AMapi: An Application Programming Interface for Additive Manufacturing Systems

Raquel De Souza Borges Ferreira[1], Kevin Amstutz[2], and Arman Sabbaghi[2] (PI)
[1]Intel Corporation [2]Purdue University Department of Statistics

Lead PI of U.S. National Science Foundation Grant Nos. CMMI-1544841 and CMMI-1544917: Qiang Huang, University of Southern California Daniel J. Epstein Department of Industrial and Systems Engineering

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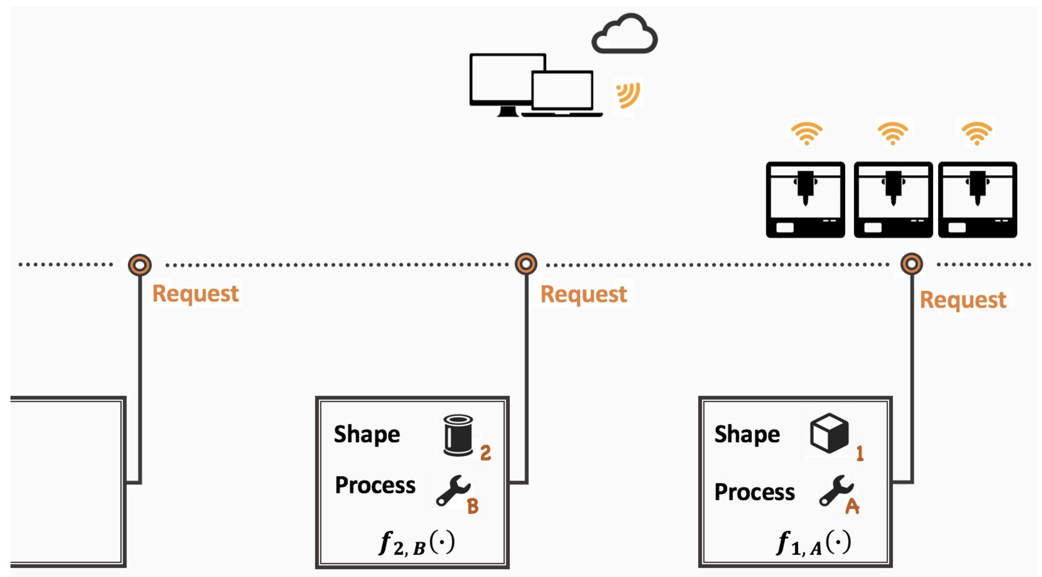
Deviation Modeling and Control in CPAMS



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 of CPAMS is negatively impacted by shape deviations.

Machine learning (ML) algorithms can enable automated modeling of shape deviations based on point cloud data collected from CPAMS (Ferreira, Sabbaghi, and Huang, 2019).

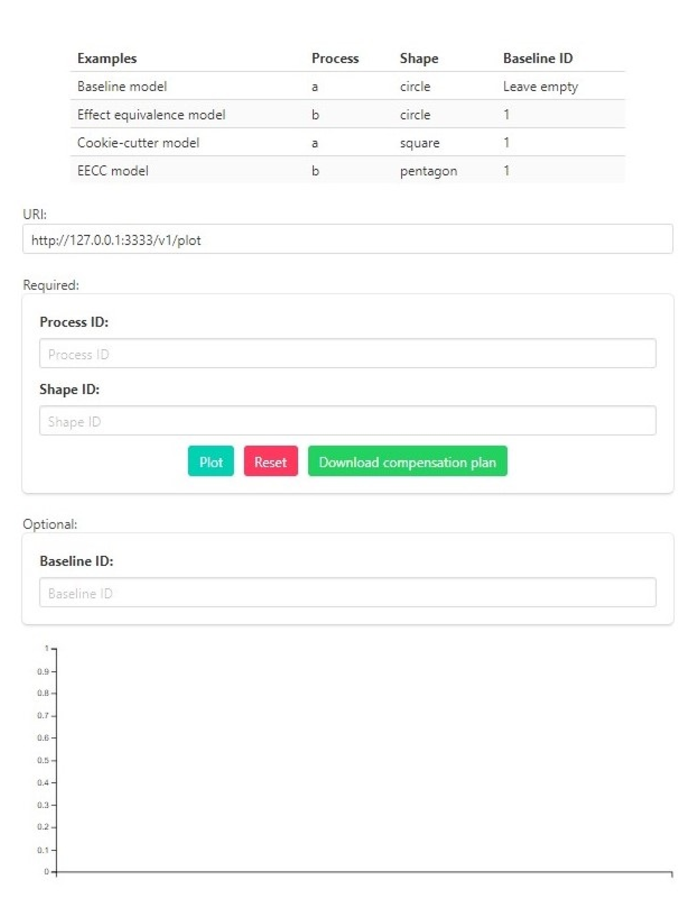
Of critical importance for shape deviation control in CPAMS is a software platform that enables

