Machine Learning Can Advance Ultra-high Precision Quality Control for Robotic Composite Aircraft Assembly

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Abstract

We propose systematic machine learning methodologies to improve the quality and productivity of composite aircraft assembly. Specifically, a statistical calibration method is developed to calibrate and validate digital twin simulator and improve its accuracy; partitioned active learning is proposed to increase the data collection efficiency; surrogate model considering input uncertainty is proposed for predictive analytics of virtual assembly and robotic automation of aircraft assembly.

The objective of this poster is to demonstrate how powerful machine learning is for advancing ultra-high precision quality control of composite aircraft assembly.

Motivation

Inevitable uncertainties in manufacturing systems and the complex characteristics of composite materials induce fatal defects in composite aircraft assembly.

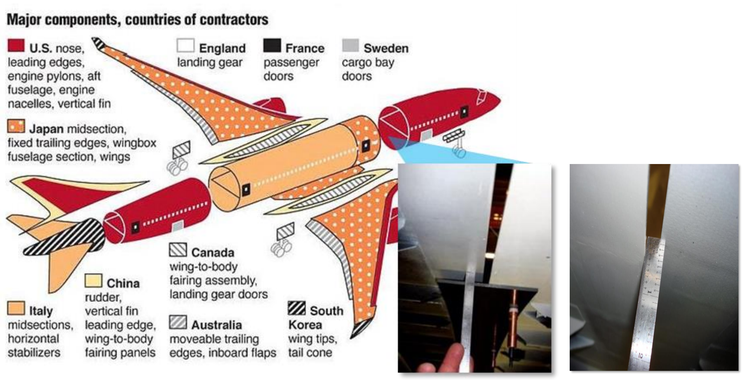


Figure 1. Quality defects in assembly of Boeing 787 fuselage in Seattle Times (2007) and halted deliveries by FAA (2021)

Challenges:

- Compliant nature and anisotropic/nonlinear characteristics of composite fuselage
- Ultra-high precision requirement: 200 v.s. **(<0.007)** inches

Current Practice and Limitations:

Ten adjustable actuators are used.

- **Low efficiency**: long flow time
- **Non-optimality**: acceptable rather than optimal
- **Highly skilled engineers required**

Figure 2. Actuators Setup

Statistical Calibration of Digital Twin Simulator [1]

Goal: to find the optimal values of the model parameters, under which the simulator outputs match the physical experimental observations.

Contribution: to overcome the curse of dimensionality in calibration (limited physical experiments, a large amount of model parameters)

$$\hat{\theta}_n = \underset{\theta}{\operatorname{argmin}}\, L(\boldsymbol{Y}^p, \boldsymbol{Y}^s_\theta) + \lambda_n \| \theta - \theta_0 \|$$

$$= \underset{\theta}{\operatorname{argmin}} (\boldsymbol{Y}^p - \boldsymbol{Y}^s_\theta)^T (\tau^2 \Phi_\theta + \sigma^2 I_n)^{-1} (\boldsymbol{Y}^p - \boldsymbol{Y}^s_\theta) + \lambda_n \sum_{i=1}^{m} |\theta_i - \theta_i^{(0)}|$$

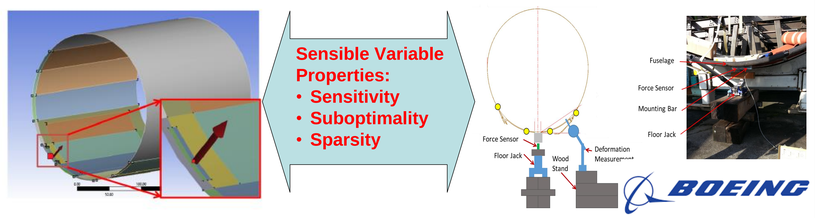


Figure 3. Computer simulator v.s. Physical experiment

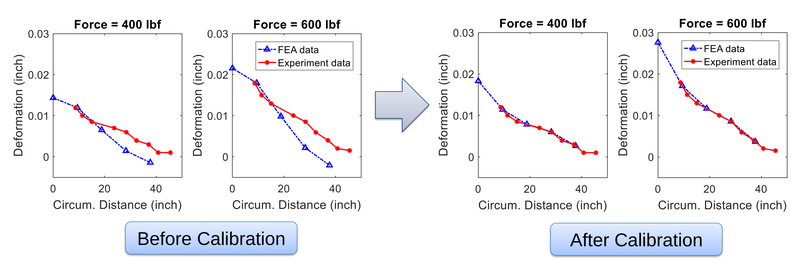


Figure 4. Calibration results

Surrogate Model considering Uncertainty [2-3]

