Georgia Tech ISyE
H. Milton Stewart School of Industrial and Systems Engineering

Quality Science for Smart Manufacturing in the Era of Data-Driven Automation

Dr. Jianjun Shi

The Carolyn J. Stewart Chair and Professor

Georgia Institute of Technology

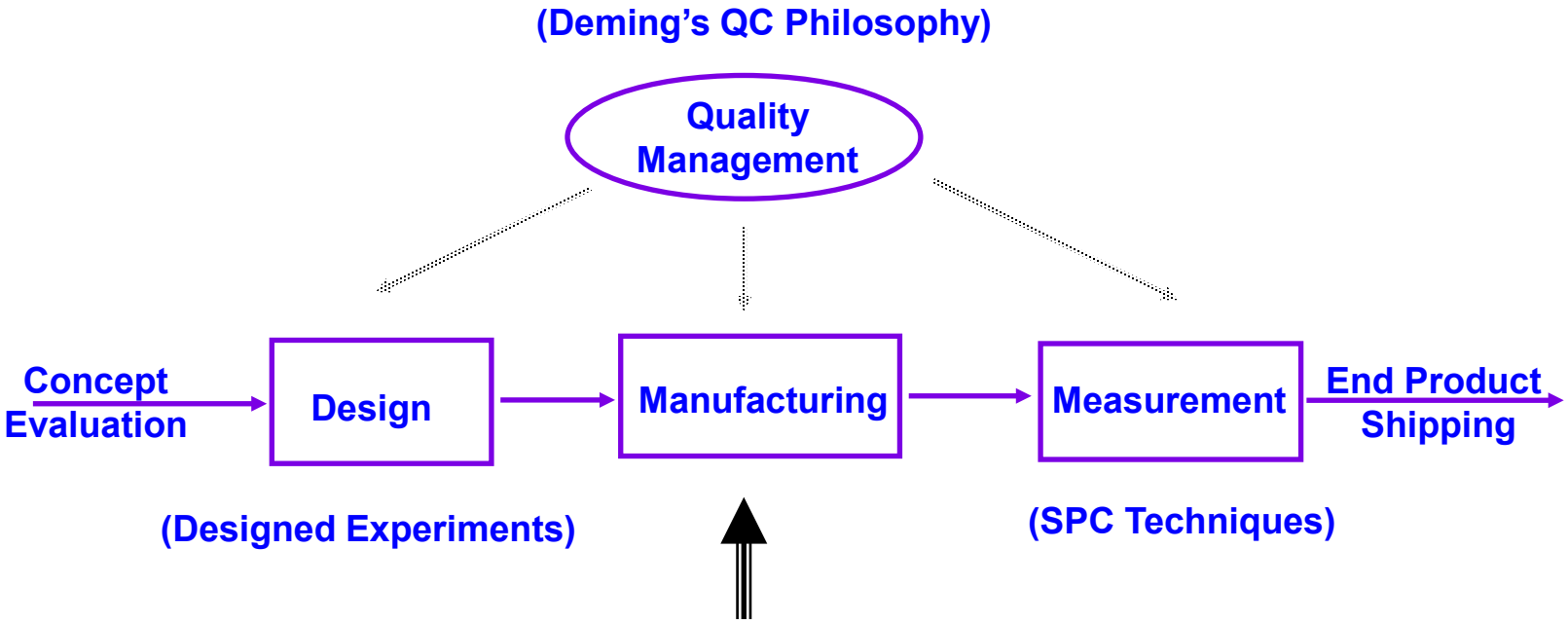
contact: jianjun.shi@isye.gatech.edu

https://pwp.gatech.edu/jianjun-shi/

Outline

- Introduction
  - Quality Science with In-Process Quality Improvements (IPQI)
  - Smart Manufacturing
  - Data-Driven Automation
- Data-Driven Automation for IPQI
  - SoV-Based Automatic Control for Multistage Manufacturing Processes
  - Sparse Learning and Control in Fuselage Assembly
  - Physics-Driven Causation-Based Process Control
  - DOE-based Automatic Process Control
  - Image-based Process Control
- Summary

In-Process Quality Improvement



IPQI

Real-Time Defect Prevention during the stage of manufacturing via on-line monitoring, root cause diagnosis, and automatic compensation/control

- Shi, faculty interview in Dept. of IOE at UM in 1995
- Shi, "**In-Process Quality Improvement",** NSF CAREER DMI- 9624402, 1996

What is Data-Driven Automation?

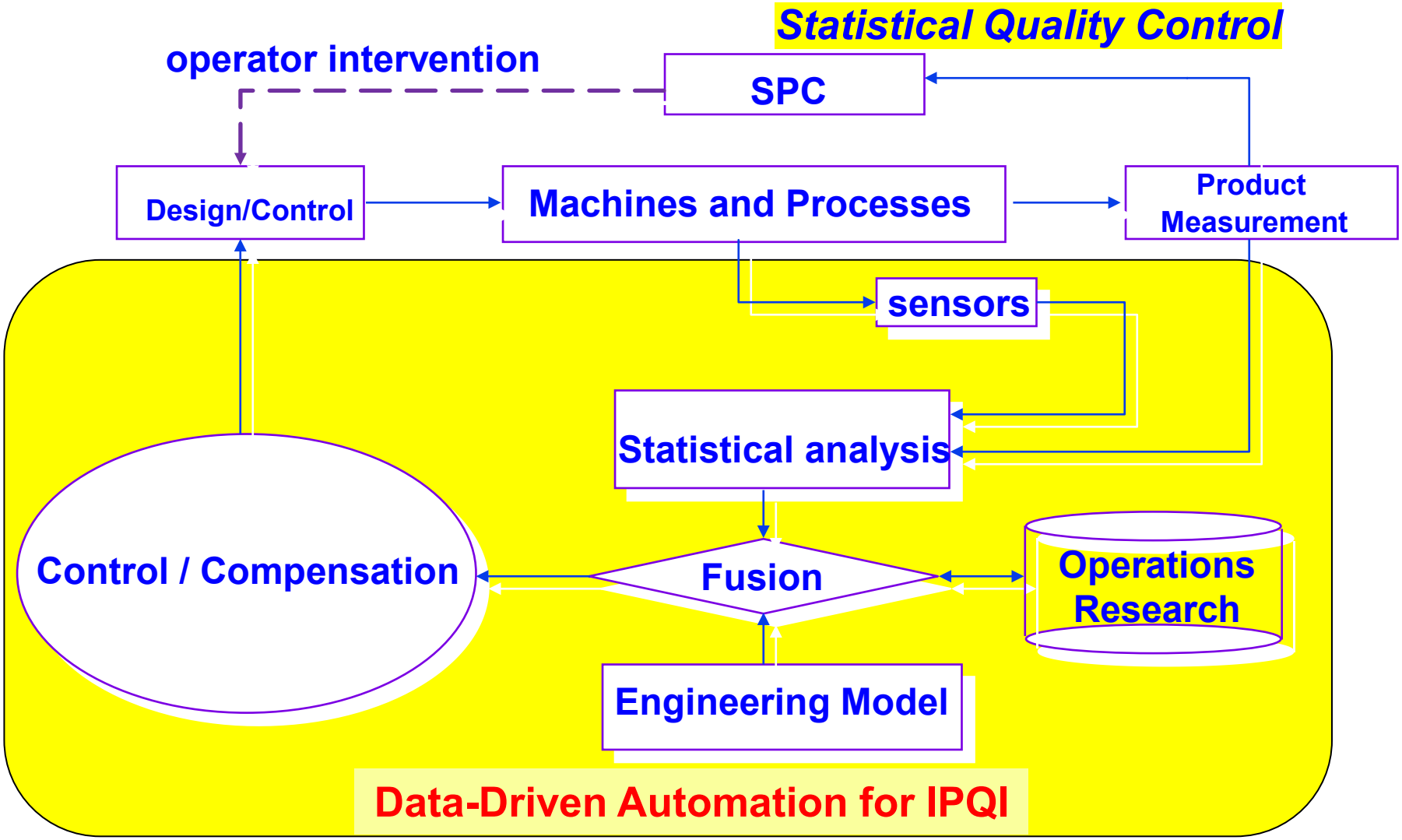
Automation: automatically controlled operation of an device, process, or system by mechanical or electronic devices that take the place of human labor

- Sensors
- Internet of Things
- Big Data
- Cloud Computing
- AI and Machine Learning
- Advanced Mfg System
- Cyber Security
- Robotics and Automation
- Algorithms & Virtualization
- Data Fusion Analytics

Smart Manufacturing

The broad coalition of new technologies enables data-driven automation capabilities to achieve high quality, productivity, flexibility with reduced cost.

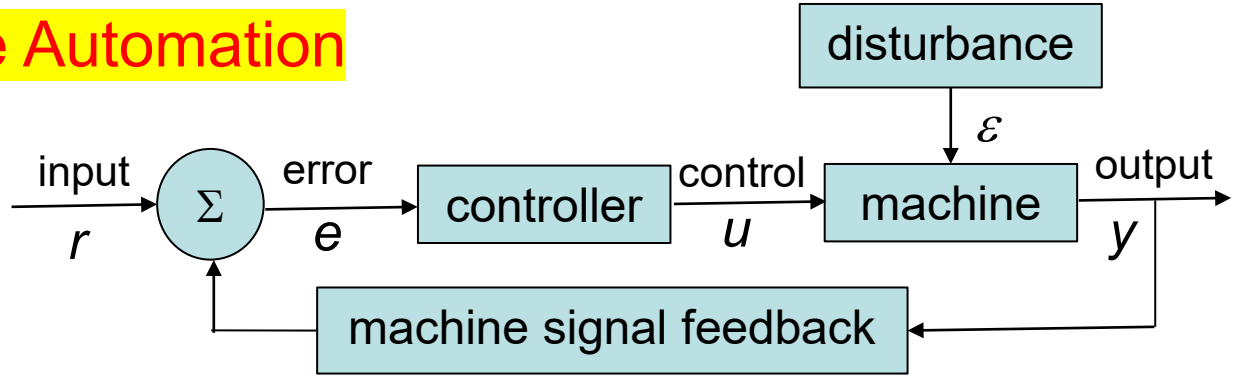
In-Process Quality Improvements vs. Statistical Quality Control



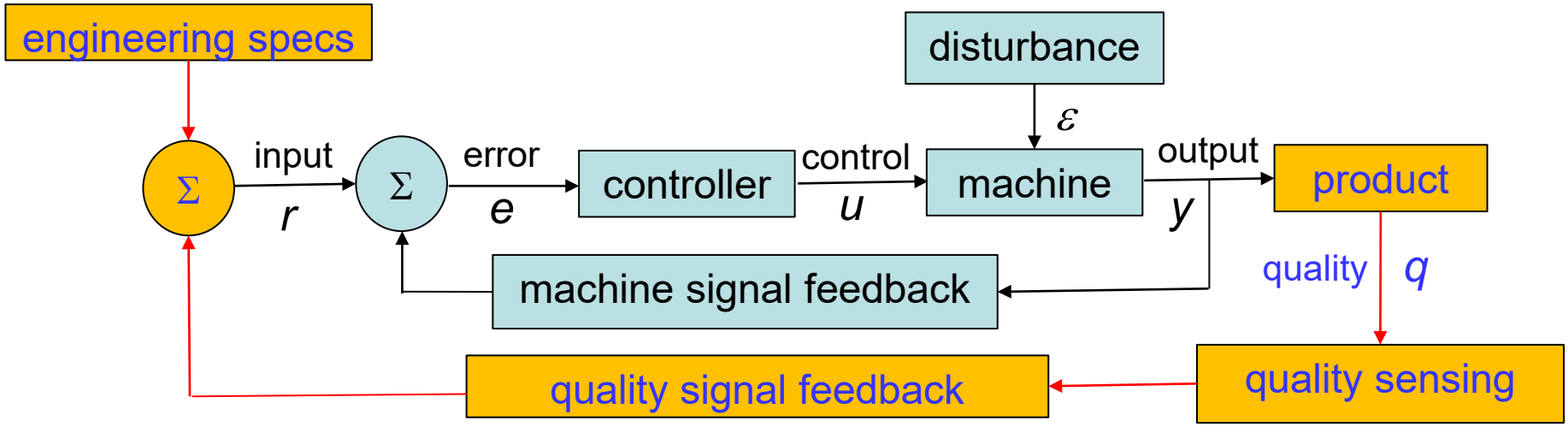
IPQI emphasizes engineering-driven modeling and data analysis to link the process sensing data with the product quality characteristics.

"Machine Automation" vs "Data-Driven Automation for IPQI"

Machine Automation

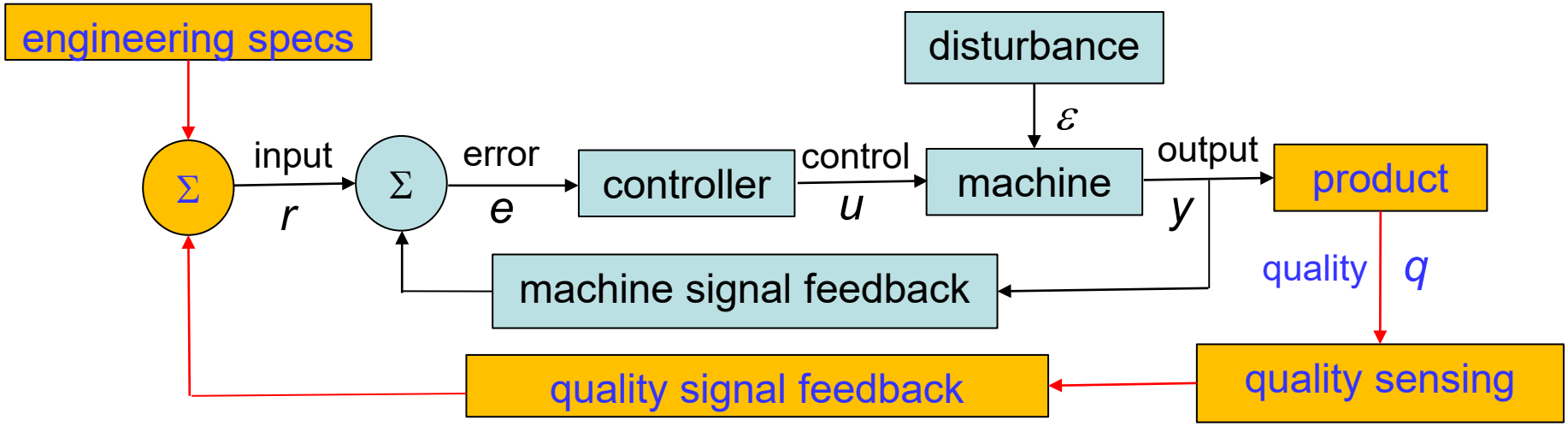


Data-Driven Automation for IPQI



Data-Driven Automation for IPQI demands fundamental research and development in modeling and control for quality improvements.