- the execution of ML algorithms for learning deviation models,
- model transfer across shapes, processes, or lurking variables, and
- the creation of compensation plans based on learned models.

Aim: API for CPAMS

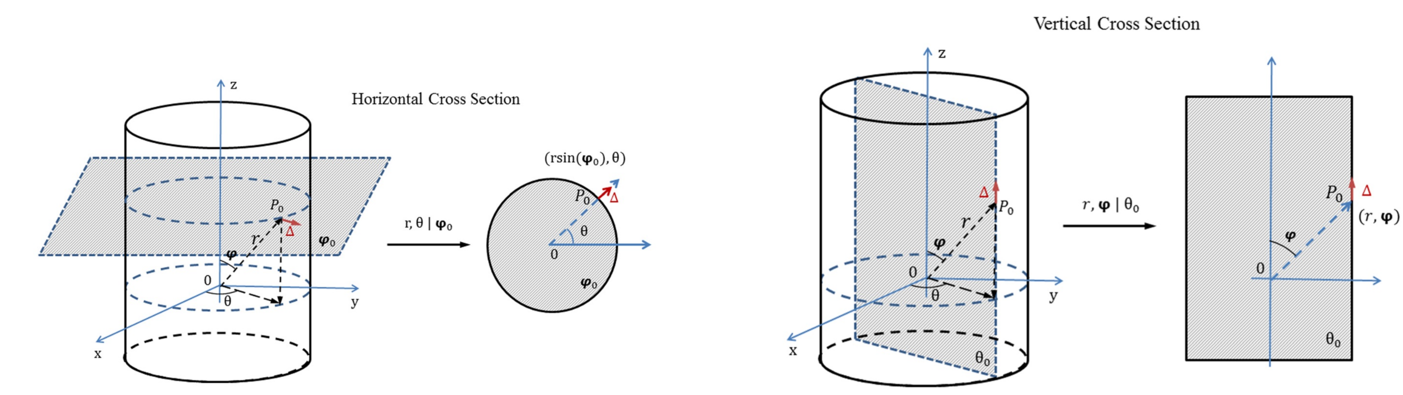
Shape deviation control in CPAMS requires an application programming interface (API) that facilitates ML for deviation modeling and compensation plan construction across different settings.

We developed a new API, called AMapi, that enables automated deviation modeling, model transfer, and compensation plan construction via ML.