Goal: to predict deformation and stress accurately, based on the doubly corrupted data .

$$\boxed{y(x)} = \boxed{f}(x + \boxed{u}) + \boxed{\epsilon}, \quad x \in \Omega$$

Actual Observation; Target Function $\sim NNGP(\mu^L, k^L)$; Input Noise $\sim \mathcal{U}(0, \sigma_u^2)$; Observation Noise $\sim \mathcal{N}(0, \sigma_\epsilon^2)$

- Input Uncertainty
  Consider input uncertainty (actuator/part variability) by adjusting the kernel of NNGP with respect to noise.

$$k_{NNGPIU}(x, x') = \mathrm{Cov}[y(x), y(x')] = \mathbb{E}_{u,u'}[f(x+u) f(x'+u')]$$

- Hyperparameter Estimation and Prediction
  Maximum likelihood is used for estimation of hyperparameters. Prediction at unobserved x_* is

$$\bar{f}(x_*) = K_*^L (K^L + \sigma_\epsilon^2 I)^{-1} y,$$
$$\sigma_f^2(x_*) = k^L(x_*) - K_*^L (K^L + \sigma_\epsilon^2 I)^{-1} K_*^{L^\top}$$

Theoretical and Case Study Results

Theoretical Properties:

Proposition 1. NNGPIU is a best linear unbiased predictor of f.

Proposition 2. The MSPE of NNGPIU is less than or equal to that of NNGP.

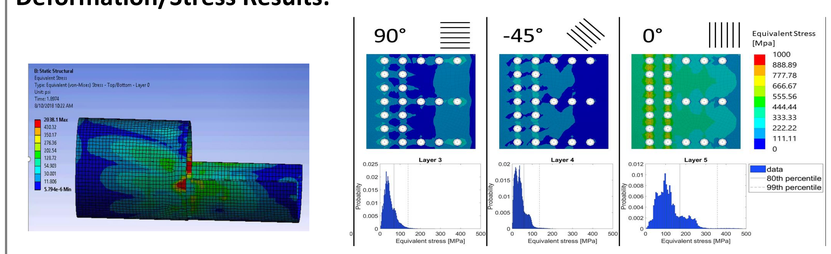
More detailed theoretical investigation about KALE, KALEN and Stochastic Kriging can be found in [3].

Prediction Results:

Table 1. Averaged MAEs in the case study.

Model (MAE)	Linear	GP	NNGP	KALE	NNGPIU
Deformation ($\times 10^{-3}$in)	9.37	9.42	10.84	9.29	9.35
Residual Stress (psi)	18.143	13.668	13.619	13.742	11.884

Deformation/Stress Results:



Quality Control Results:

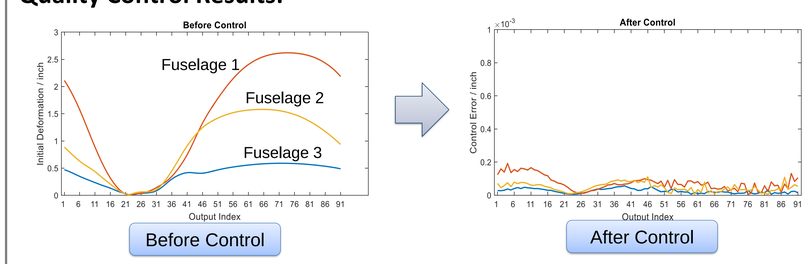


Figure 5. Quality control results

The proposed method can achieve **ultra-high dimensional accuracy (<0.007 inches)** with large initial deformation (3 inches).

Acknowledgments

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References

[1] Wang, Y., et al. (2020) "Effective Model Calibration via Sensible Variable Identification and Adjustment with application to Composite Fuselage Simulation", *Annals of Applied Statistics*, 14(4). (**ASA Statistics in Physical Engineering Sciences (SPES) Award in 2022**)

[2] Lee, C., et al. (2021) "Neural Network Gaussian Process considering Input Uncertainty for Composite Structures Assembly", *IEEE/ASME Transactions on Mechatronics*. (**IISE DAIS Best Student Paper Award in 2020**)