“Machine Automation” vs “Data-Driven Automation for IPQI”



	Machine automation	Data-Driven Automation for IPQI
Control inputs	digital	digital
Output variables	digital	heterogeneous (digital, text, image)
Model	differential or discrete equations	various (not well studied)
Data sampling freq.	uniform high freq. sampling	mixed sampling, low frequency
Control algorithms	PID, adaptive, robust, fuzzy, etc.	depending on the model & objective
System character	dynamic system	dynamic or static, or mixed system

Data-Driven Automation for IPQI rises new challenges for modeling, prediction and control research and implementation

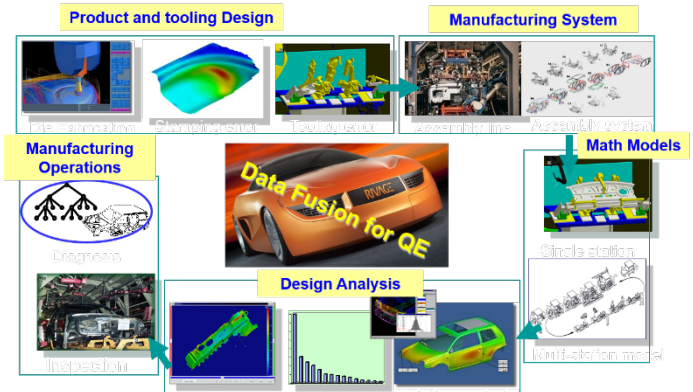
Opportunities and Challenges of Data Driven Automation for IPQI

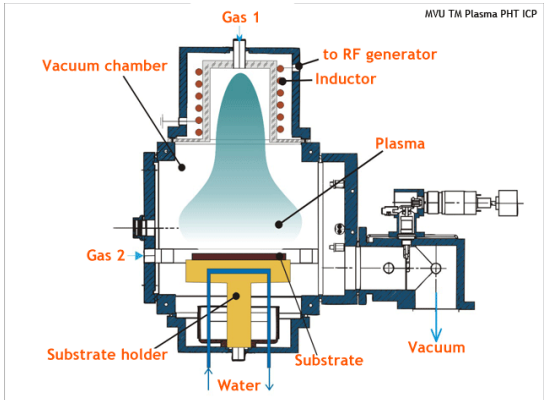
Opportunities

- Ubiquitous availability of process sensing and product measurements due to IIoT
- System operations become transparent
- Technological capabilities and flexibilities of individual machine
- Advancements in data science, machine learning and computing capabilities
- …

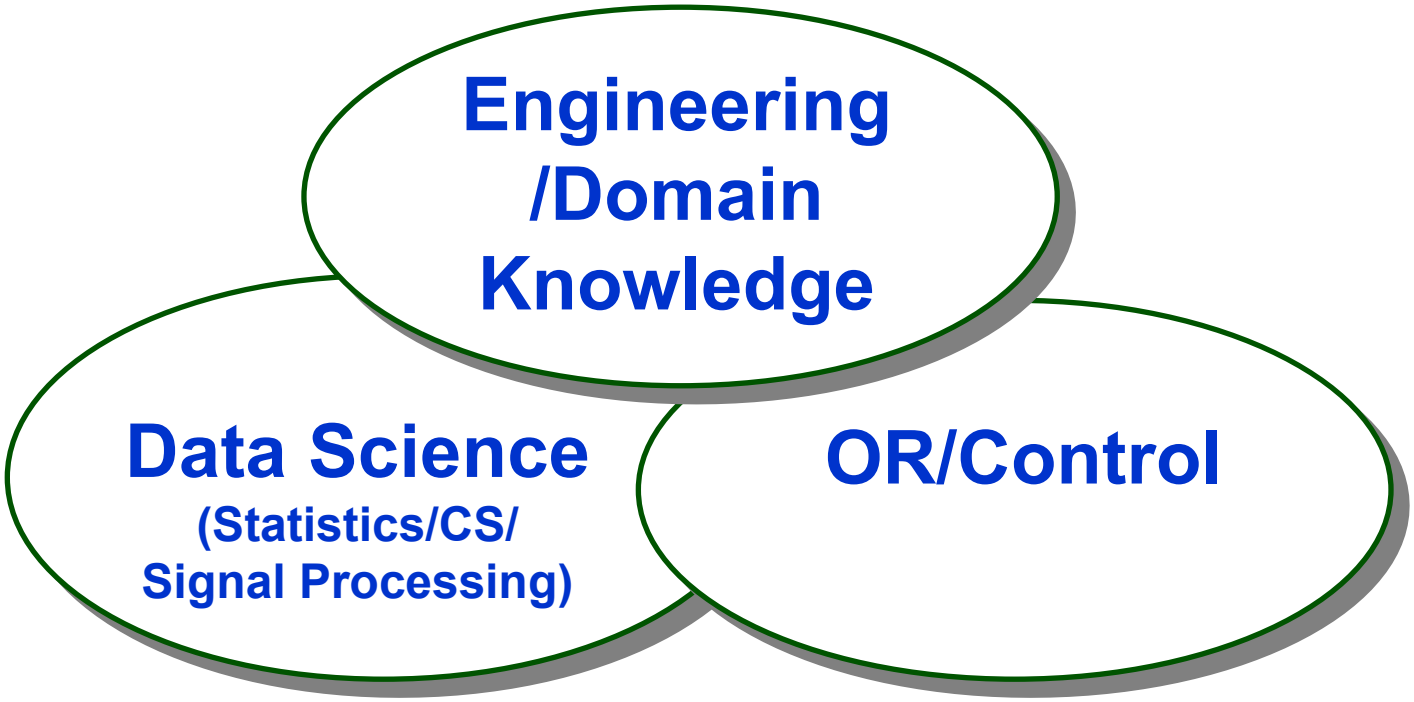
Challenges

- Multiple engineering and quality objectives and modeling of relevant information for IPQI from all stages of a manufacturing system
- Trade-off between model/control precision, sensing capability and quality specifications
- Hydrogenous data in material prosperities, process sensing signals, and product quality measurements, and associated issues in modeling, analysis, and control
- Lack of unified model/strategy to make a (real time) control for "quality" issues
- Lack of deep integration of data science, control theory, quality science, and design & manufacturing engineering.
- …





Interdisciplinary Framework: Fusion of Engineering, Data Science, OR/Control



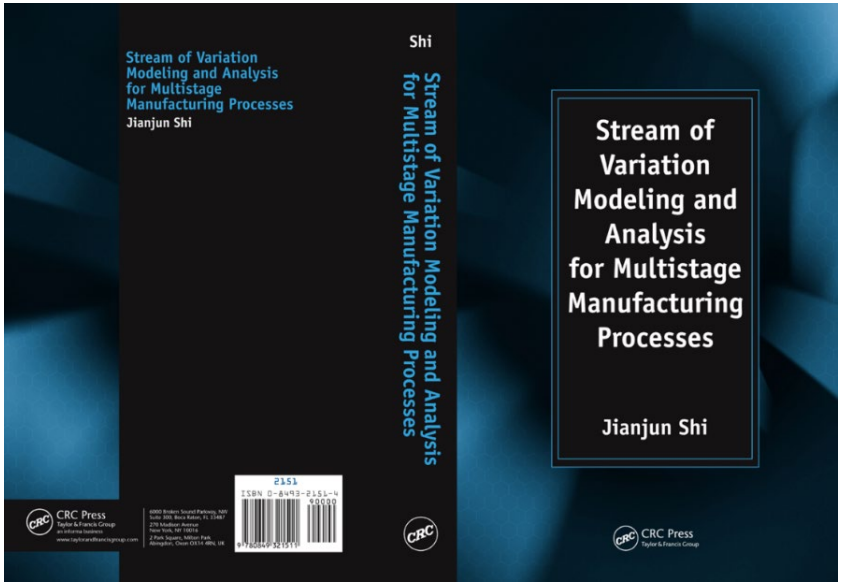
Outline

- Introduction
  - Quality Science with In-Process Quality Improvements (IPQI)
  - Smart Manufacturing
  - Data-Driven Automation

- **Data-Driven Automation for IPQI**
  - **SoV-Based Automatic Control for Multistage Manufacutring Processes**
  - **Sparse Learning and Control in Fuselage Assembly**
  - **Physics-Driven Causation-Based Process Control**
  - **DOE-based Automatic Process Control**
  - **Image-based Process Control**

- Summary

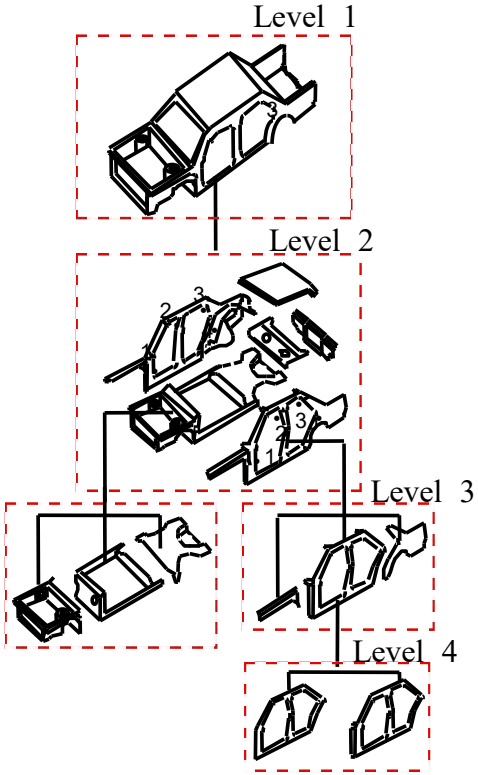
Stream of Variation Methodologies for Multistage Manufacturing Processes



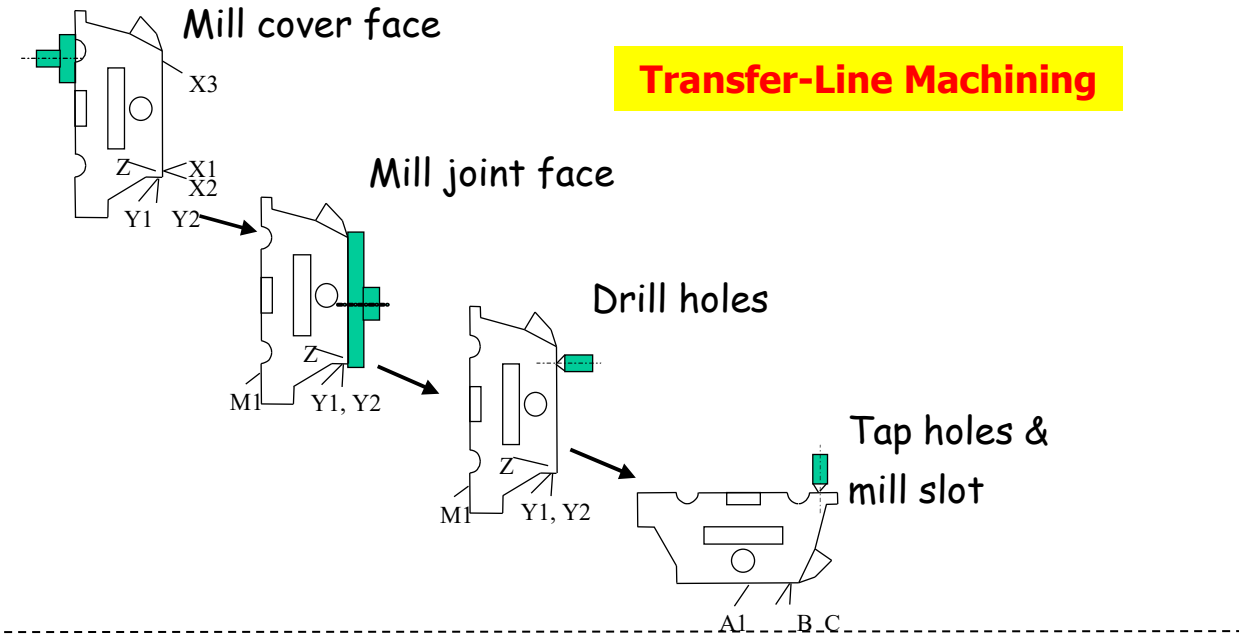
- Jianjun Shi, *"Stream of Variation Modeling and Analysis for Multistage Manufacturing Processes"*, ISBN: 0-8493-2151-4, CRC Press, Taylor & Francis Group, 2006. 469pp.
- Shi, J. and Zhou, S., 2009, *"Quality Control and Improvement for Multistage Systems: A Survey"*, *IIE Transactions*, Vol. 41, No.9, pp744-753.

Multistage Manufacturing System:

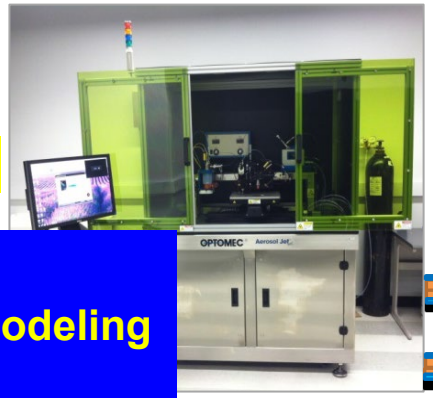
Processes with multiple workstations and/or multiple operations



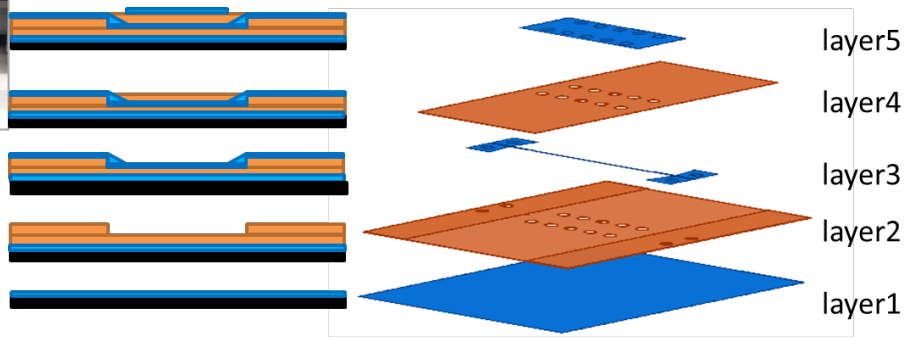
Automotive Body Assembly



Transfer-Line Machining



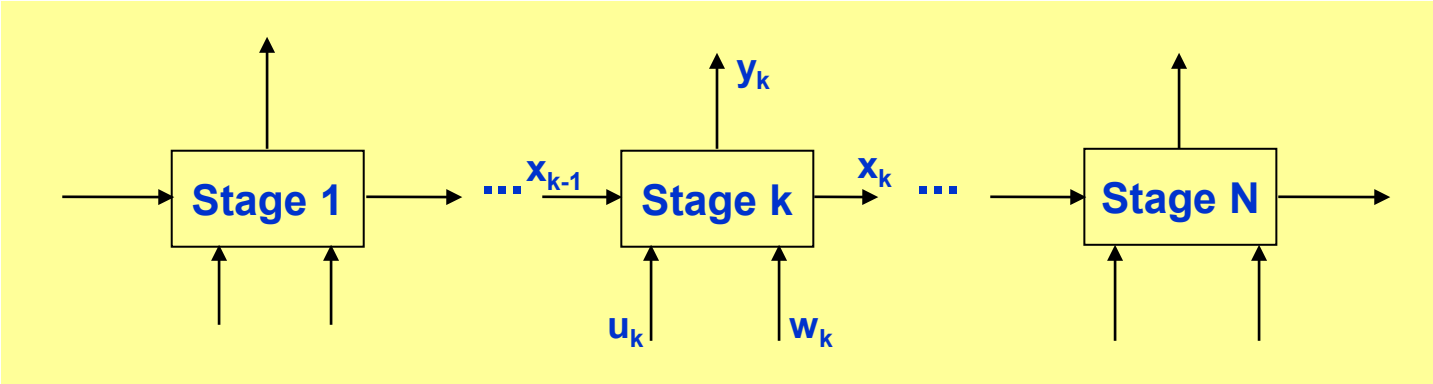
3D Printing / Multilayer Additive Manufacturing



Challenges:

- Variation propagation modeling
- Tolerance synthesis
- Root cause diagnosis
- Distributed sensing
- Critical station identification
- Automatic Compensation

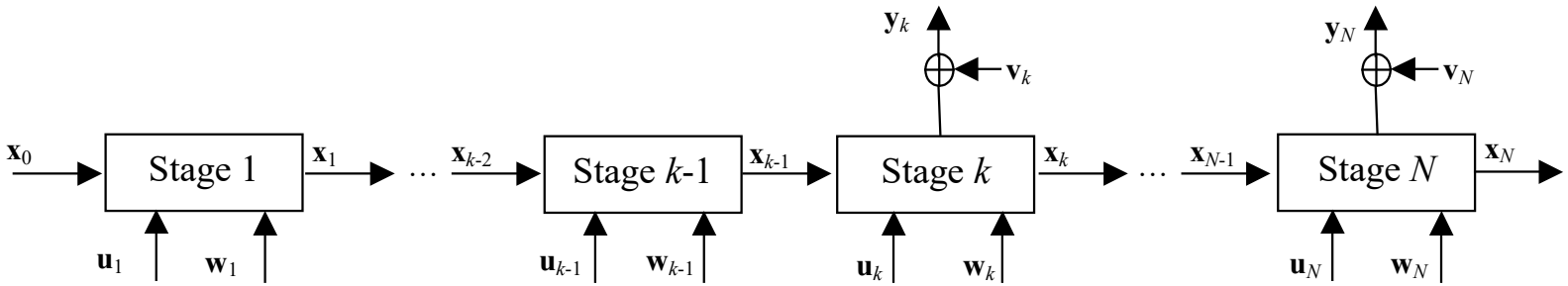
Basic Concepts and Model of SoV



- **Variation Propagation Model**
  - System Equation: $x_k = A_{k-1}\, x_{k-1} + B_k\, u_k + w_k$ (k=1,2,…N)
  - Observation Equation: $y_k = C_k\, x_k + v_k$

- **State Space Modeling:**
  - The variation propagation can be modeled as a state-space linear system where a manufacturing stage plays the role of time
  - Concepts and theorem in control and system theory need to be revisited due to new definition of "k" in the model.

