Automated Geometric Shape Deviation Modeling for Additive Manufacturing Processes via Bayesian Neural Networks

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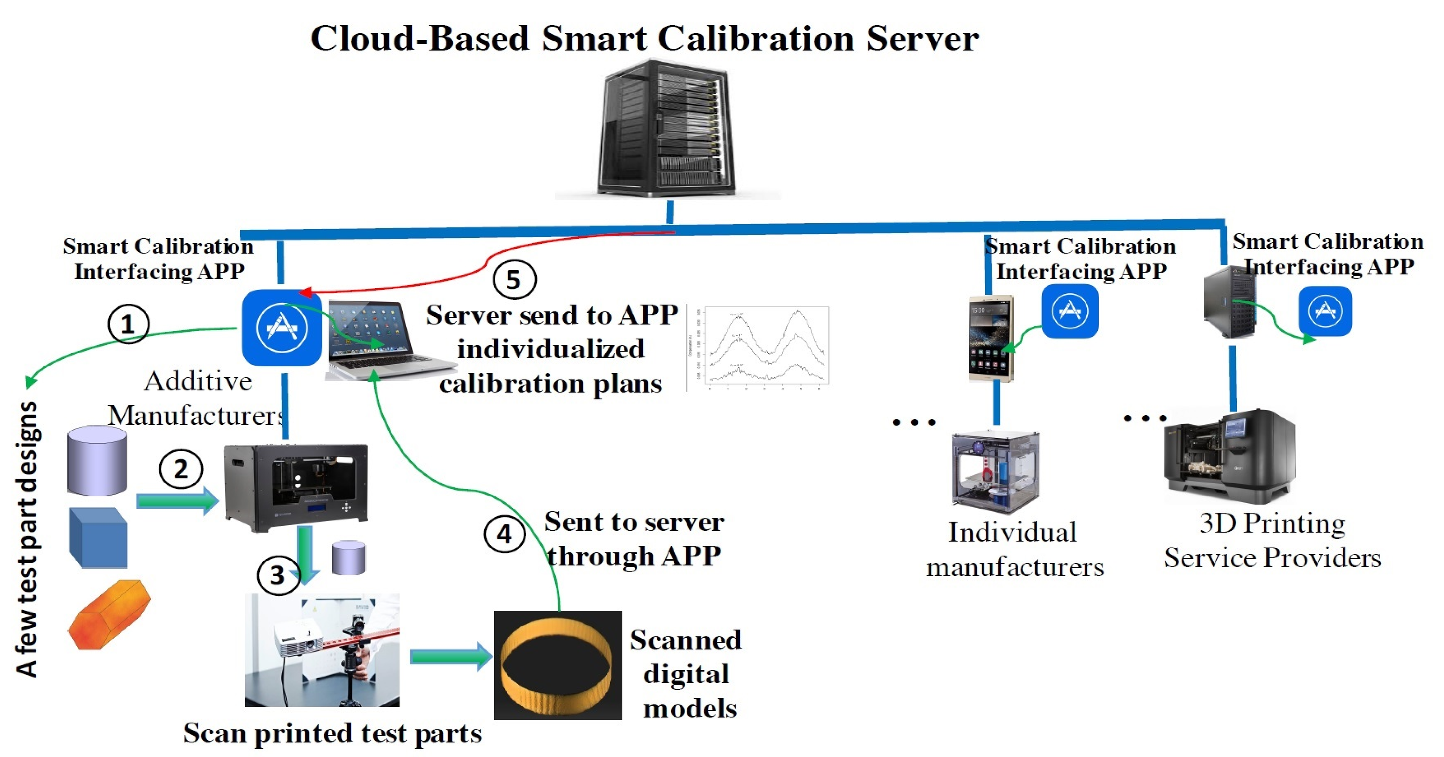
Shape Deviation Control in CPAMS



A significant trajectory of additive manufacturing (AM) technologies is cyber-physical AM systems (CPAMS) that seamlessly integrate computer-aided design models and physical AM processes.

