Physics-informed Machine Learning for System Intelligence

Data Analytics for Advanced Manufacturing Group

Data Analytics for Advanced Manufacturing Group is led by Dr. Xiaowei Yue in Grado department of industrial and systems engineering, Virginia Tech.

VIRGINIA TECH

RESEARCH TASK & OVERVIEW

Our research group has the following main research areas:
- Ultra-high precision Quality Control for Intelligent Manufacturing
- Predictive Modeling, Uncertainty Quantification, and Optimization of Complex Engineering Systems
- Computational Algorithms and Information Fusion for System Intelligence

The best key words that represent our group's identity are
- Data Science
- Advanced Manufacturing
- System Intelligence

MOTIVATION

Boeing 787 Dreamliner is one of the most successful commercial aircraft, which is benefitted from the innovative composite structures. However, the manufacturer has experience frequent delivery halt due to quality defects associated with gaps between fuselage sections.

It compels manufacturers to conduct shape adjustment for assembly and maintenance, while the process is challenging because of the followings:
(i) Intrinsic uncertainty (from material or structure uniformity)
(ii) Composite material complexity (nonlinearity, anisotropicity)

Data analytics is promising to breakthrough the conventional trial-and-error based shape control process, while the problem is subject to
(i) Expensive experiment cost
(ii) Insufficient simulation credibility

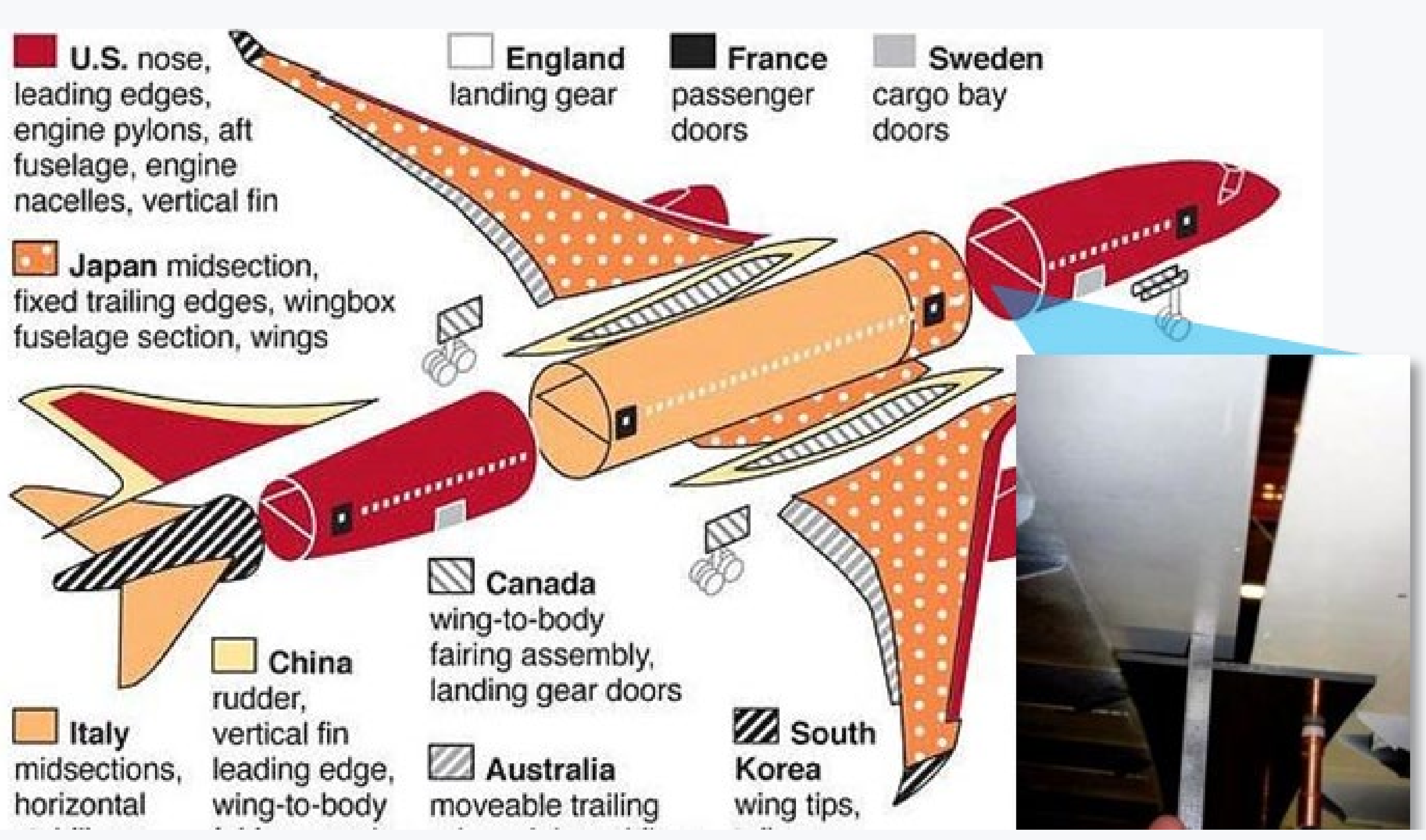


Fig. Issued quality defects in assembly of Boeing 787 fuselage in Seattle Times Aerospace Report, Seattle Times, 2007