Interpretations of SoV Model Variables



Quality feature deviation at stage *k*

Deviation transform from stage *k*-1 to stage *k*

Locator impacts on quality feature at stage *k*

Tooling locator feature deviation at stage *k*

$$\mathbf{x}_k = \mathbf{A}_{k-1}\mathbf{x}_{k-1} + \mathbf{B}_k\mathbf{u}_k + \mathbf{w}_k$$

$$\mathbf{y}_k = \mathbf{C}_k\mathbf{x}_k + \mathbf{v}_k$$

Un-modeled system error

Critical quality feature deviation at stage k

Linear combination of quality feature deviation

Measurement error

- Jin, J. and Shi, J., 1999, *"State Space Modeling of Sheet Metal Assembly for Dimensional Control"*, *ASME Transactions, Journal of Manufacturing Science and Engineering*, Vol. 121, No.4, Nov. 1999, pp756-762.
- Zhou, S., Huang, Q. and Shi, J., 2003, *"State Space Modeling for Dimensional Monitoring of Multistage Machining Process Using Differential Motion Vector"*, *IEEE Transactions on Robotics and Automation*, April 2003, Vol. 19, No.2, pp296-309.
- Liu, J., Jin, J. and Shi, J. 2010 *"State Space Modeling for 3-Dimensional Variation Propagation in Rigid-Body Multistage Assembly Processes"*, *IEEE Transactions on Automation Science and Engineering*, Vol. 7, No.2, pp274-290.
- Zhang, T., and Shi, J., 2016, "Modeling Variation Propagation of Multi-Station Assembly System with Compliant Composite Parts", *ASME Transactions, Journal of Manufacturing Science and Engineering,* Vol. 138, No. 12, 121004.

Multidisciplinary Research:
- SoV Model-Based Multistage Process Control

System and Control Theory

Multivariate Statistical Analysis

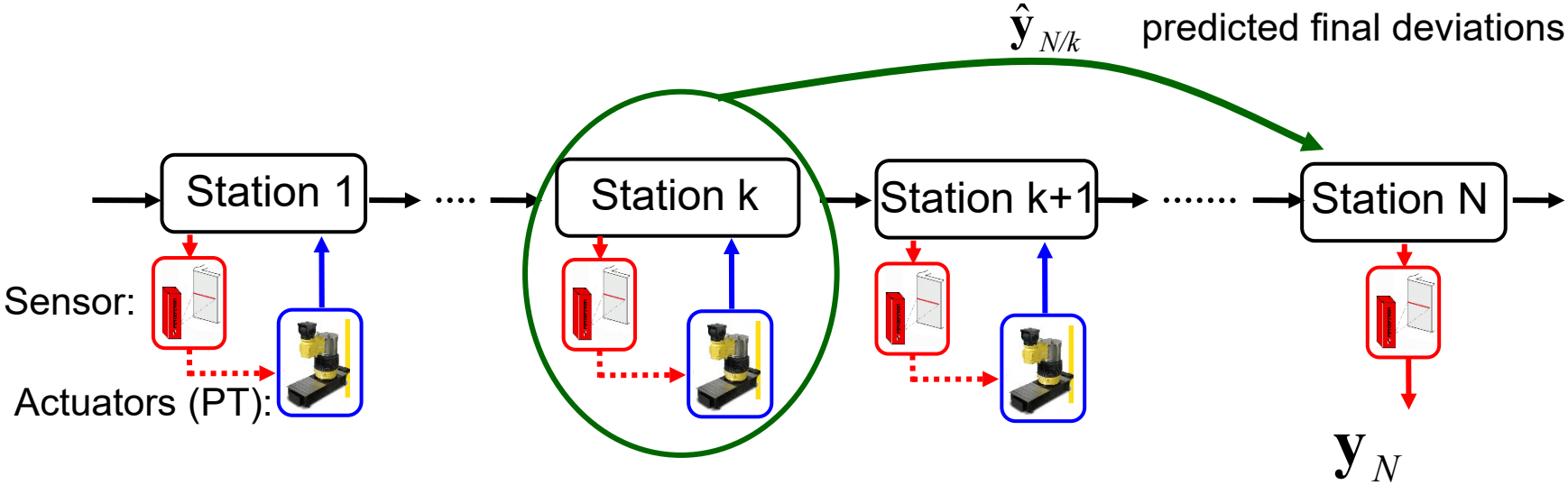
SoV-State Space Model

$$\mathbf{x}_k = \mathbf{A}_{k-1}\mathbf{x}_{k-1} + \mathbf{B}_k\mathbf{u}_k + \mathbf{w}_k \qquad \mathbf{y}_k = \mathbf{C}_k\mathbf{x}_k + \mathbf{v}_k$$

Multistage Process Control

The SoV model provides a solid scientific foundation to use <u>system/control theory</u> and <u>advanced statistics</u> in the Multistage process monitoring and diagnostics.

SoV Model-Based Automation for IPQI



$$J = \min_{\mathbf{u}_k} \hat{\mathbf{y}}_{N/k} \cdot \mathbf{Q} \cdot \hat{\mathbf{y}}_{N/k}^T$$

System Equation: $x_k = A_{k-1}\, x_{k-1} + B_k\, u_k + w_k$ (k=1,2,…N)

Observation Equation: $y_k = C_k\, x_k + v_k$

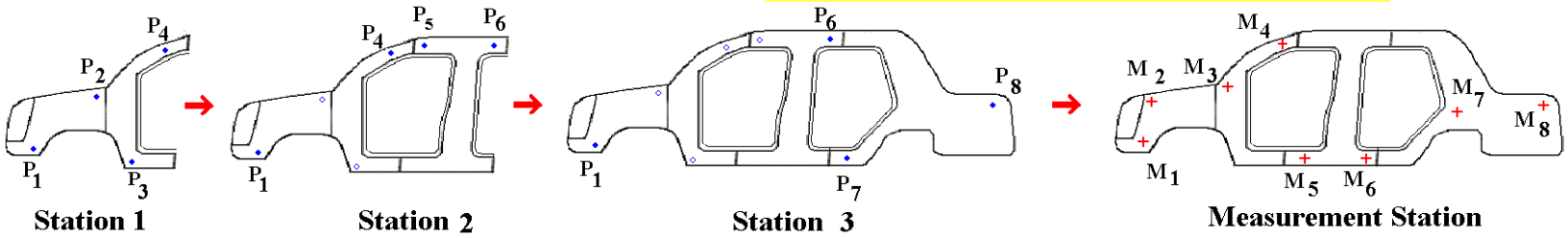
Key Ideas:

- **At station k, all quality features (x_k) up to stage k can be obtained;**
- **Make a prediction of the final product quality at stage N, assume $u_j \equiv 0$, j=k+1, k+2, …, N-1**
- **Make an adjustment of tolling locator (u_k) at station k to minimize the predicted quality to the target at stage N**

Example: Active Control and Compensation in MMP

- **Assemble 4 parts in 3 stations**

$$\mathbf{x}_k = \mathbf{A}_{k-1}\mathbf{x}_{k-1} + \mathbf{B}_k\mathbf{u}_k + \mathbf{w}_k \qquad k = 1,\ldots,N$$
$$\mathbf{y}_k = \mathbf{C}_k\mathbf{x}_k + \mathbf{v}_k$$

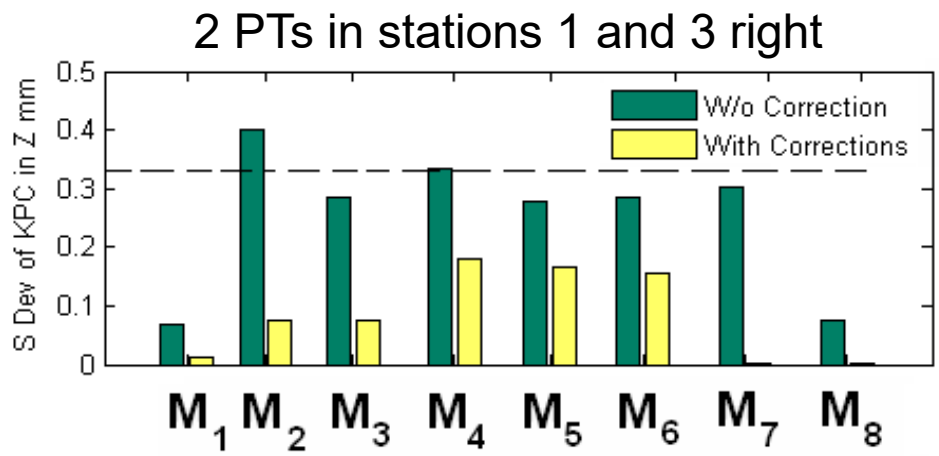


$$J = \min_{\mathbf{u}_k} \hat{\mathbf{y}}_{N/k} \cdot \mathbf{Q} \cdot \hat{\mathbf{y}}_{N/k}^T$$

$$\text{s.t.} \quad \hat{\mathbf{y}}_{N/k} \in [LSL, \text{USL}]$$

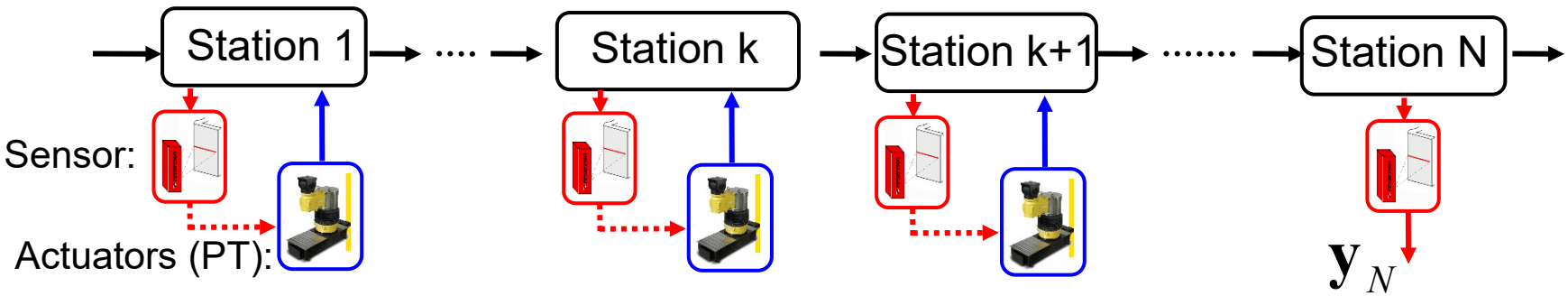
$$\mathbf{u}_{\min} \le \mathbf{u}_{ck} \le \mathbf{u}_{\max}$$

$$\mathbf{u}_{ck} = \begin{cases} \mathbf{u}_{ck} & \text{if } |\mathbf{u}_{ck}| > \Delta_u \\ 0 & \text{otherwise} \end{cases}$$



- Zhong, J., Liu, J. and Shi, J., 2010, *"Predictive Control Considering Model Uncertainty for Variation Reduction in Multistage Assembly Processes"*, *IEEE Transactions on Automation Science and Engineering*, Vol. 7, No.4, pp724-735.
- Luis E. Izquierdo, Jianjun Shi, S. Jack Hu, and Charles W. Wampler, 2007, *"Feedforward Control of Multistage Assembly Processes Using Programmable Tooling"*, *Transactions of NAMRI/SME*, Vol. 35.

Research Issues in SoV-model based Automation for IPQI:

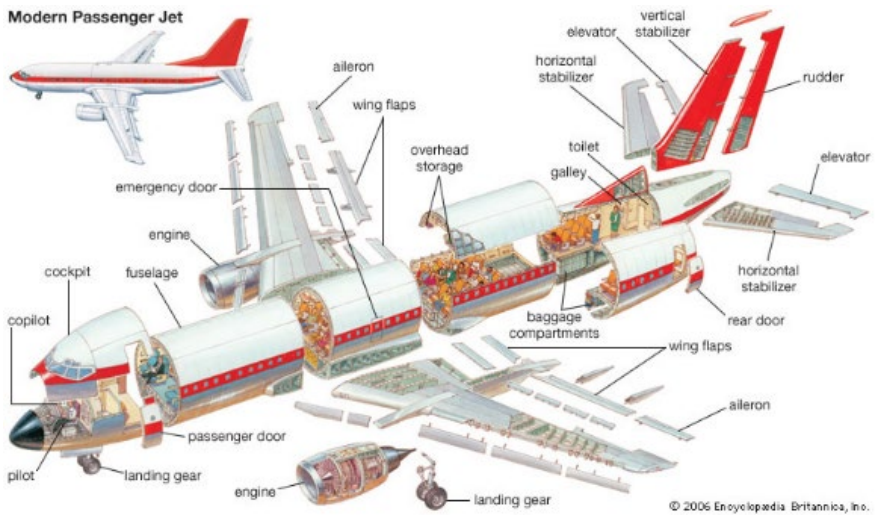


- Sensor placement and observability/diagnosability
- Actuator placement and controllability
- Cautious control and uncertainty management due to modeling error and sensing noise
- Automation for mixed serial-parallel configurated MMPs
- Integrated design for tooling, sensing, automation, for MMPs

Machine Learning Enabled Shape Control for Fuselage Assembly

- Du, J., Yue, X., Hunt, J. H., and Shi, J. 2019." Optimal Placement of Actuators via Sparse Learning for Composite Fuselage Shape Control." *Journal of Manufacturing Science and Engineering*, Vol.141, No.10.pp1-37.
- Yue, X., Wen, Y., Hunt, J. H., Shi, J., 2018, "Surrogate Model-Based Control Considering Uncertainties for Composite Fuselage Assembly", *ASME Transactions, Journal of Manufacturing Science and Engineering*. Vol. 140, No. 4, 041017.
- Yue, X., Shi, J., 2017, "Surrogate-Model based Optimal Feed-forward Control for Dimensional Variation Reduction in Composites Assembly Processes", *Journal of Quality Technology*. Vol. 50, No. 8. pp279-289.
- Wen, Y., Yue, X., Hunt, J. H., Shi, J., 2017, "Feasibility Analysis of Composite Fuselage Shape Control via Finite Element Analysis", *Journal of Manufacturing Systems*, Vol. 46, pp272-281.
- Yue, X., Wen, Y., Hunt, J.H., Shi, J., (2020) " Active Learning for Gaussian Process considering Uncertainties, with an Application to Automatic Shape Control of Composite Fuselage", *IEEE* Transactions on Automation Science and Engineering, vol. 18, no. 1, pp. 36-46, Jan. 2021, doi: 10.1109/TASE.2020.2990401.