Notations and Definitions

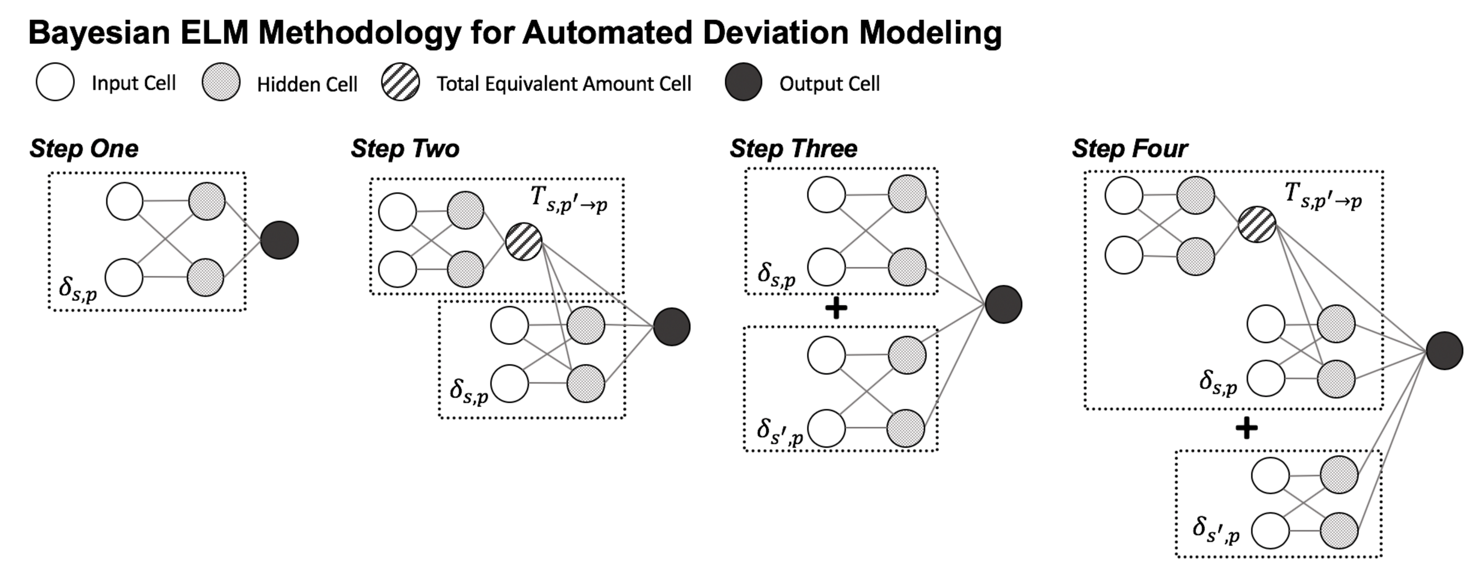
We transform point cloud measurements of a shape to decouple geometric shape complexity from the task of modeling (Huang et al., 2015).



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

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

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



Features of AMapi

RESTful Software Architectural Design of AMapi
AMapi's RESTful architecture makes it flexible and horizontally scalable.

Users can integrate their own tools with our proprietary ML algorithms, on top of a flexible, programming language-agnostic API.

AMapi can be integrated into any modern app, with its choice of front-ends and graphical user interfaces.

AMapi and Go
AMapi is written in Go, which enables it to be simple, fast, and have excellent readability, networking, and multiprocessing capabilities.

As Go is a compiled language, AMapi can be written and reduced to a single binary that could be run on any modern system.

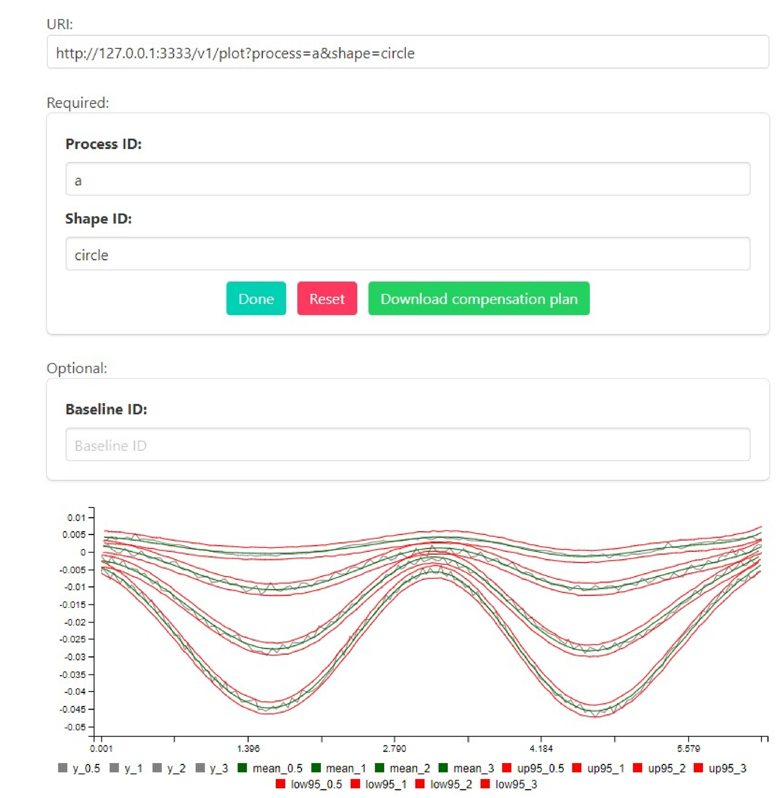
Resources of AMapi
The alpha version of AMapi runs a performant web server that serves up two primary resources: data and models.