The future growth and adoption of CPAMS is negatively impacted by geometric shape deviations that are introduced by AM processes.

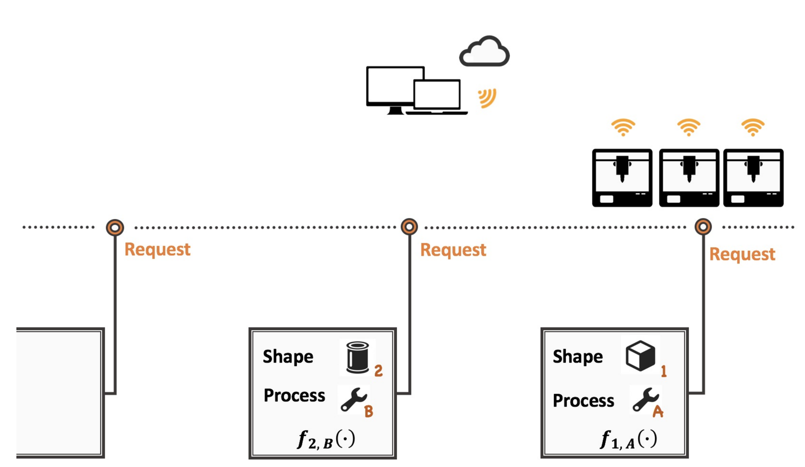
Due to its nature and capability of one-of-a-kind manufacturing, shape deviation modeling and control in CPAMS is complicated by three features.

- Wide variety of shapes with varying geometric complexities.
- Vast spectrum of distinct AM processes in CPAMS.
- Small samples of tests shapes that could possibly be manufactured.

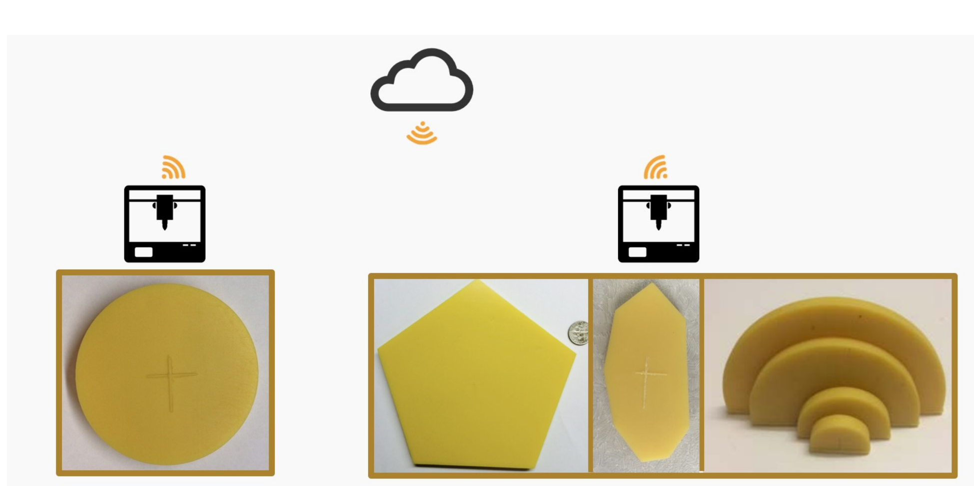
Current shape deviation modeling and control methods cannot address all of these novel features of CPAMS in an automated or efficient manner.

Objective: Automated Modeling in CPAMS

Geometric shape deviation control in CPAMS requires efficient learning of deviation models across new AM processes and shape varieties.