Machine Learning Enabled Shape Control for Fuselage Assembly



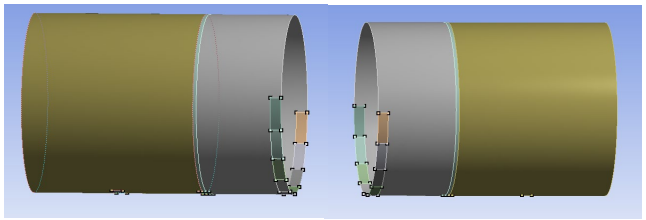
Current Practice

- Manual shimming to reduce the dimensional deviations and get the required shape of the parts.
- The adjustment is conducted by using **trial and error** method.

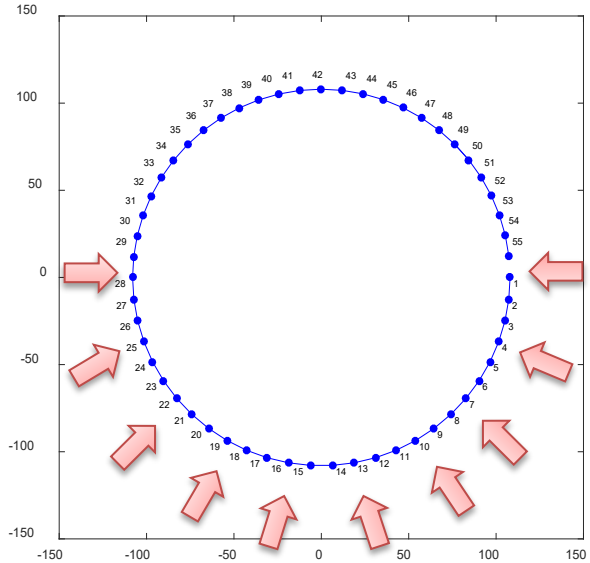
Limitations of the Current Practice

- **low efficiency:** it may take longer time and multiple trials to adjust actuators to achieve the desired shape/dimension;
- **Non-optimal**: it may reach an acceptable dimensional quality rather than the optimal deviation reduction.
- **Highly skilled engineers required**: the effectiveness and efficiency of assembly depends on the skills of engineers.

GOAL: Automatic Optimal Shape Control (AOSC) System



Section 41 Section 43



Start here

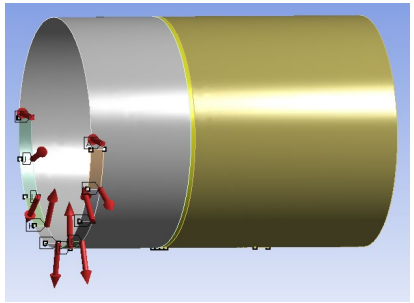
Sections Line Up

3D Laser Metrology

Automatic Optimal Shape Control System

- **SoV Model Prediction;**
- **Iterative Virtual Shape Adjustment;**
- **Optimal forces applied via actuators**

Deformation Control



Measurement Confirmation & Assembly

End here

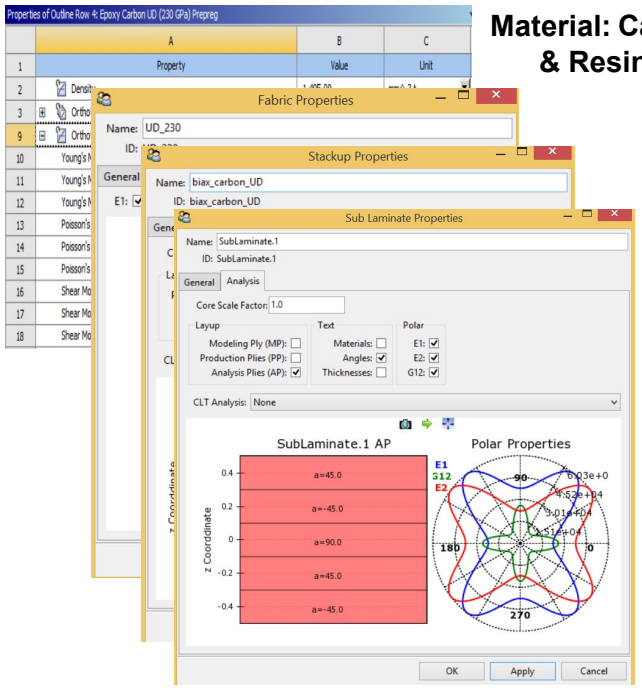
Advantage:

Reduce flow time; Increase productivity; Achieve high quality; Applicable to all part joins.

Sparse Learning and Model Calibration for Composite Fuselage Shape Control

- Wang, Y., Yue, X., Tuo, R., Hunt, J. H., Shi, J., 2020 "Effective Model Calibration via Sensible Variable Identification and Adjustment, with application to Composite Fuselage Simulation", *The Annals of Applied Statistics,* Vol. 14, No. 4, 1759–1776 https://doi.org/10.1214/20-AOAS1353 (This paper won the QSR Best Refereed Paper Finalist Award for the 2017 INFORMS Conference.)
- Du, J., Yue, X., Hunt, J. H., and Shi, J. 2019." Optimal Placement of Actuators via Sparse Learning for Composite Fuselage Shape Control." *Journal of Manufacturing Science and Engineering*, Vol.141, No.10.pp1-37.

FEA Simulation Platform and Validation

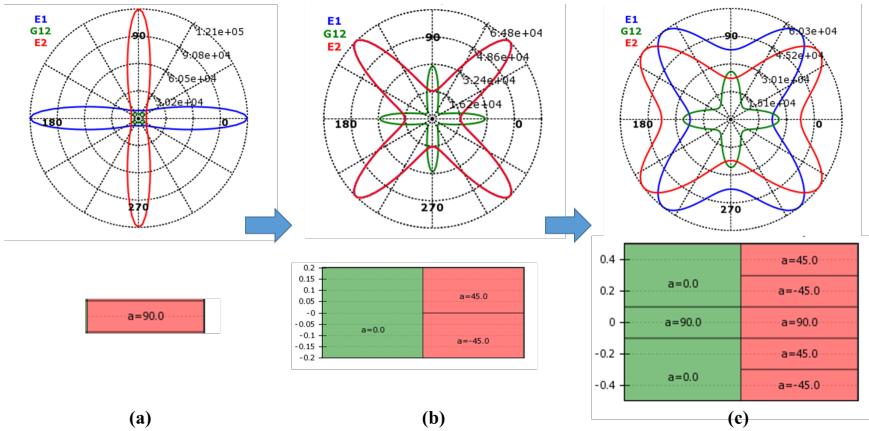


Material: Carbon fiber & Resin Epoxy

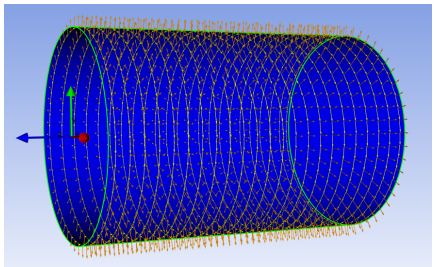
Fabrics

Stackups

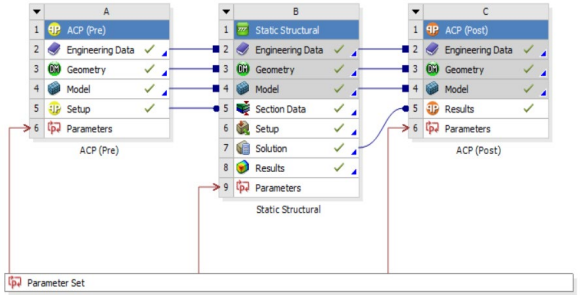
Sub Laminates



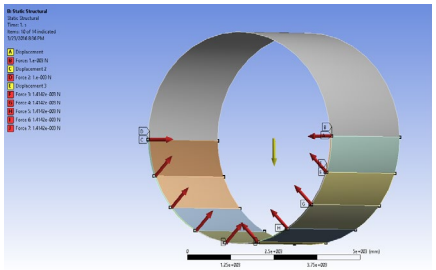
Fabrication Process



Carbon Fiber Orientation



ANSYS Workbench: Composite Prepost

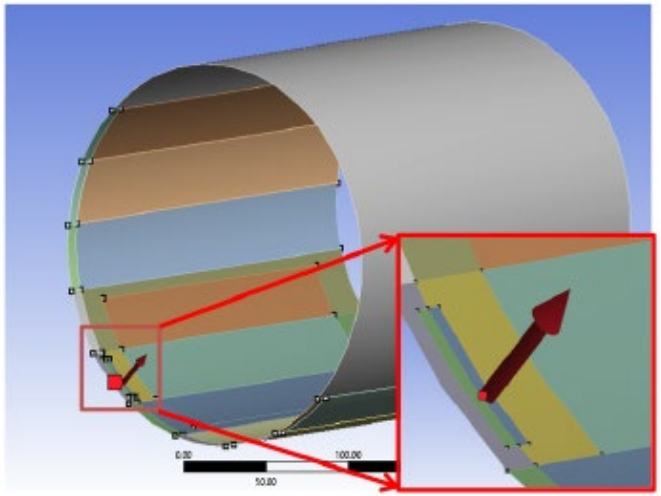


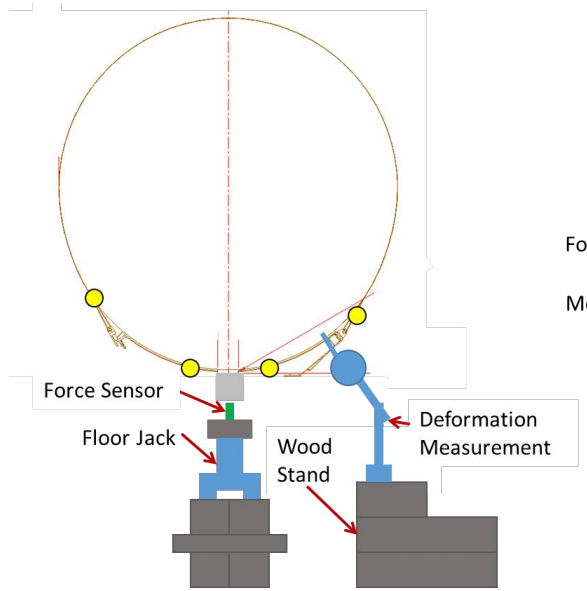
Ten Actuators

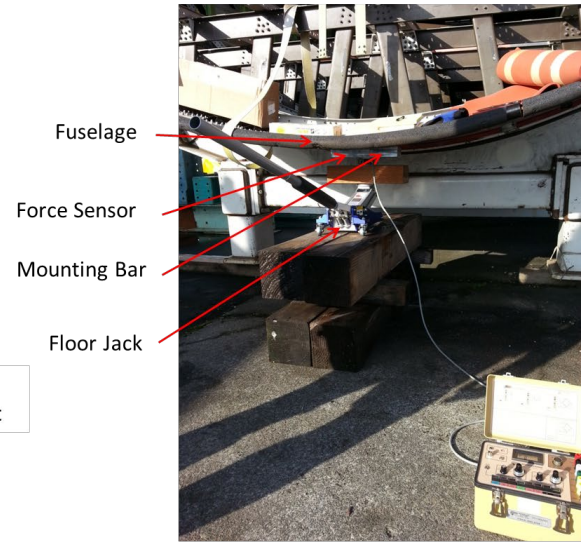
***Note:* The FEA model mimics the real fabrication process of the large composite fuselage.**

Wen, Y., Yue, X., Hunt, J. H., Shi, J., 2019 "Virtual Assembly and Residual Stress Analysis for Composite Fuselage Assembly Process Journal of Manufacturing Systems", *Journal of Manufacturing Systems*, Vol.52, pp55-62.

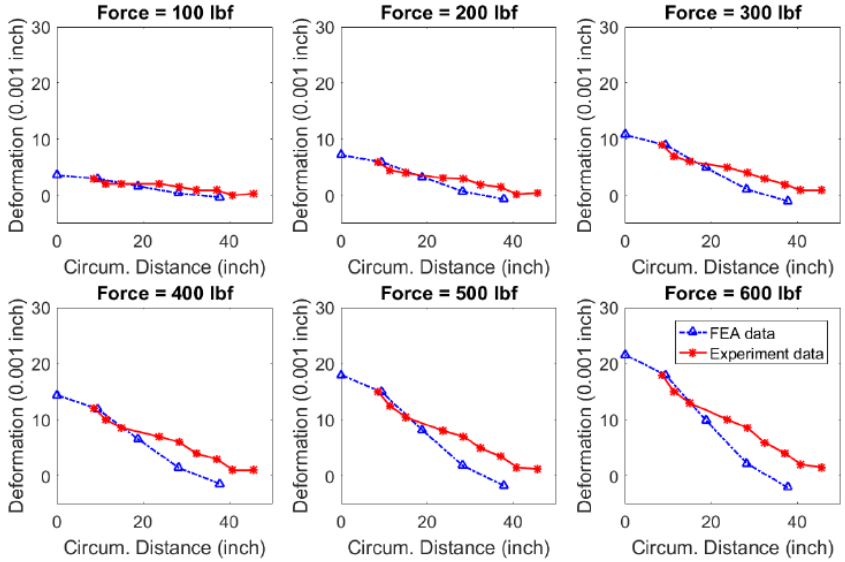
Field Test: *Computer Model v.s. Physical Experiment*







Deviations without calibration



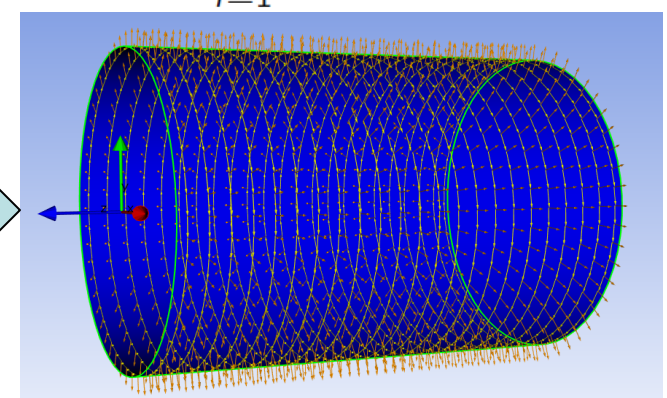
Model Calibration via Sensible Variable Identification

- **Goal**: find the optimal values of the model parameters, under which the finite element outputs match the structural load experimental observations of the composite fuselage;
- **Challenge:**
  Limited Physical Experiment Sample: the corresponding physical experiment is expensive to run
  Many Model Parameters: computer experiments may have a number of calibration parameters.

$$\hat{\theta}_n = \underset{\boldsymbol{\theta}}{\operatorname{argmin}}\, L(\boldsymbol{Y}^p, \boldsymbol{Y}^s_{\boldsymbol{\theta}}) + \lambda_n \parallel \boldsymbol{\theta} - \boldsymbol{\theta}_0 \parallel$$

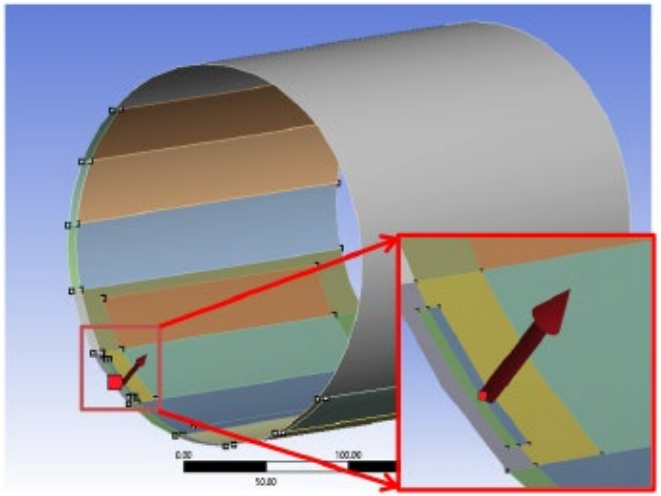
$$= \underset{\boldsymbol{\theta}}{\operatorname{argmin}} (\boldsymbol{Y}^p - \boldsymbol{Y}^s_{\boldsymbol{\theta}})^T (\tau^2 \boldsymbol{\Phi}_\theta + \sigma^2 I_n)^{-1} (\boldsymbol{Y}^p - \boldsymbol{Y}^s_{\boldsymbol{\theta}}) + \lambda_n \sum_{i=1}^{m} |\theta_i - \theta_i^{(0)}|$$