Users can tag, upload, fetch, and delete datasets that can be used to build models for geometric shape deviation. AMapi is connected to a SQLite database backend, and uploaded datasets are saved into it.

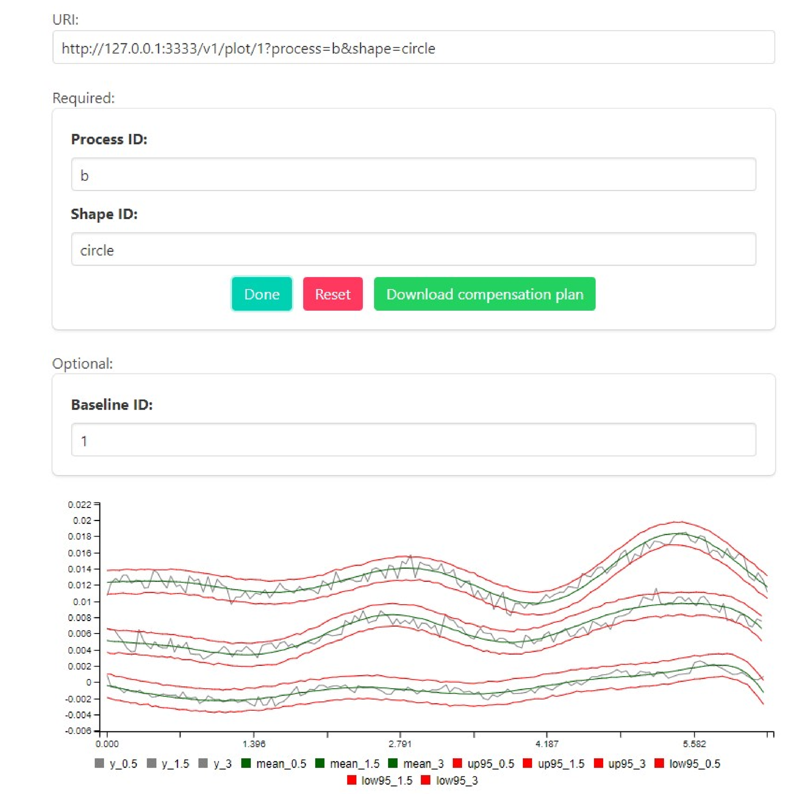
Once data are uploaded, AMapi automates ML for deviation models and compensation plans across shapes, processes, or lurking variables.

