CPS: Synergy: Collaborative Research: Smart Calibration Through Deep Learning for High-Confidence and Interoperable Cyber-Physical Additive Manufacturing Systems

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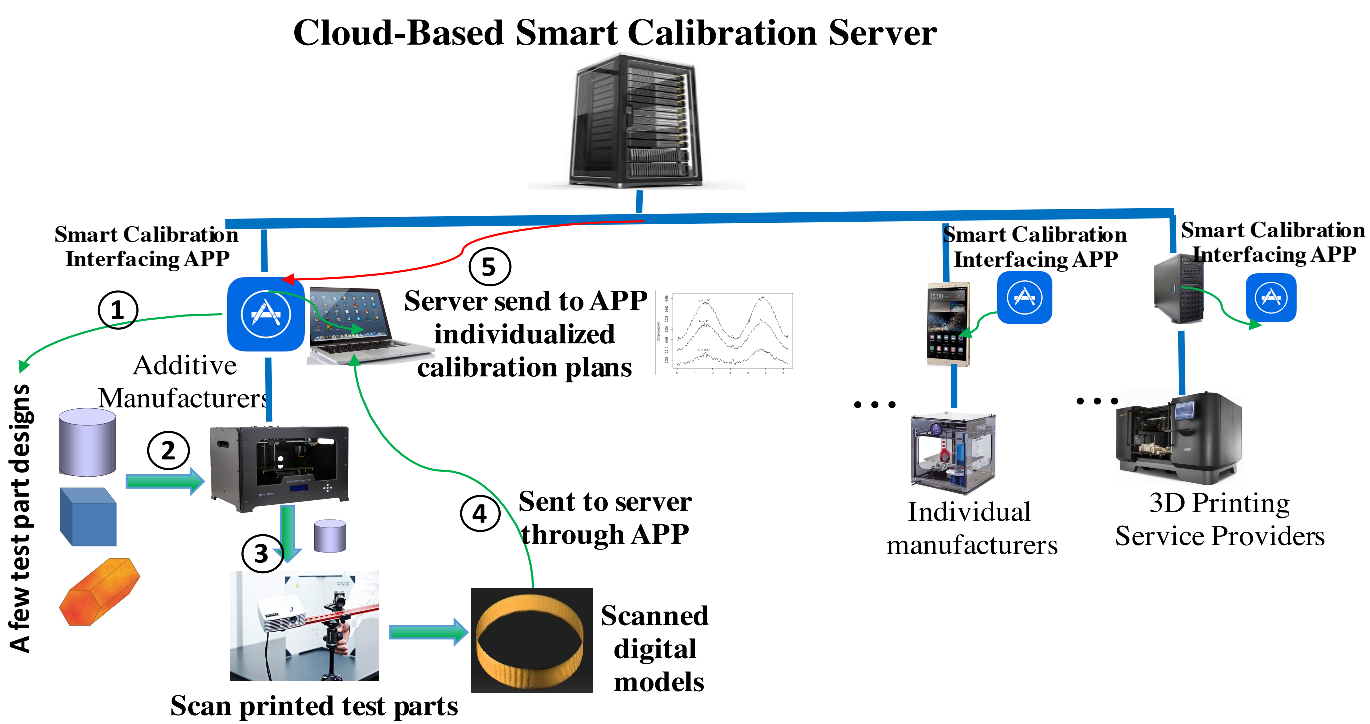
Description

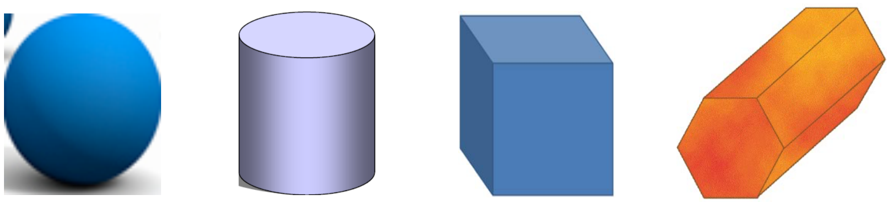
Smart and dynamic calibration of cyber-physical additive manufacturing systems (CPAMS) through machine learning



Findings: Statistical Monitoring of AM Built Products

- Traditional Statistical Process Control (SPC) can be directly applied to CPAMS
- A new prescriptive SPC scheme is established to monitor the AM processes