GOALS & OBJECTIVES

Our research objective is to develop ultra-high precision quality control for composite assembly, which has the following subobjectives.
(i) Highly expressive and robust surrogate modeling
(ii) Novel active learning for efficient and safe data acquisition
(iii) Incorporating background knowledge (e.g., physics)

METHODOLOGY

I. Neural Network Gaussian Process considering Input Uncertainty (NNGPIU) [1]

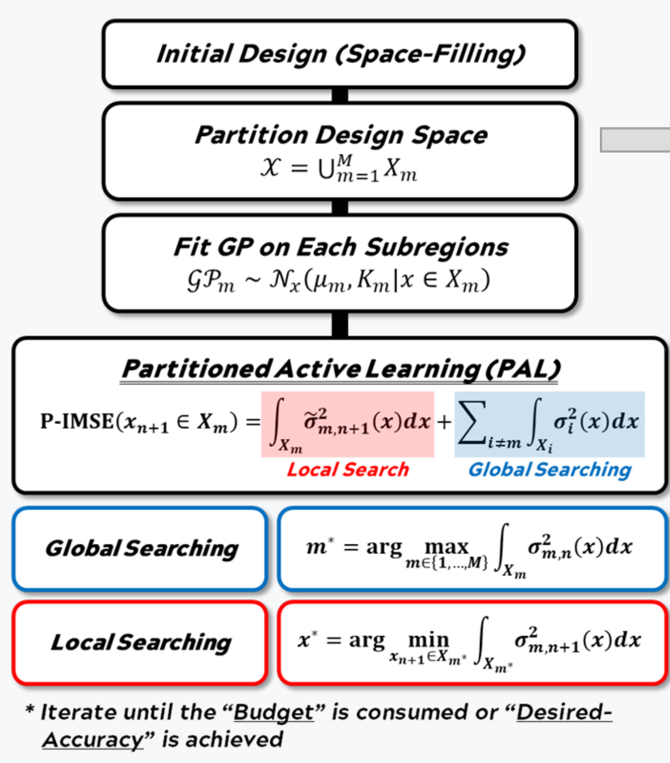
- High expressivity: To accommodate the complex nature of composite materials, we employ the neural network Gaussian process (NNGP) as the underlying function.
- Input Uncertainty: Consider input uncertainty by adjusting the kernel of NNGP with respect to noise.