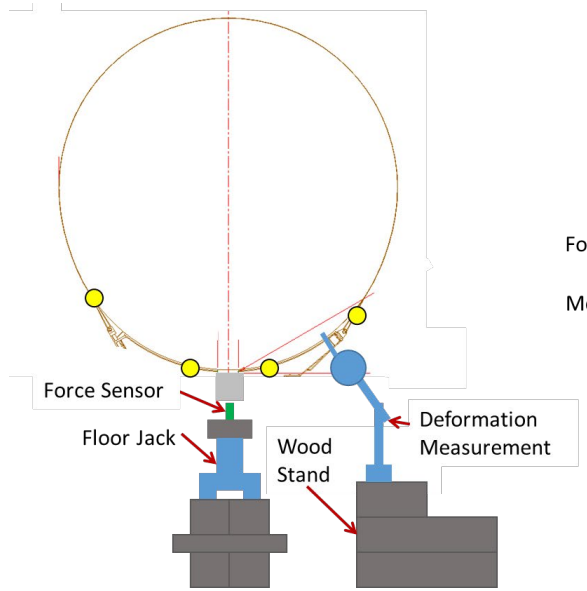
Sensible Variable Properties:
- **Sensitivity**
- **Suboptimality**
- **Sparsity**



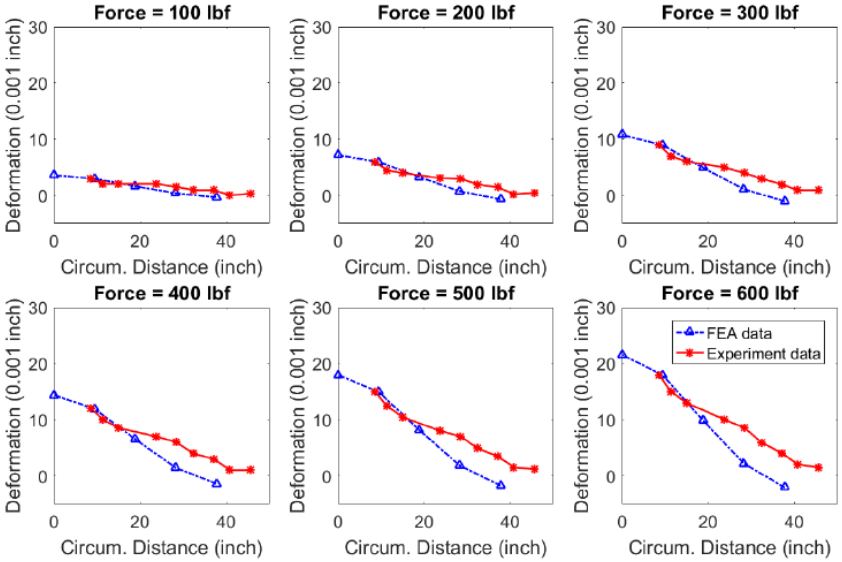
Wang, Y., Yue, X., Tuo, R., Hunt, J. H., Shi, J., 2020 "Effective Model Calibration via Sensible Variable Identification and Adjustment, with application to Composite Fuselage Simulation", *The Annals of Applied Statistics,* Vol. 14, No. 4, 1759–1776 (This paper won the QSR Best Refereed Paper Finalist Award for the 2017 INFORMS QSR Section.)

Field Test: *Computer Model v.s. Physical Experiment*

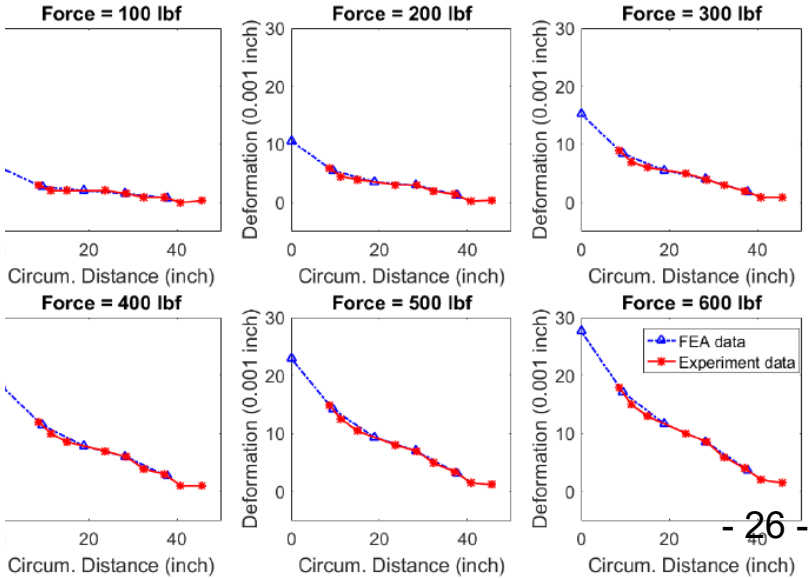




Deviations without calibration



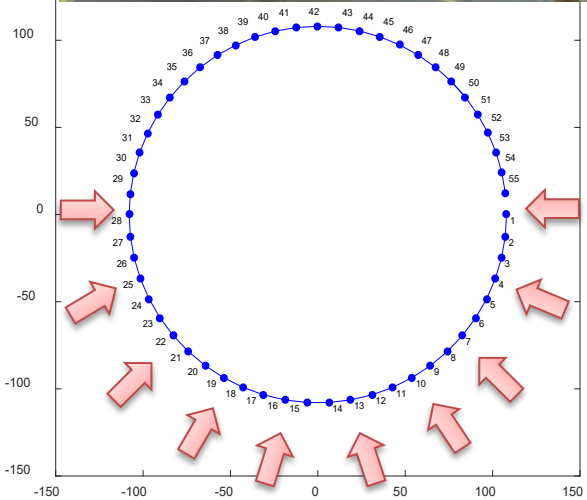
Deviations after calibration

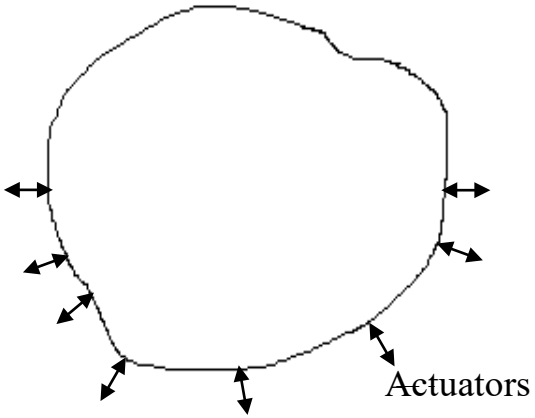


Optimal Actuator Placement for Fuselage Shape Adjustment

- **Current Practice** (Yue, et al, 2018): **Actuators are placed in equal distance between two adjacent actuators**
  - **Limitations**
    - **Non-optimal**
    - **Larger actuator forces may be applied for some locations than needed**

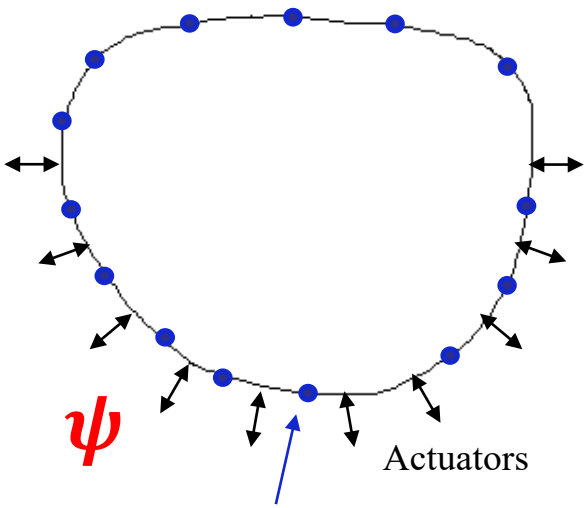
- **Proposed Sparse Learning for Optimal Actuator Placement and Control** (Juan, et al, 2019)
    - **Considering incoming fuselage dimensions**
    - **Convex formulation**
    - **ADMM algorithm: Efficiently solved with global optimum**





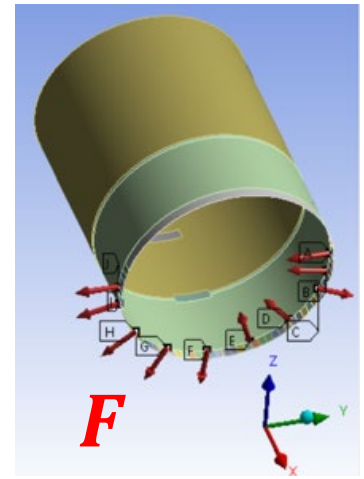
- Yue, X., Wen, Y., Hunt, J. H., Shi, J., 2018, "Surrogate Model-Based Control Considering Uncertainties for Composite Fuselage Assembly", *ASME Transactions, Journal of Manufacturing Science and Engineering*. Vol. 140, No. 4, 041017.
- Du, J., Yue, X., Hunt, J. H., and Shi, J. 2019." Optimal Placement of Actuators via Sparse Learning for Composite Fuselage Shape Control." *ASME Transactions, Journal of Manufacturing Science and Engineering*, Vol.141, No.10.pp1-37.

Problem Formulation



n measured points

m available actuator positions along the fuselage



Required M actuators for adjustments $M < m$

Output : Weighted mean square of adjusted shape deviations (WMSD)

Input : Initial shape distortion $\boldsymbol{\psi} \in R^n$

Input : Weight matrix Positive diagonal $\boldsymbol{B} \in R^{n\times n}$

Part Property: Displacement Matrix $\boldsymbol{U} \in R^{n\times m}$

$$\min_{\boldsymbol{F}} \delta_{rms}^2 = (\boldsymbol{\psi} + \boldsymbol{UF})' \boldsymbol{B} (\boldsymbol{\psi} + \boldsymbol{UF})$$

$$s.t.\ \|\boldsymbol{F}\|_0 = M, \boldsymbol{F}_L \preccurlyeq \boldsymbol{F} \preccurlyeq \boldsymbol{F}_Q$$

Actuator force $\boldsymbol{F} \in R^m$

Sparsity requirement of $\boldsymbol{F}$

Deviations after shape adjustments

Safety requirement

Sparse Learning Modeling and Estimation

$$\min_{\boldsymbol{F}} L(\boldsymbol{F}) = (\boldsymbol{\psi} + \boldsymbol{U}\boldsymbol{F})'\boldsymbol{B}(\boldsymbol{\psi} + \boldsymbol{U}\boldsymbol{F}) \ + \lambda\|\boldsymbol{F}\|_1, \text{ s.t. } \boldsymbol{F}_L \preccurlyeq \boldsymbol{F} \preccurlyeq \boldsymbol{F}_Q$$

- ***Proposition* 1. The ADMM** (alternating direction method of multipliers) **of the optimization problem can be derived as**

  $\boldsymbol{F}^{k+1} := \prod_C \left((2\boldsymbol{U}'\boldsymbol{B}\boldsymbol{U} + \rho\boldsymbol{I})^{-1} \left(\rho\boldsymbol{z}^k - \rho\boldsymbol{u}^k - 2\boldsymbol{U}'\boldsymbol{B}\boldsymbol{\psi} \right) \right)$

  $\boldsymbol{z}^{k+1} := S_{\lambda/\rho}(\boldsymbol{F}^{k+1} + \boldsymbol{u}^k)$

  $\boldsymbol{u}^{k+1} := \boldsymbol{u}^k + \boldsymbol{F}^{k+1} - \boldsymbol{z}^{k+1}$.

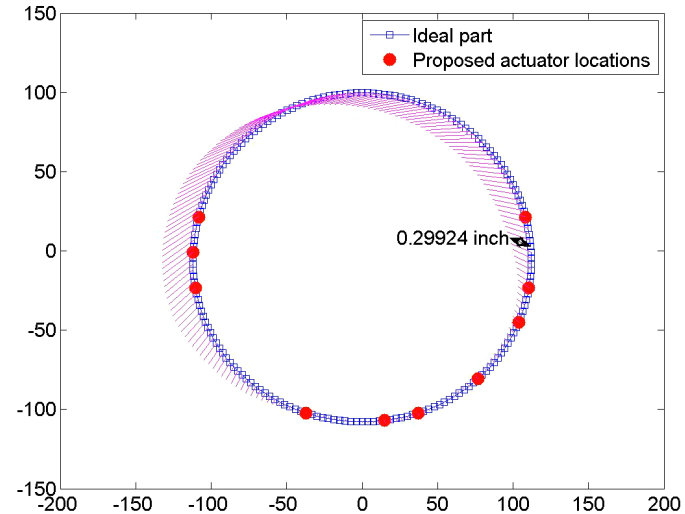
  $\boldsymbol{I} \in R^{m\times m}$ is an identity matrix. $\prod_C$ is an Euclidean projection onto the convex set $C = \{\boldsymbol{F} \in R^m\colon \boldsymbol{F}_L \preccurlyeq \boldsymbol{F} \preccurlyeq \boldsymbol{F}_Q\}$, which can be denoted as

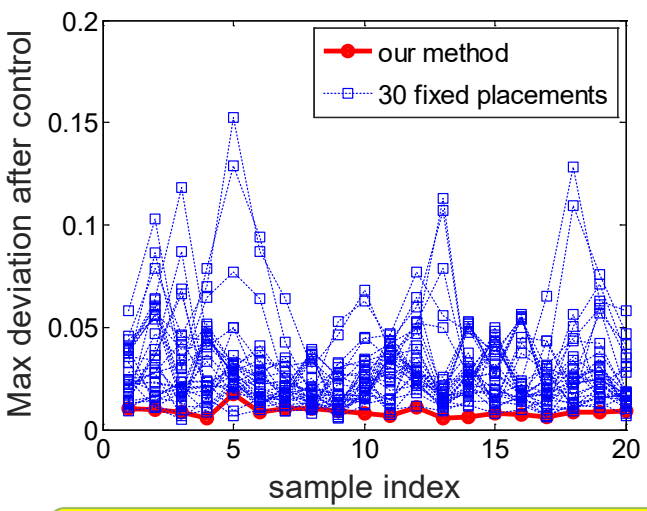
  $\prod_C(v) = \underset{\boldsymbol{F}\in C}{\operatorname{argmin}}(\|\boldsymbol{F} - \boldsymbol{v}\|_2)$

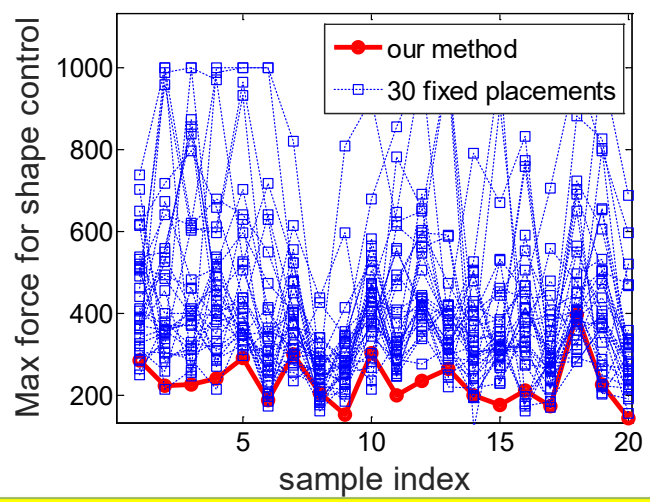
  $S_{\lambda/\rho}(v) = (v - \lambda/\rho)_+ \ (-v - \lambda/\rho)_+$, where $(x)_+$ is short for $\max\{x, 0\}$.