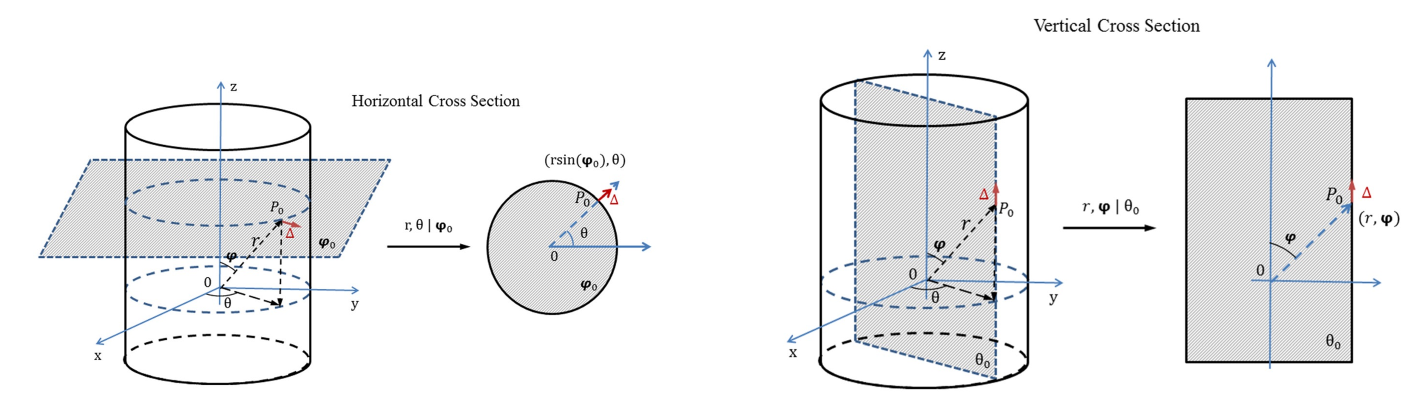


We developed a general Bayesian neural network methodology that enables automated and flexible deviation modeling from point cloud data collected across different processes and shapes in CPAMS.



Background and Notation

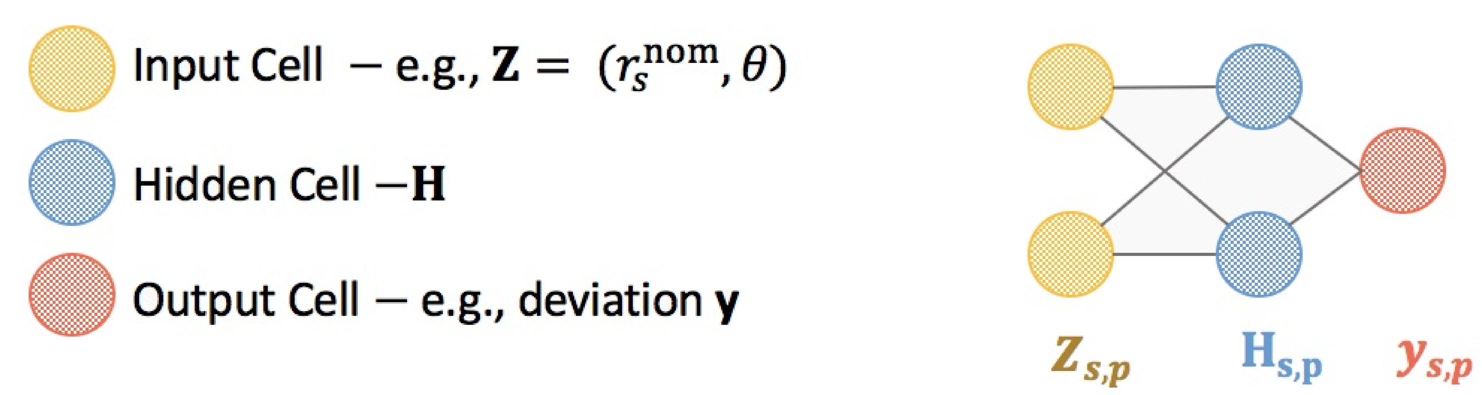
We transform point cloud measurements of a shape to decouple geometric shape complexity from the task of modeling (Huang et al., 2015).