Applications of AMapi

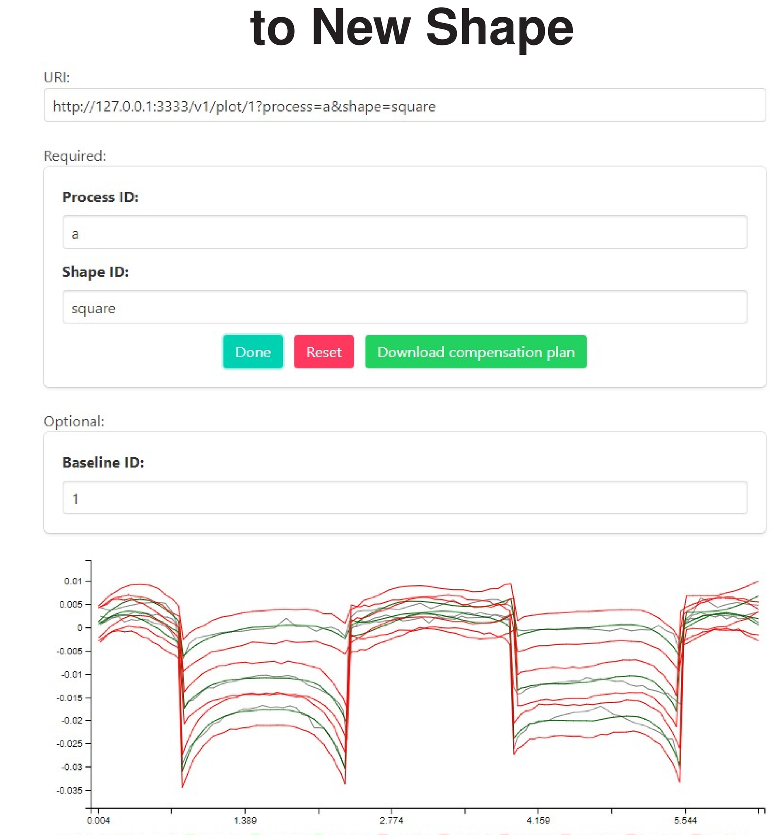
Fitting Baseline Deviation Model



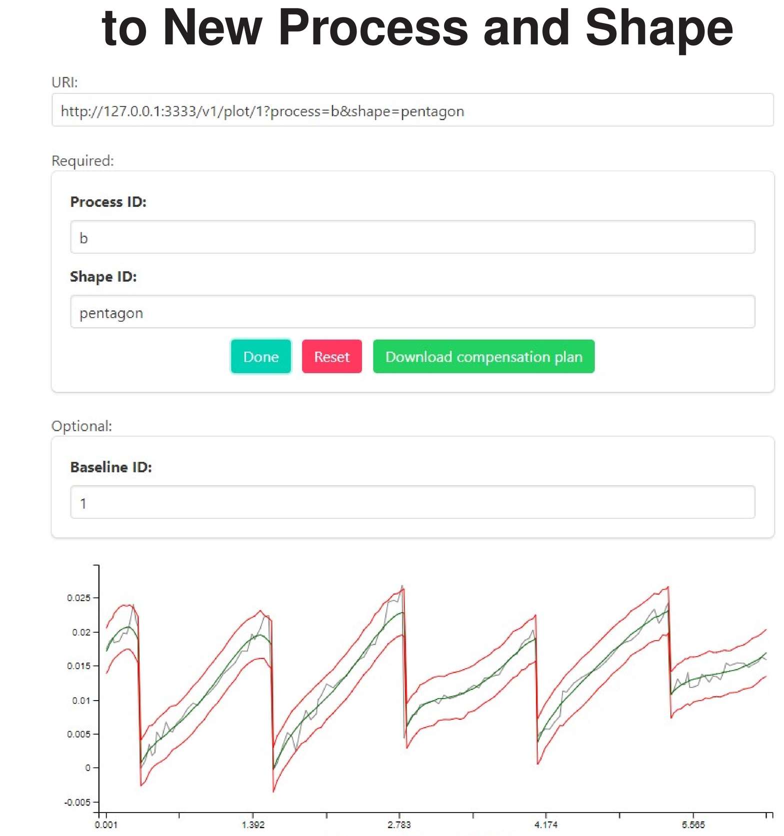
Transferring Deviation Model to New Process



Transferring Deviation Model to New Shape



Transferring Deviation Model to New Process and Shape



Broader Impacts

Our new API for CPAMS helps to address the objective of facilitating ML for automated deviation model building and compensation plan construction in CPAMS.

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

Our API can ultimately enable dynamic and automated recalibration of CPAMS.

Acknowledgments

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References

Ferreira R., Sabbaghi A., Huang Q. (2019). Automated geometric shape deviation modeling for additive manufacturing processes via Bayesian neural networks. *IEEE Transactions on Automation Science and Engineering* (to appear).