Comparison with Fixed Actuator Placement

- We randomly select M actuators from m feasible locations without replacements.
- 20 fuselages with 30 fixed actuator placements for each fuselages.
- Evaluation
  - Max deviations (MD) after shape control
  - Maximum force (MF) for shape control







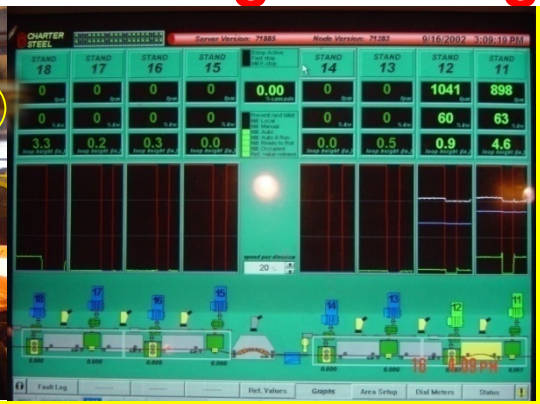
Method	Max Deviation (inch)	Max Force (lbf)
Sparse learning	**0.0083**	**175.25**
Current Practice	0.0137	309.42

Result: the optimal actuator placement uses less forces to achieve smaller shape deviations compared to the fixed actuator placements

Physics-Driven Machine Learning and Modeling in Multistage Manufacturing Process

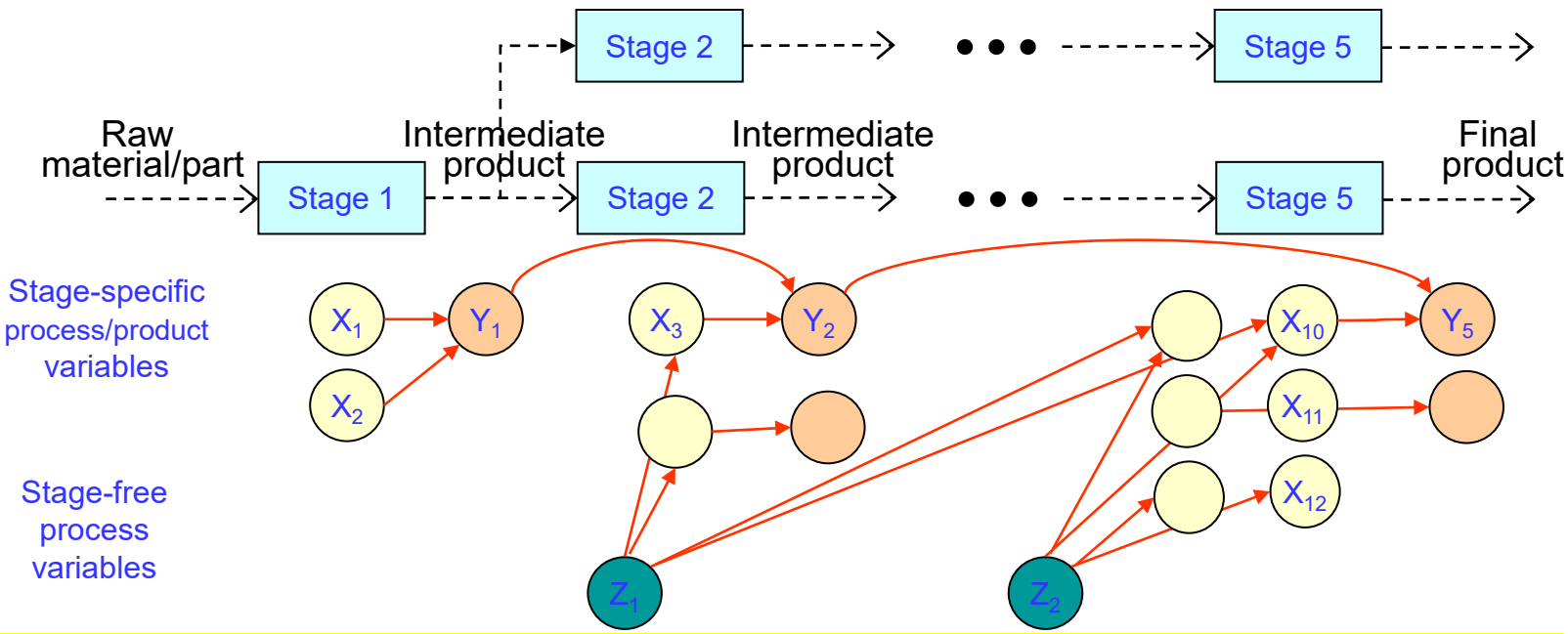
- Li, J., and Shi, J., 2007, *"Knowledge Discovery from Observational Data for Process Control through Causal Bayesian Networks"*, *IIE Transactions*, Vol. 39, pp681-690.
- Liu, K., and Shi, J., 2013, *"Objective-Oriented Optimal Sensor Allocation Strategy for Process Monitoring and Diagnosis by Multivariate Analysis in a Bayesian Network"*, *IIE Transactions*, Vol. 45, No. 6, pp630-643.
- Liu, K., Zhang, X. and Shi, J., 2013, *"Adaptive Sensor Allocation Strategy for Process Monitoring and Diagnosis in a Bayesian Network"*, *IEEE Transactions on Automation Science and Engineering*. No. 2, pp452-462.

Physics-Driven Machine Learning and Modeling for Multistage Rolling Process



- 50 to 80 roller stations w/ miles long line.
- Each station has more than 15 typical variables (speed, temp, force, lub, etc…)
- Heterogeneous data with uncertainties
- Complex interactions among the variables
- No math models to link in-line product quality with massive process data
- Cost and energy loss due to quality and defects are HIGH!!!

Physics-Driven Machine Learning and Modeling

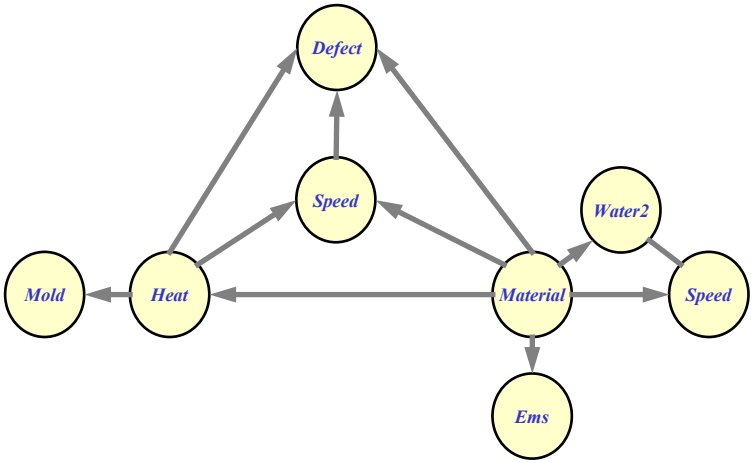


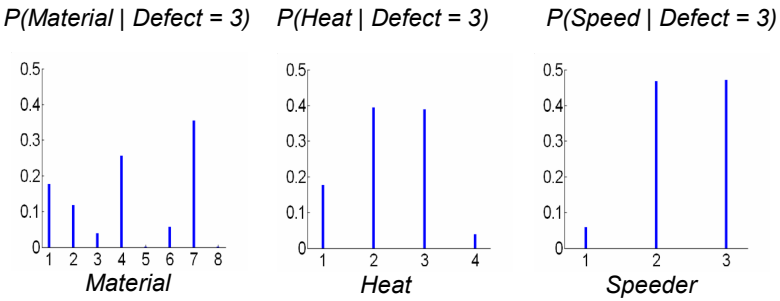
Causation-Based Process Monitoring, Diagnosis and Control

- Li, J., and Shi, J., 2007, *"Knowledge Discovery from Observational Data for Process Control through Causal Bayesian Networks"*, *IIE Transactions*, Vol. 39, pp681-690.

Causation-Based Process Control for Rolling

- **Causal relationship modeling by integrating manufacturing domain knowledge with Bayesian network learning algorithm**
  - Variable and data preprocessing**: variable selection, discretization, variable grouping**
  - Learning**: production sequence, engineering-specified correlations**
  - Model selection and validation
- **Causal model based process control**
  - Diagnosis: **Given quality problem, identify the trouble-making process conditions**
  - Quality prediction: **Given process conditions, predict the product quality level**



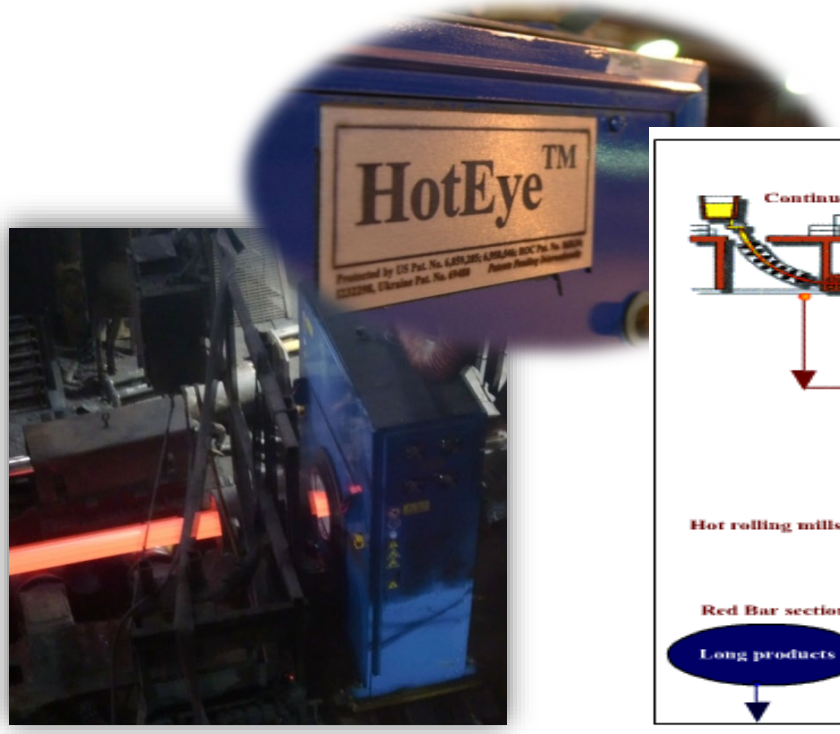


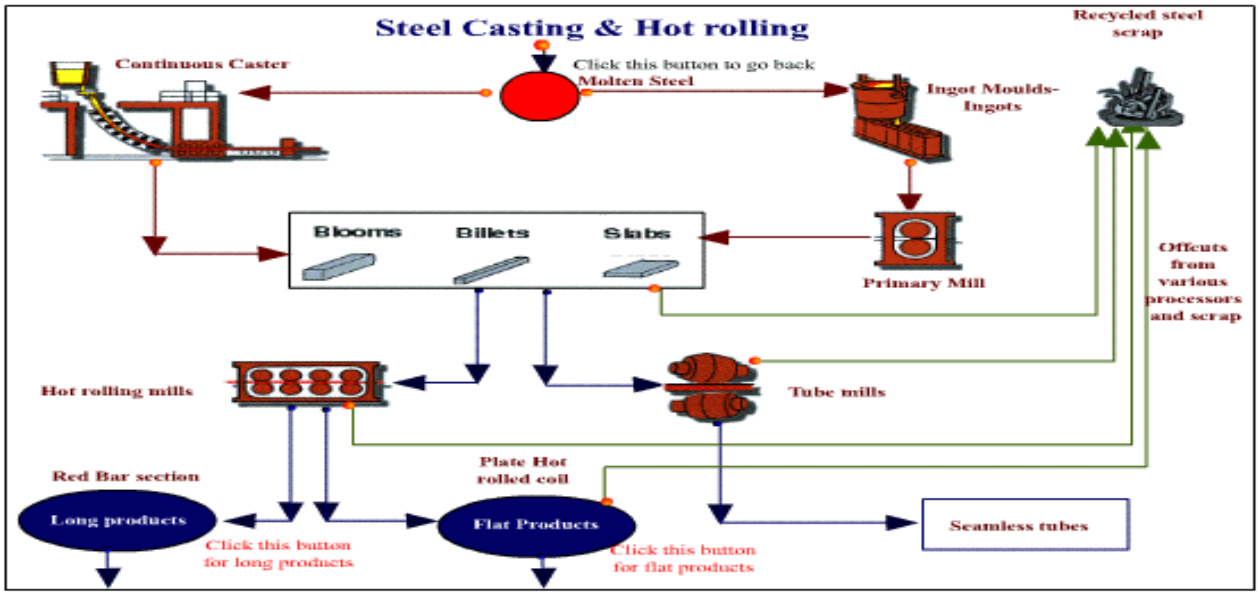
- Li, J., and Shi, J., 2007, *"Knowledge Discovery from Observational Data for Process Control through Causal Bayesian Networks"*, *IIE Transactions*, Vol. 39, pp681-690.
- Li, J., Jin, J., and Shi, J., 2008, *"Causation-based T2 Decomposition for Multivariate Process Monitoring and Diagnosis"*, *Journal of Quality Technology*, Vol. 40, No. 1, pp. 46-58.

Industrial Impacts of the Rolling Process Control

- The technology has been implemented in OGT's HotEye® systems, which are in use by over 50 plants in the US, Argentina, Brazil, Canada, China, France, Germany, India, Japan, Korea, Singapore, and UK.

- The implementation of the developed technology has resulted in over $100 millions in cost saving, 1.2 billion KWh in energy savings, and 50,000 tons of CO2 emission reduction per year.

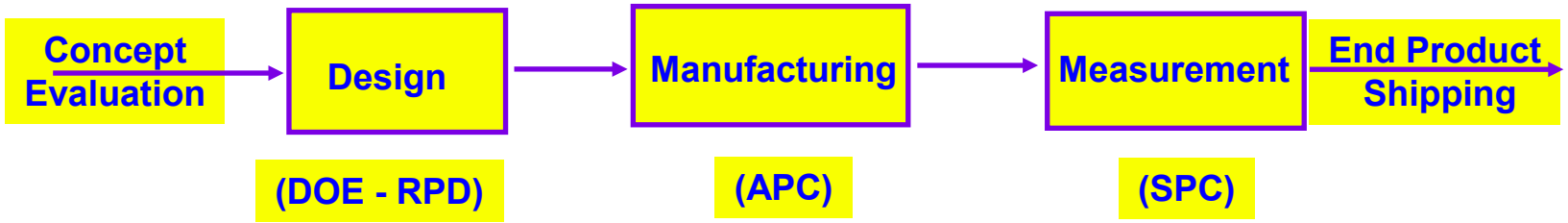




Design of Experiments (DOE) - based Automatic Process Control (APC)

- Zhong, J., Shi, J., and J. Wu, 2010, *"Design of DOE-based Automatic Process Controller with Consideration of Model and Observation"*, *IEEE Transactions on Automation Science and Engineering*, Vol.7, No.2, pp266-273.
- Ye, L., Pan, E., and Shi, J., 2009, *"Design of regression model based automatic process control with reduced adjustment frequency"*, *Quality and Reliability Engineering International,* Vol. 25, No. 8, pp997-1013.