Training data



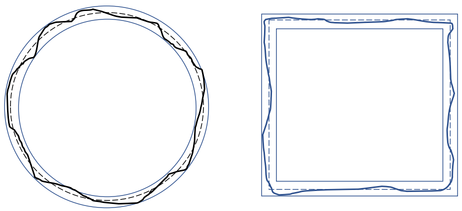
Assumption: training products fabricated under stable conditions

Objective: determining whether the process is in-control when building a new shape in a CPAMS

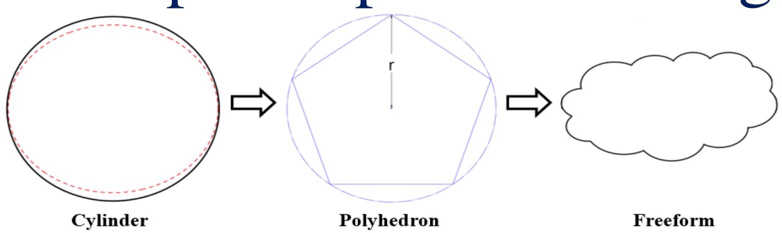
Findings: A Prescriptive SPC Scheme

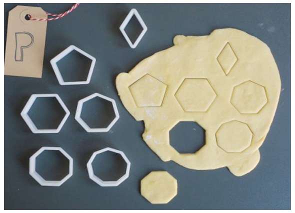
- Define a universal monitoring statistic applicable from shape to shape under a controlled false alarm rate

$$\eta_b = \frac{\Big| |\Delta S|_{Actual} - \int_0^{2\pi} r_0(\theta) \big| f(\theta, r_0(\theta) + x(\theta)) + x(\theta) \big| d\theta \Big|}{S_{Nominal}}$$



- Use our prescriptive modeling method for prediction



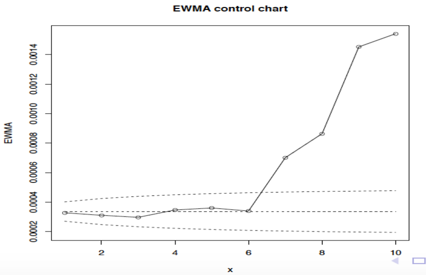


"Cookie-cutter modeling" framework

Huang et al, (2014)
Luan & Huang (2017)

- Enable a universal capability index for AM machines

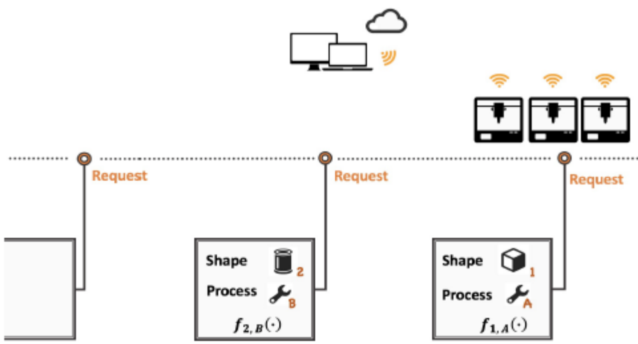
$$C_p = \frac{USL - \mu_\eta}{3\sigma_\eta}$$



A EWMA control chart
(Luan & Huang, 2017b)

Finds: Automated Modeling Through Bayesian Neural Network

- Automatic learning product quality data for future prediction in CPAMS



1: Specify a Bayesian ELM model $f_{s,p}(\cdot)$ for shape s under process p.

2: For a new process p', use the posterior under $f_{s,p}(\cdot)$ to learn the total equivalent amount $T(\cdot)$ (Sabbaghi & Huang, 2017) of p', with

$$f_{s,p'} \equiv f_{s,p}(T(\cdot)) + T(\cdot).$$

3: For a new shape s', use the posterior under $f_{s,p}(\cdot)$ to learn its deviation feature $\delta_{s'}(\cdot)$ (Huang et al., 2014; Sabbaghi et al., 2017), with

$$f_{s',p} \equiv f_{s,p}(\cdot) + \delta_{s'}(\cdot).$$

4: Model the deviation of a new shape s' under a new process p' by performing Steps 2 and 3 in succession.