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

Table. Composite fuselage deformation prediction result

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

II. Partitioned Active Learning (PAL) [2]



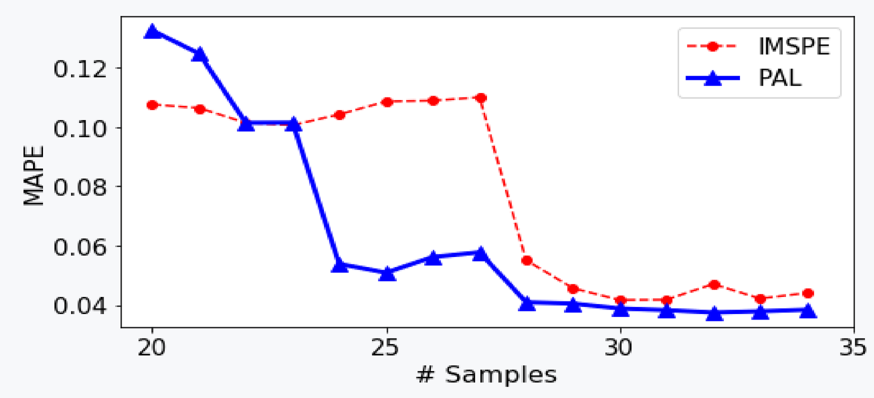
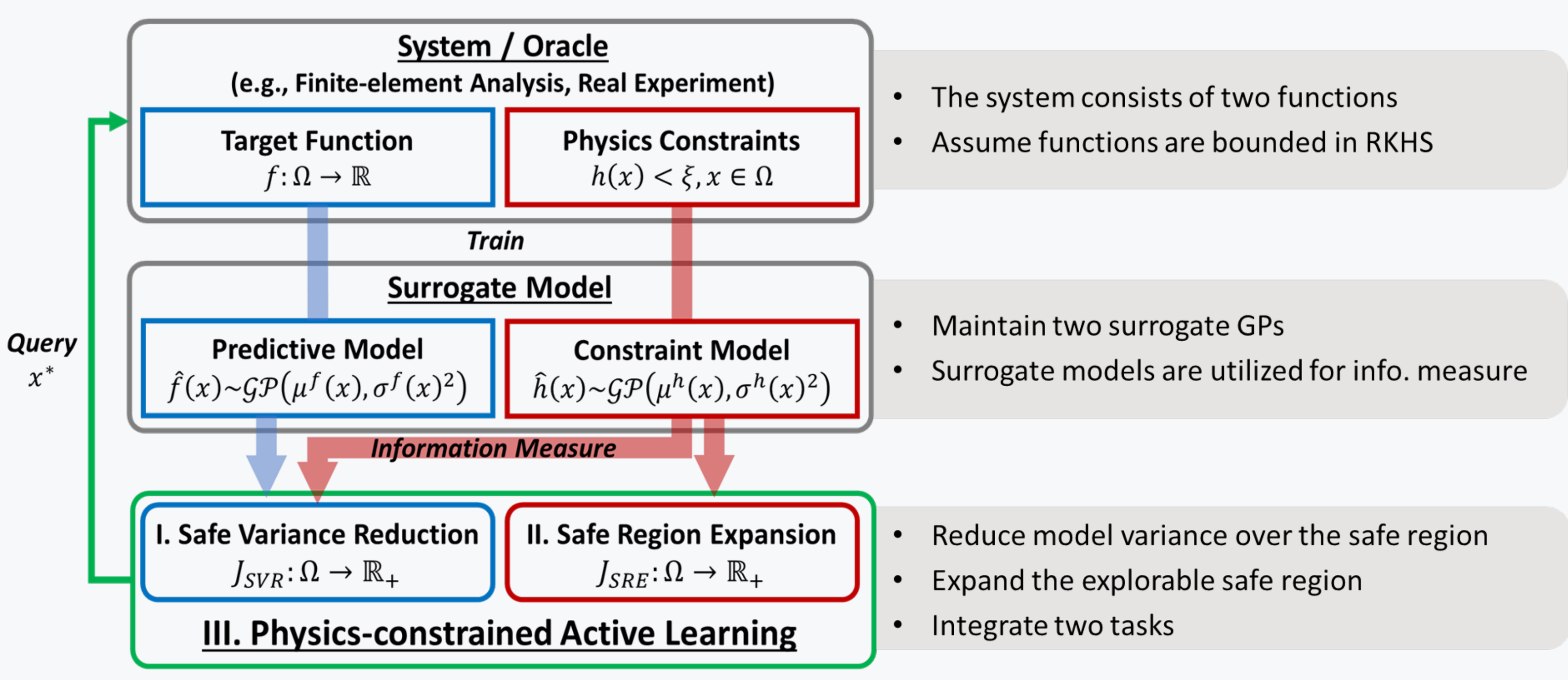


Fig. Learning curves on fuselage deformation

III. Physics-constrained Active Learning (PhysCAL) [3]



Methods	Random		Max Entropy		IMSE		SEGP		Proposed Method	
	MAE	# Fail	MAE	# Fail	MAE	# Fail	MAE	# Fail	MAE	# Fail
Mean (Std/μm)	5.383 (2.345)	0.4 (0.5)	2.244 (0.470)	4.1 (0.3)	2.046 (0.441)	3.8 (0.6)	2.297 (0.305)	1.0 (0.8)	2.832 (0.518)	0.1 (0.3)

Table. Result on learning fuselage deformation subject to material failures

FUTURE RESEARCH

The proposed methods are not limited to composite structures assembly, but applicable to other domains (e.g., biostatistics, material design, robotics [2]). Our group has done also other research on model calibration, digital twin, and Bayesian optimization for end-to-end quality control for complex manufacturing systems.

CONTACTS & REFERENCES

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[1] Lee et al. "Neural network gaussian process considering input uncertainty for composite structures assembly." *IEEE/ASME TMECH* (2020). (**2019 IISE DAIS Best Paper Award**)
[2] Lee et al. "Partitioned Active Learning for Heterogeneous Systems." *arXiv:2105.08547* (2021). (**2021 INFORMS QSR Best Paper Award Finalist**)
[3] Lee et al. "Failure-Averse Active Learning for Physics-Constrained Systems." *IEEE TASE* (2022). (**2022 INFORMS DMDA Workshop Best Paper Finalist**)