Problem Statement

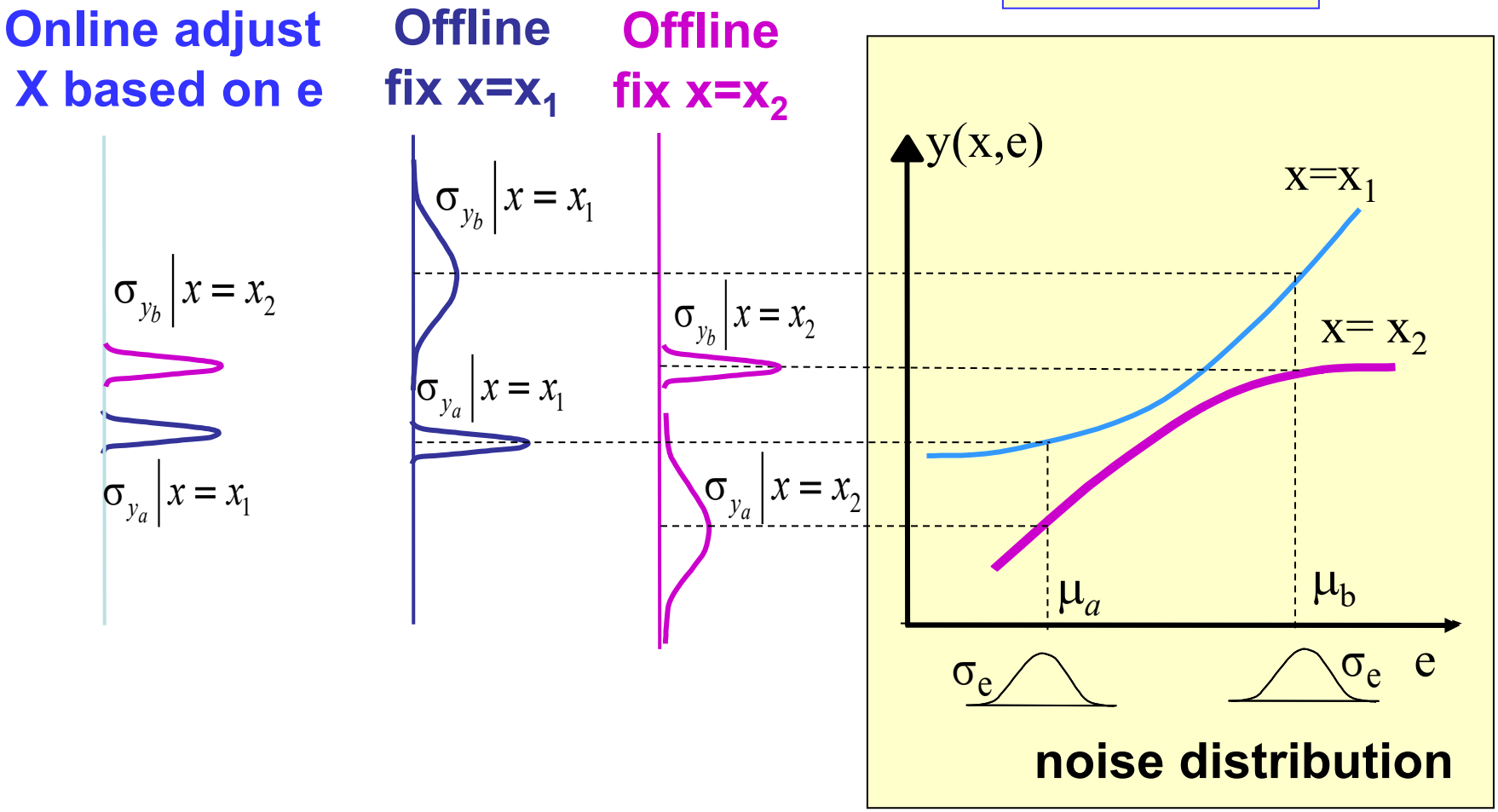


- **Motivation:** Variability of product quality is mainly caused by the change of unavoidable noise factors in a manufacturing process.
- **Robust Parameter Design (DOE-RPD):** Mainly used at the design stage to set an optimal constant level for controllable factors based on the noise distribution that can ensure noise factors have a minimal influence on process responses.
- **Statistical Process Control (SPC):** Monitor process changes and out-of-control points based on product measurements
- **Automatic Process Control (APC):** real-time adjust control factors to compensate the change of noise factors.

- **Proposed DOE-based APC:** On-line adjust of control variables based on the DOE regression model according to real-time monitoring of noise variables.

Illustration of DOE-Based APC Concepts

$$y = f(\mathbf{x}, \mathbf{e})$$



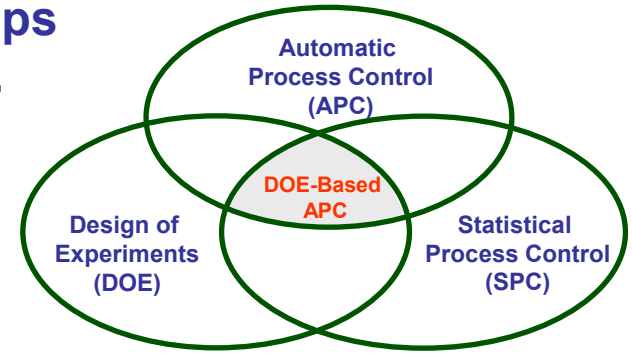
Question: How to get the model f, noise level changes, and control setting?

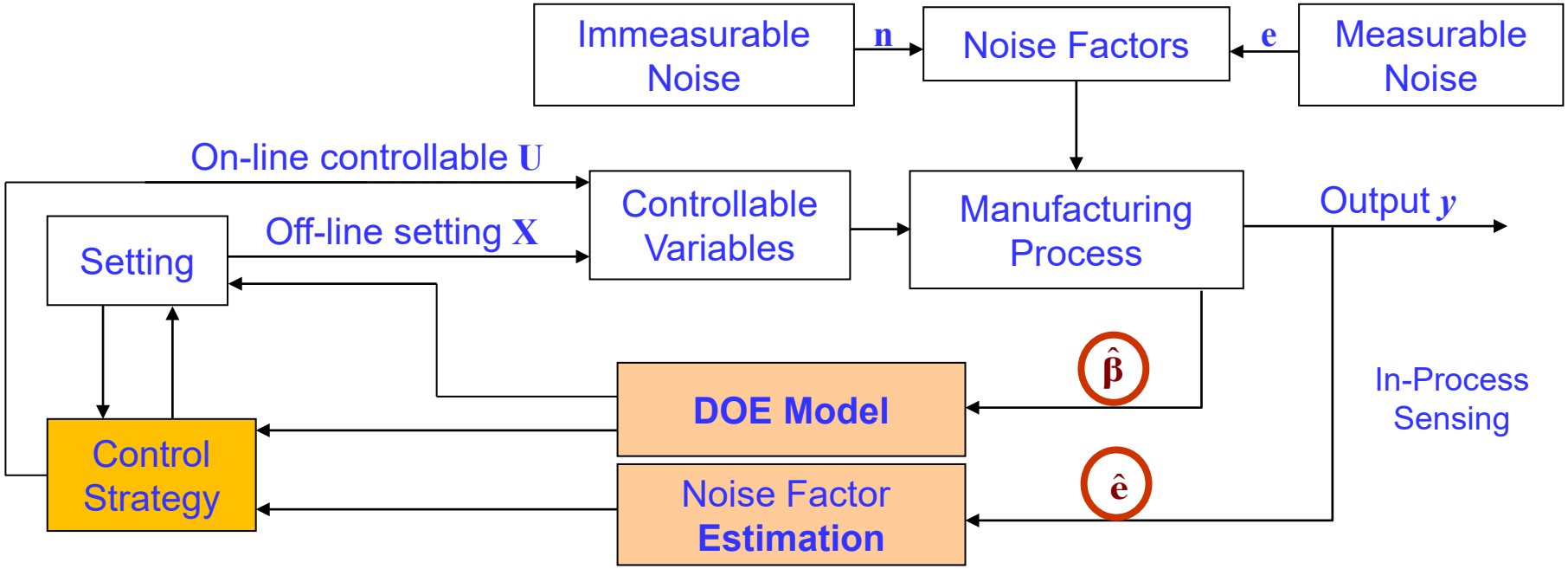
DOE-based APC: Key Ideas

DOE: Identify the key factors and model the relationships among quality response, control variables, and noises.

SPC: monitor and estimate the quality responses and noise variable levels/changes.

APC: Make adjustment on control variables to compensate changes in noise variables.





Applicable Conditions: (i) Design of Experiments can be used to obtained the model; (ii) Some noise factors can be measured/estimated on-line; (iii) Some control factors can be adjusted on-line.

DOE-Based APC System Framework

Model obtained from DOE:

$$y = \beta_0 + \boldsymbol{\beta}_1^T \mathbf{X} + \boldsymbol{\beta}_2^T \mathbf{U} + \boldsymbol{\beta}_3^T \mathbf{e} + \boldsymbol{\beta}_4^T \mathbf{n} + \mathbf{X}^T \mathbf{B}_1 \mathbf{e} + \mathbf{U}^T \mathbf{B}_2 \mathbf{e} + \mathbf{X}^T \mathbf{B}_3 \mathbf{n} + \mathbf{U}^T \mathbf{B}_4 \mathbf{n} + \varepsilon$$

Key variables in the model:

- unobservable noise factors (n) and on-line measurable for noise factors (e)
- off-line setting factors (X) and real-time adjustable factors (U)

Control Objective Function:

$$J_{APC}\left(\mathbf{X}, \mathbf{U} \mid \hat{\mathbf{e}}, \hat{\boldsymbol{\beta}}\right) = E_{\mathbf{e},\mathbf{n},\boldsymbol{\beta},\varepsilon}\left[c(y-t)^2 \middle| \hat{\mathbf{e}}, \hat{\boldsymbol{\beta}}\right]$$

Control Law:

$$(\mathbf{X}^*, \mathbf{U}^*) = \arg \min_{\|\mathbf{X}\|_\infty \le 1, \|\mathbf{U}\|_\infty \le 1} J_{APC}(\mathbf{X}, \mathbf{U})$$

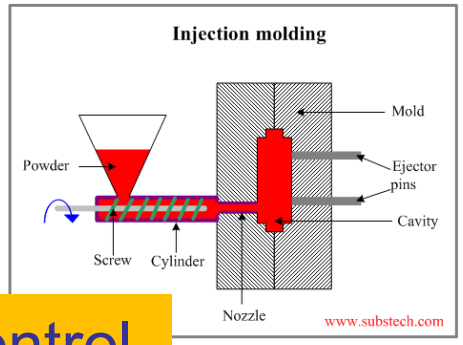
Cautious Control Law:

$$(\mathbf{X}^{C*}, \mathbf{U}^{C*}) = \arg \min_{\|\mathbf{X}\|_\infty \le 1, \|\mathbf{U}\|_\infty \le 1} J_{Cautious\_APC}\left(\mathbf{X}, \mathbf{U}, \Sigma_{\tilde{\beta}}, \Sigma_e\right)$$

- Zhong, J., Shi, J., and J. Wu, 2010, *"Design of DOE-based Automatic Process Controller with Consideration of Model and Observation"*, *IEEE Transactions on Automation Science and Engineering*, Vol.7, No.2, pp266-273.

A Case Study: injection molding process

Controllable Factors		Noise Factors	
Off-Line (x)	*On-Line* (u)	*Measurable* (e)	*Unmeasurable* (n)
x_1 : Mold temperature	u_1 : Cycle time	e_1 : Moisture content	n_1 : Percentage reground
x_2 : Cavity thickness	u_2 : Holding pressure	e_2 : Ambient temperature	
x_3 : Gate size	u_3 : Injection speed		
	u_4 : Holding time		



DoE Modeling → off-line setting → on-line control

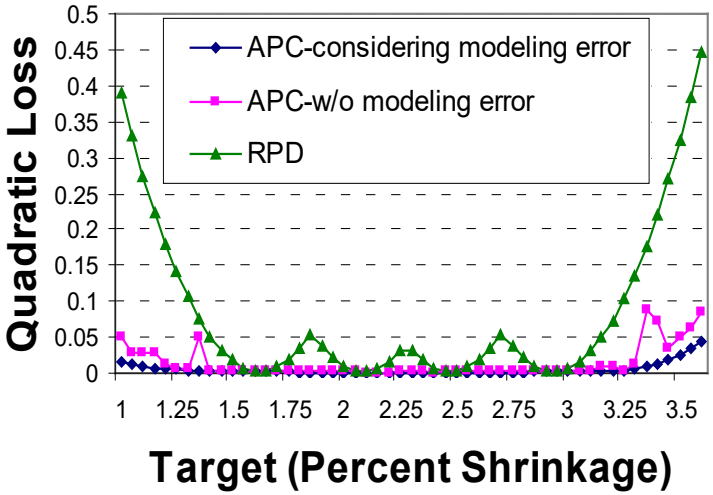
Assuming $e_1 \sim N(0,0.25)$ $n_1 \sim N(0,0.25)$ $\tilde{e}_1 \sim N(0,0.025)$

Optimal Off-line Setting

$$\mathbf{X}^* = [0.5121 \quad -0.2817 \quad 0.5085]^T$$

Cautious control law performs much better than RPD

Control Strategy Evaluation



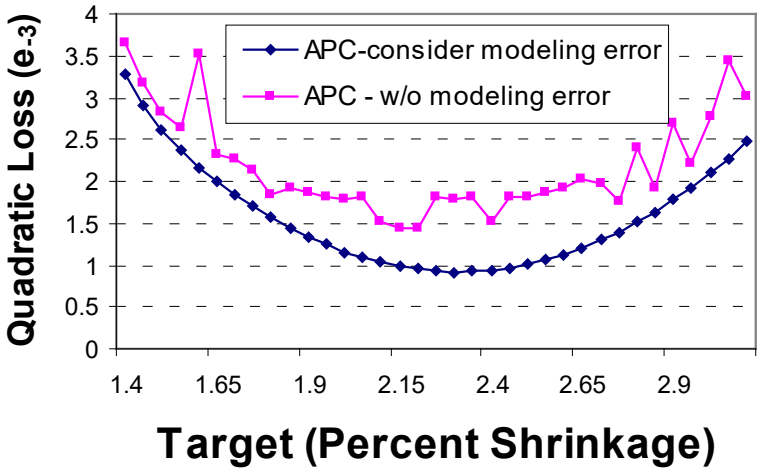


Image-Based Feedback Control Using Tensor Analysis

- Zhen Zhong, Kamran Paynabar, and Jianjun Shi "Image-Based Feedback Control using Tensor Analysis", *Technometrics* (under review, Best Paper of the 2019 INFORMS QSR Section)
- Reisi Gahrooei, M., Yan, H., Paynabar, K., Shi, J., 2020, "Multiple Tensor on Tensor Regression: An approach for modeling processes with heterogeneous sources of data", *Technometrics,* 63:2, 147-159, DOI: 1080/00401706.2019.1708463

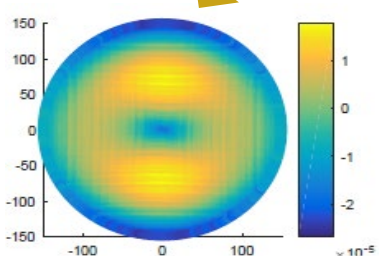
Motivation for Image-based Control

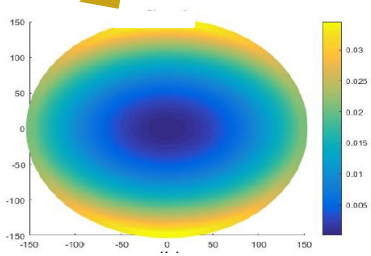
- **The product quality measure are sequential images or videos.**
- **The adjustment of process control variables will impact on the product quality.**

Stage position L_i, lens height h_i,…

Stage position L_j, lens height h_j,…

Lithography Machine





A set of control variables ⇒
Minimize overlay output

Cutting Depth D_i, Speed v_i

Cutting Depth D_j, Speed v_j

Machining process

A set of control variables ⇒
Minimize the deviations from nominal

Objective and Challenges

Objective:

Develop an optimal control framework for streaming image outputs by adjusting the input variables.