The deviation for point θ on shape s under process p is defined as

$$y_{s,p}(\theta) = r_{s,p}^{\text{obs}}(\theta) - r_s^{\text{nom}}(\theta).$$

We utilize extreme learning machines (ELMs, Huang et al., 2004) as a basic building block of our deviation modeling methodology for CPAMS.



Bayesian Neural Network Methodology

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

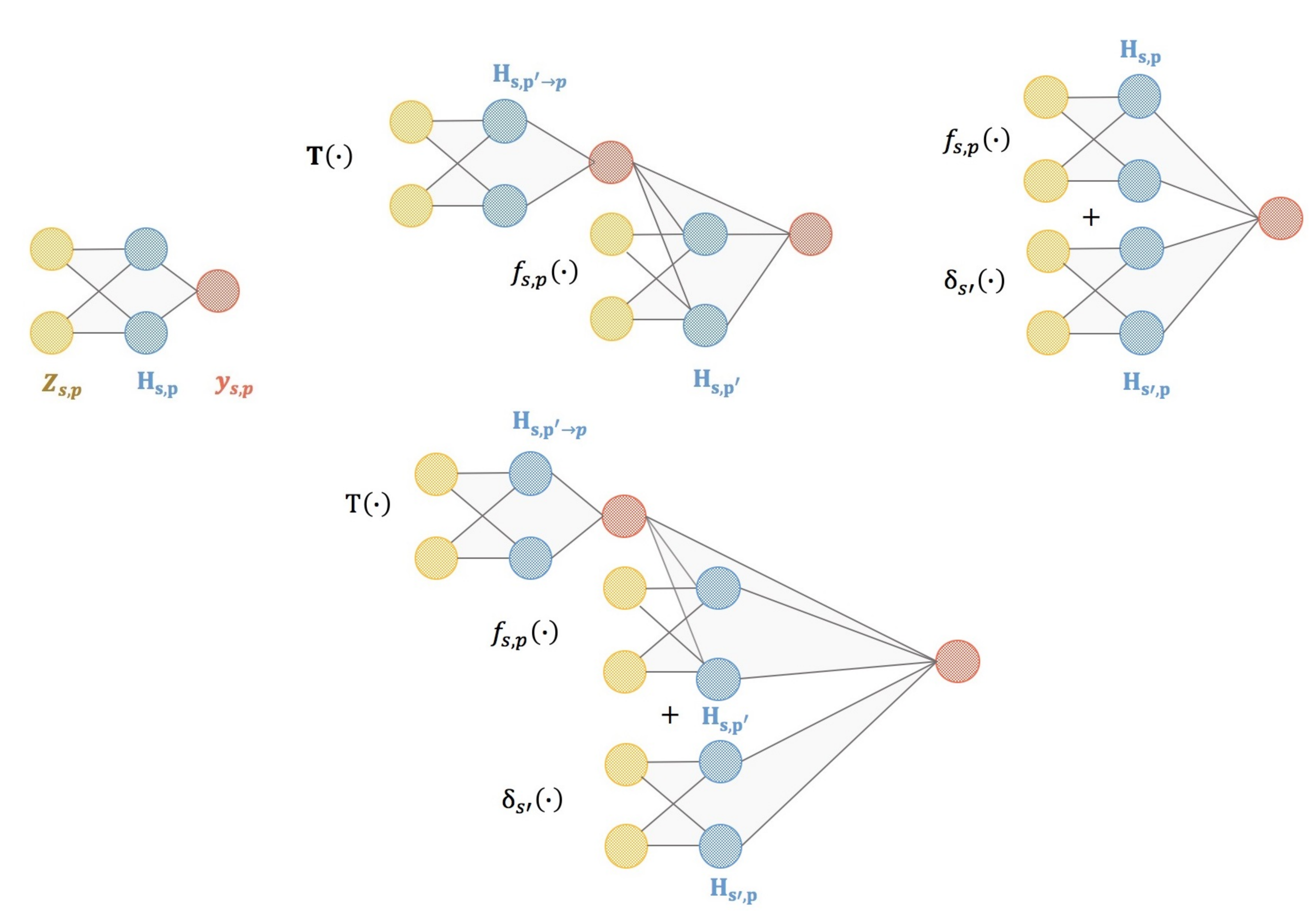
2: For a new process p', use the posterior under $f_{s,p}(\cdot)$ to learn the total equivalent amount $T(\cdot)$ (Sabbaghi & Huang, 2017) of p', with

