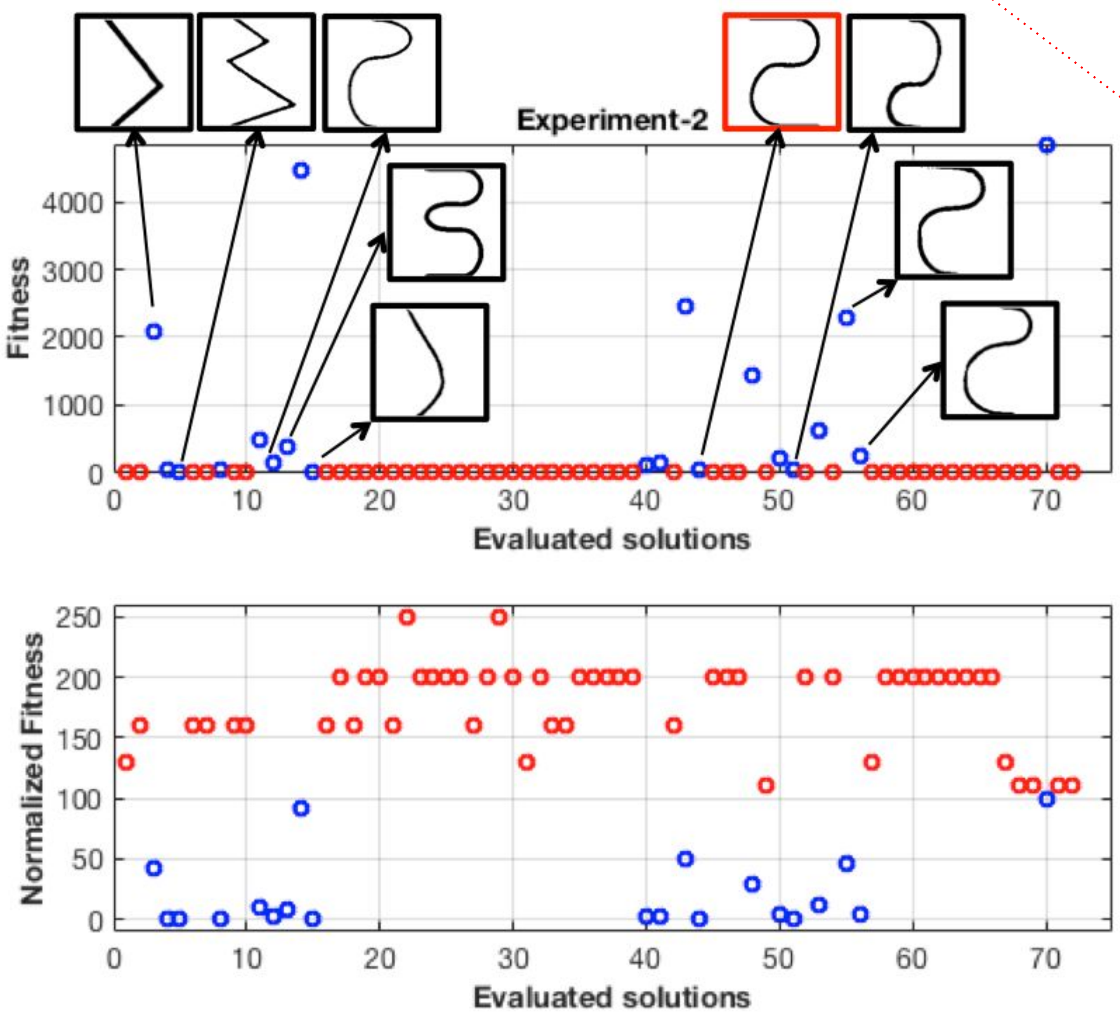
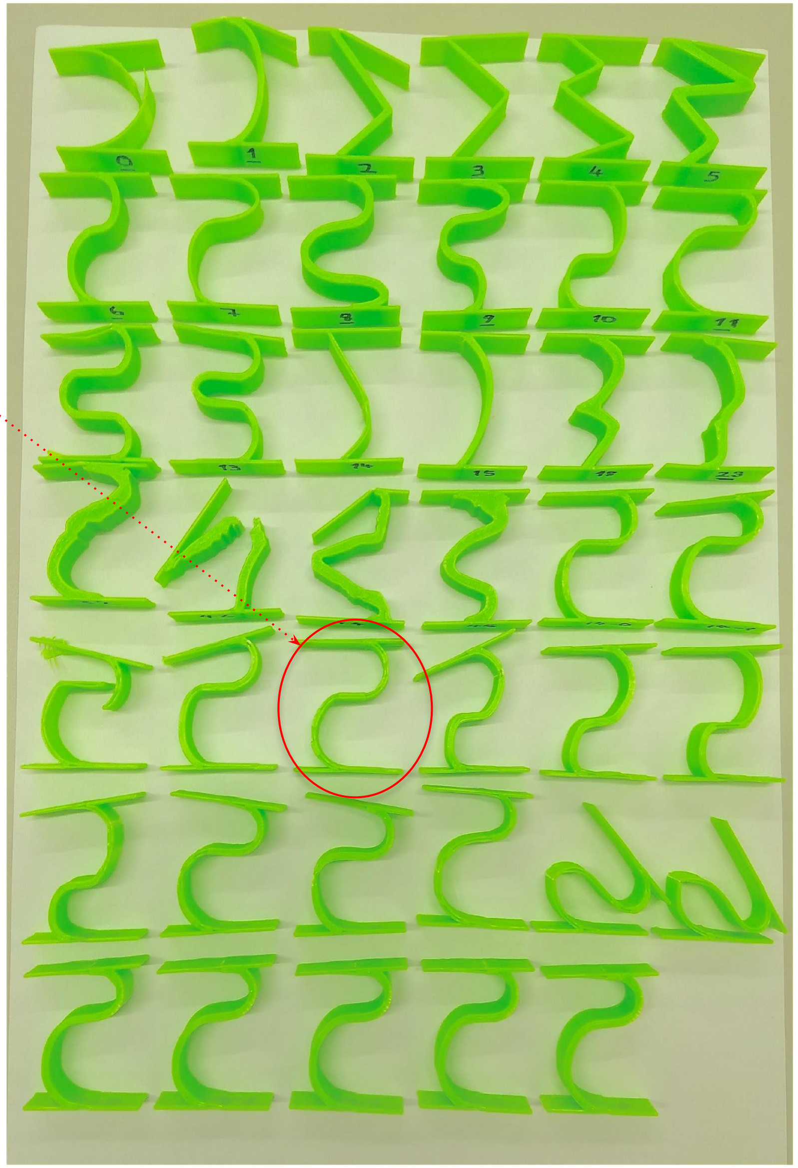
Experiments

Optimal Solution





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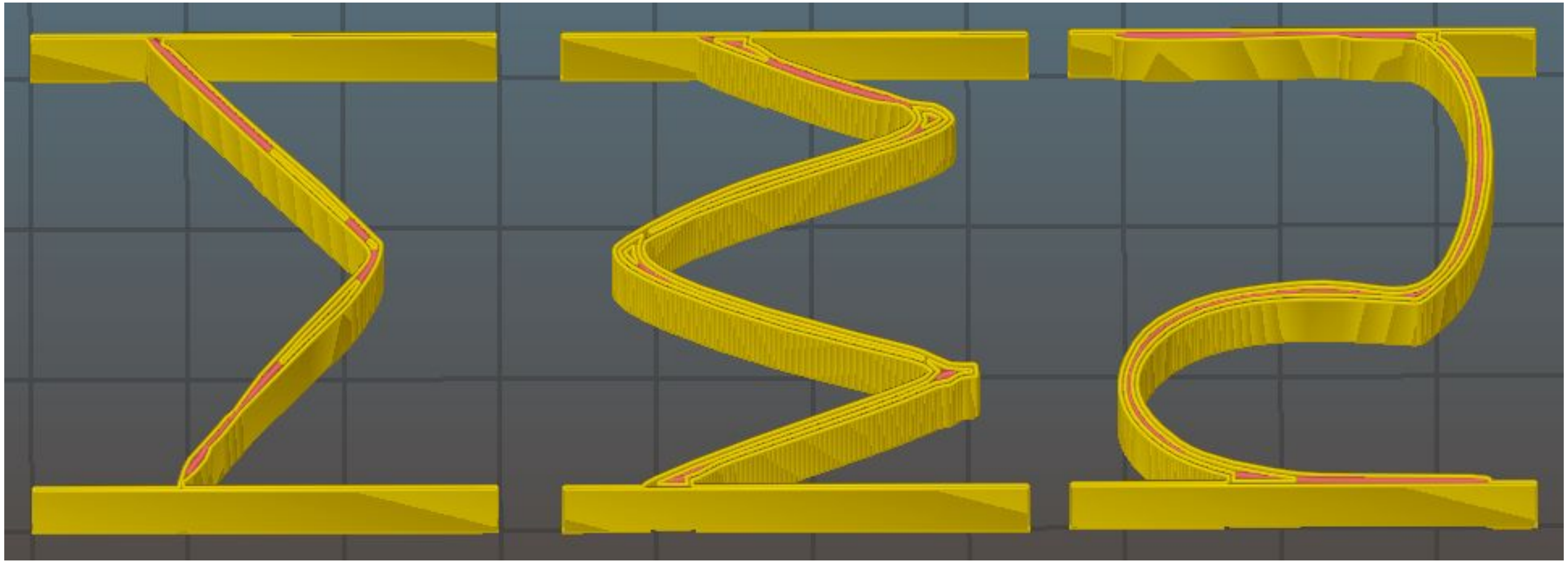
Discussion

- Gaps (red) cause fracture (i.e., act like “hinge”).
- Do we have to avoid gaps?



Focus Project: Functional Generative Design

Discussion

- No, gaps can be useful if they are used right!
- A fabrication rule is discovered automatically