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

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

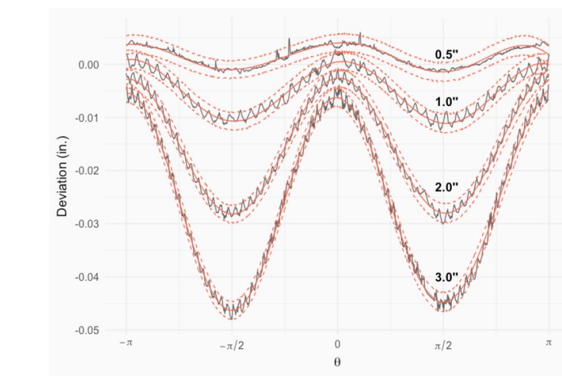
$$f_{s',p} \equiv f_{s,p}(\cdot) + \delta_{s'}(\cdot).$$

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

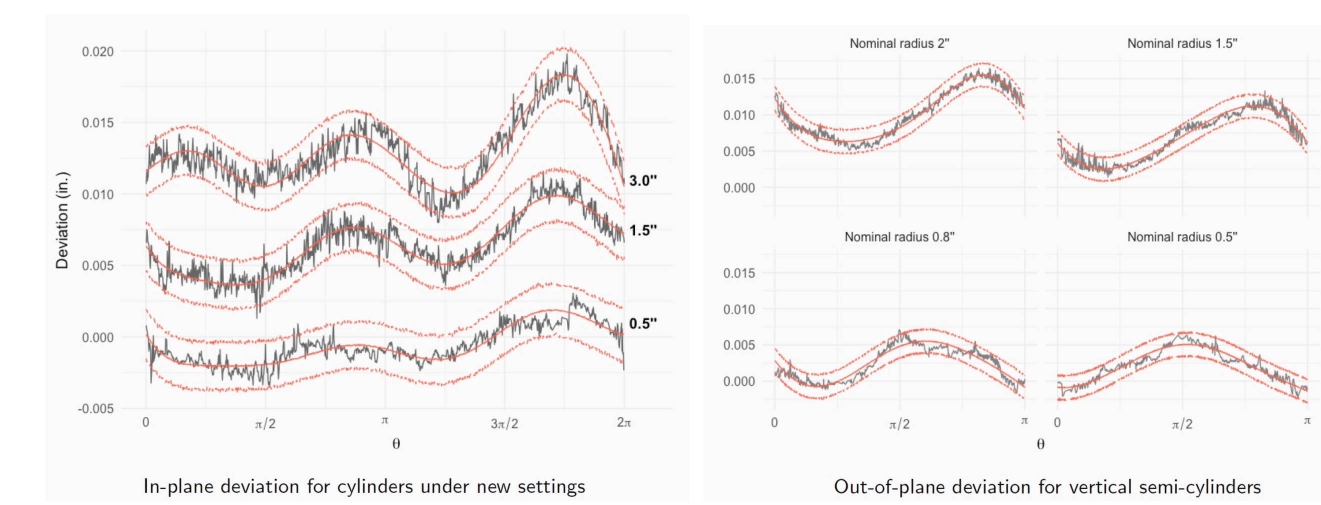


Application of Bayesian Methodology

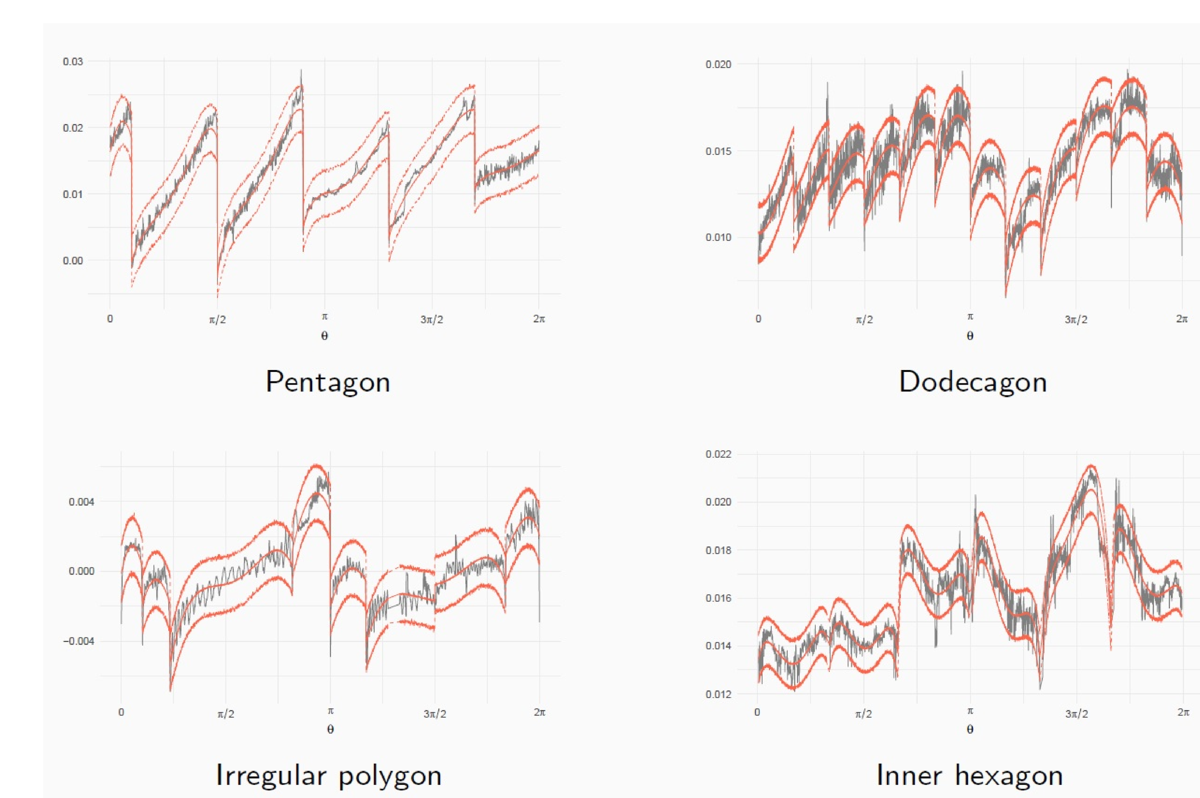
Bayesian ELM model fit for the in-plane deviations of four cylinders.



Deviation modeling of cylinders under new processes via $T(\cdot)$.



Deviation modeling of new shapes and processes via $T(\cdot)$ and $\delta_{s'}(\cdot)$.



Broader Impact and Future Work

Our new Bayesian neural network methodology effectively utilizes small samples of data to automate and facilitate deviation modeling for a broad class of disparate shapes across distinct processes in CPAMS.

The broader impact of our methodology is smarter control of general CPAMS, with the potential of immediate practical application for a large community of AM users.

Our next step is to incorporate the algorithms of our methodology into our cloud-based app for dynamic and automatic recalibration of CPAMS.

Acknowledgments

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