Challenges

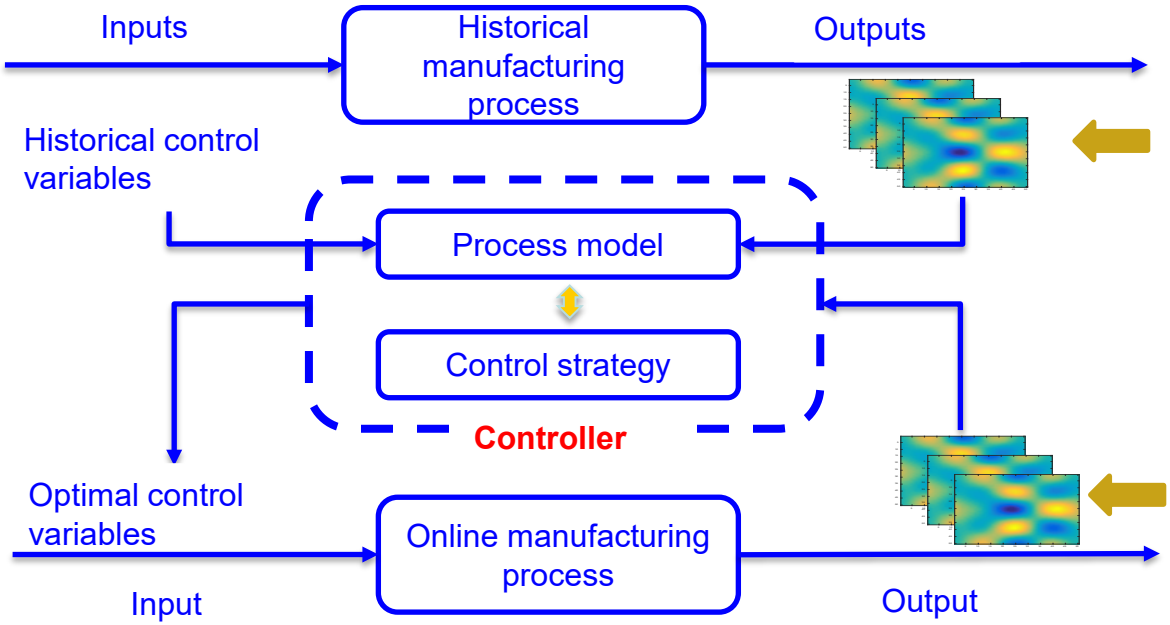
1. **High-dimensionality: How to avoid overfitting?**
2. **Spatial and temporal correlation structure: How to exploit?**
3. **Non-i.i.d Noise: How to model?**

Methodology:

Tensor-based time series modeling and control

1 2 3

Overview of Image-based Control



Novel Tensor time series modeling Technique.

Image-based feedback control:

- Derive the optimal control law;

Process model:

High dimensional coefficients

$$\boxed{\mathcal{Y}_t} = \Sigma_{j=1}^{p} \boxed{\mathcal{Y}_{t-j}} * \mathcal{A}_j + \Sigma_{n=1}^{l} \boxed{\mathcal{X}_{t-n}} * \mathcal{B}_n + \boxed{\delta E_t}$$

Current and previous image output

Control variables

Non-i.i.d Noise

How to learn

1) $\mathcal{A}$ and $\mathcal{B}$?
2) The correlation structure of $\delta\mathcal{E}$?

Control Objective function:

$$\mathrm{Min}_{\mathcal{X}_t} E\left(\hat{\mathcal{Y}}_{t+1|t}(\mathcal{X}_t) - T\right)^2$$

closed-form solution for control law $vec(\mathcal{X}_t)$

Methodology: Tensor Basis representation

$$\mathcal{Y}_t = \Sigma_{j=1}^{p} \mathcal{Y}_{t-j} * \mathcal{A}_j + \Sigma_{n=1}^{l} \mathcal{X}_{t-n} * \mathcal{B}_n + \delta E_t.$$

Use Tensor Basis representation, we have:

$$\mathcal{B}_n = \mathcal{C}_{B_n} \times_1 U_{B_n 1} \ldots \times_l U_{B_n l} \times_{l+1} V_{B_n 1} \times_{l+2} \ldots \times_{l+d} V_{B_n d}$$

$$\mathcal{A}_j = \mathcal{C}_j \times_1 U_{j1} \times_2 \ldots \times_d U_{jd} \times_{d+1} V_{j1} \times_{d+2} \ldots \times_{2d} V_{jd}$$

When $\mathcal{C}$, U, V are specified, $\mathcal{A}$ and $\mathcal{B}$ are determined.

Advantage:

$\mathcal{A} \in R^{256\times256\times256\times256}$ → 4.3×10^9 unknown parameters.

$\mathcal{C} \in R^{3\times3\times3\times3}$;
$U_1, U_2 \in R^{256\times3}$;
$V_1, V_2 \in R^{256\times3}$;
→ 3153 unknown parameters.

Methodology--- Coefficients Learning

Learn the input span basis U from the input data.

We assume Σs are known.

Assume output span basis V is known, learn core tensor C from **Proposition 1.**

Assume core tensor C is known, learn output span basis V from **Proposition 2.**

Loop until converge

Block Coordinate Descent (BCD) algorithm is exploited.

Minimizing the negative log likelihood function.

Using MLE rather than LS since the noise is non-i.i.d.

Optimal Image-based control law

Control Objective function (Quadratic Loss function):

$$\mathrm{Min}_{\mathcal{X}_t} E\left(\hat{\mathcal{Y}}_{t+1}(\mathcal{X}_t) - T\right)^2 \ (3)$$

Proposition 3 (Optimal Image-based control law)

Minimizing mean square error loss function in (3) *is equivalent to solve the equality in (4),*

$$E\mathcal{Y}_{t+1}(\mathcal{X}_t) = T, (4)$$

Where T *is target value and* $E(\cdot)$ *is the expectation operator. The solution of this equality and therefore the optimal control action can be expressed as*

$$vec(\mathcal{X}_t) = (U_{Bl} \otimes \ldots \otimes U_{B1}) C_B^{-1} (V_{Bd} \otimes \ldots V_{B2} \otimes V_{B1})^T vec(R_{Bt})$$
$$= C_B^{-1} (V_{Bd} \otimes \ldots V_{B2} \otimes V_{B1})^T vec(R_{Bt}) \qquad (5)$$

Where the $C_B \in R^{\tilde{P} \times \tilde{Q}}$ *is an unfolding of the core tensor* $\mathcal{C}_B$ *with* $\tilde{P} = \Pi_{j=1}^{l} \tilde{P}_j$ *and* $\tilde{Q} = \Pi_{j=1}^{d} \tilde{Q}_j$ *and* $R_{Bt} = T - \Sigma_{j=1}^{p} \mathcal{Y}_{t+1-j} * \mathcal{A}_j$.

Proposition 3 provide the closed-form solution for calculating next time optimal control law.

Simulation --- Data Generation

Data Generation:

$$\boldsymbol{Y}(t+1) = \mathcal{A}_1 * \boldsymbol{Y}(t) + \mathcal{A}_2 * \boldsymbol{Y}(t-1) + \mathcal{B}_1 * \boldsymbol{X}(t) + \delta \mathrm{E}_t$$

- $\boldsymbol{X}(t) \in R^{2\times 1}$: Each element randomly generated from $N(0,1)$.
- $\mathcal{A}_k = C_k \times_1 \underbrace{V_1 \times_2 V_2 \times_3 V_1 \times_4 V_2}_{\text{Fourier Basis}}$ $\qquad \mathcal{B}_1 = C_B \times_1 \underbrace{V_1 \times_2 V_2}_{\text{Fourier Basis}}$

  Random tensor

- $\delta \mathrm{E}_t \sim N(0, \Sigma_1, \Sigma_2, \Sigma_3)$

  Setting 1: $\theta = 0.001$
  Strong spatial correlation

  Setting 2: $\theta = 10000$
  Weak spatial correlation

- Spatial covariance matrices: $\Sigma_{1|i_1,i_2} = \Sigma_{2|i_1,i_2} = e^{\left(-\theta \|r_{i_1} - r_{i_2}\|^2\right)}$.
- Temporal covariance matrix: Σ_3 is auto-covariance matrix of an MA(1) process.
- Training data: 200 Samples, Testing data 200 Samples

Simulation: Result

Performance index:

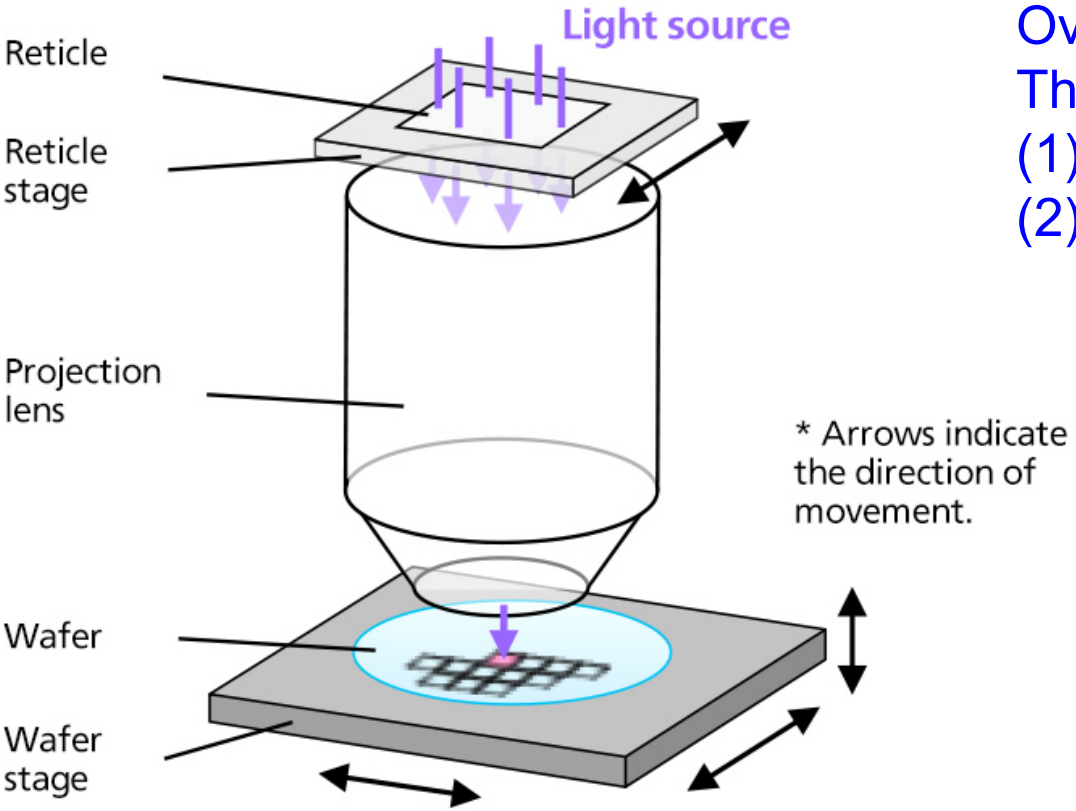
Mean square control error: $\frac{\Sigma_{i=1}^{N}\left\|Y_{aftercontrol}-T\right\|_F^2}{\Sigma_{i=1}^{N}\left\|Y_{beforecontrol}-T\right\|_F^2}$

	Proposed method	Univariate control
$\Theta = 10000$	0.7959	$3.5726 * 10^4$
$\Theta = 0.001$	0.9355	3.7013

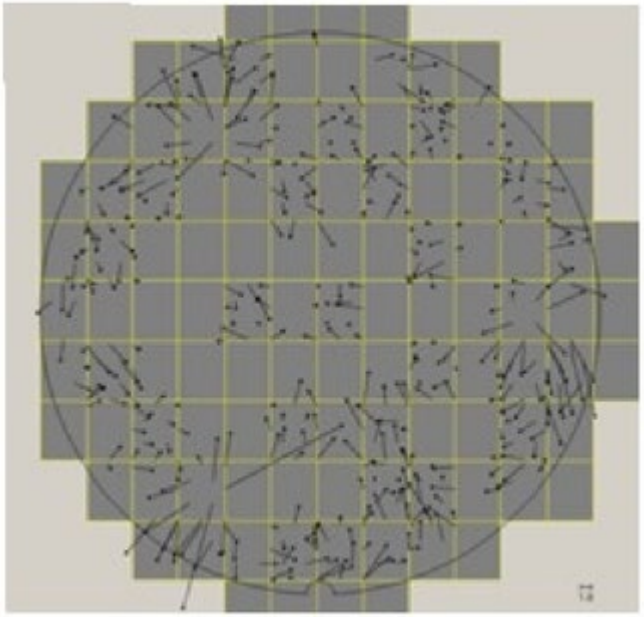
Without control

With control

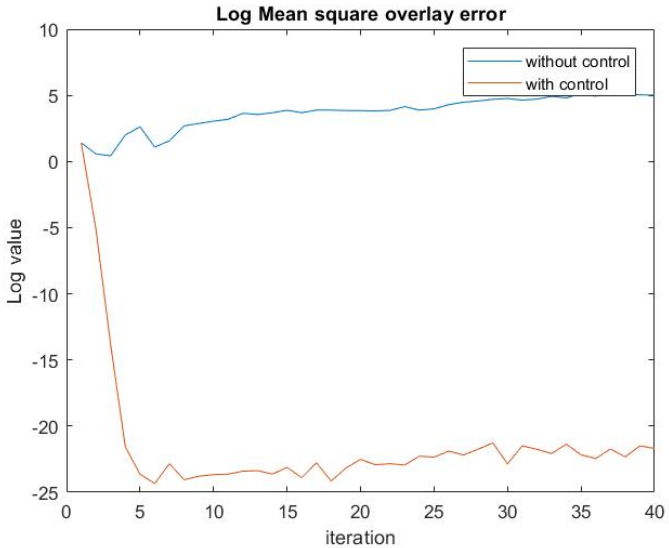
Case Study: The photolithography process



Overlay vector:
The alignment error between
(1) The projected pattern.
(2) The desired projected location on the wafer.



Case Study: Result

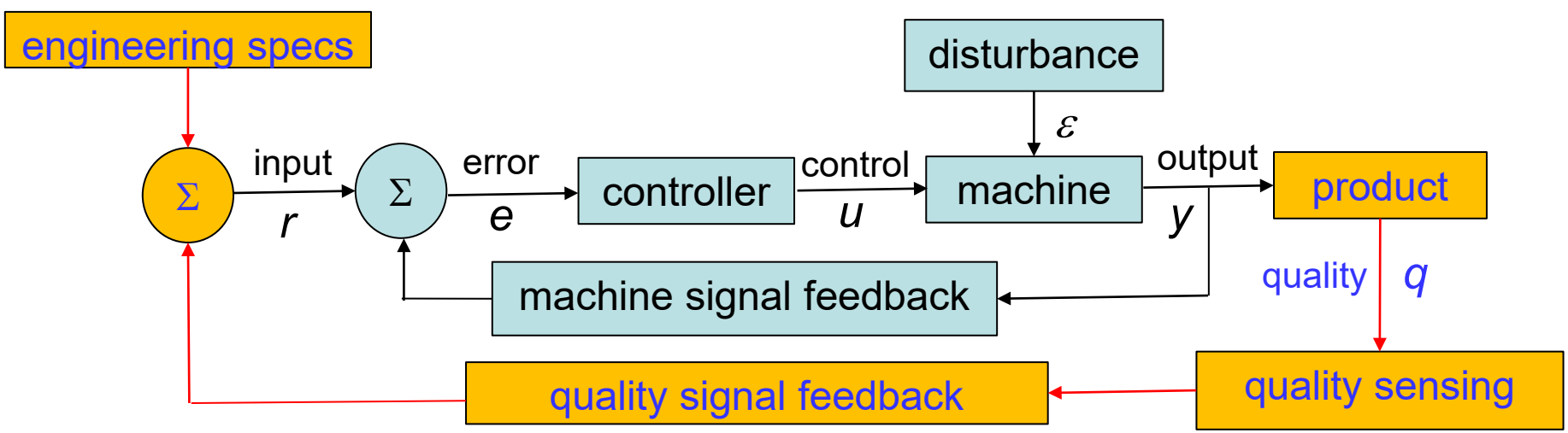


Mean square control error:

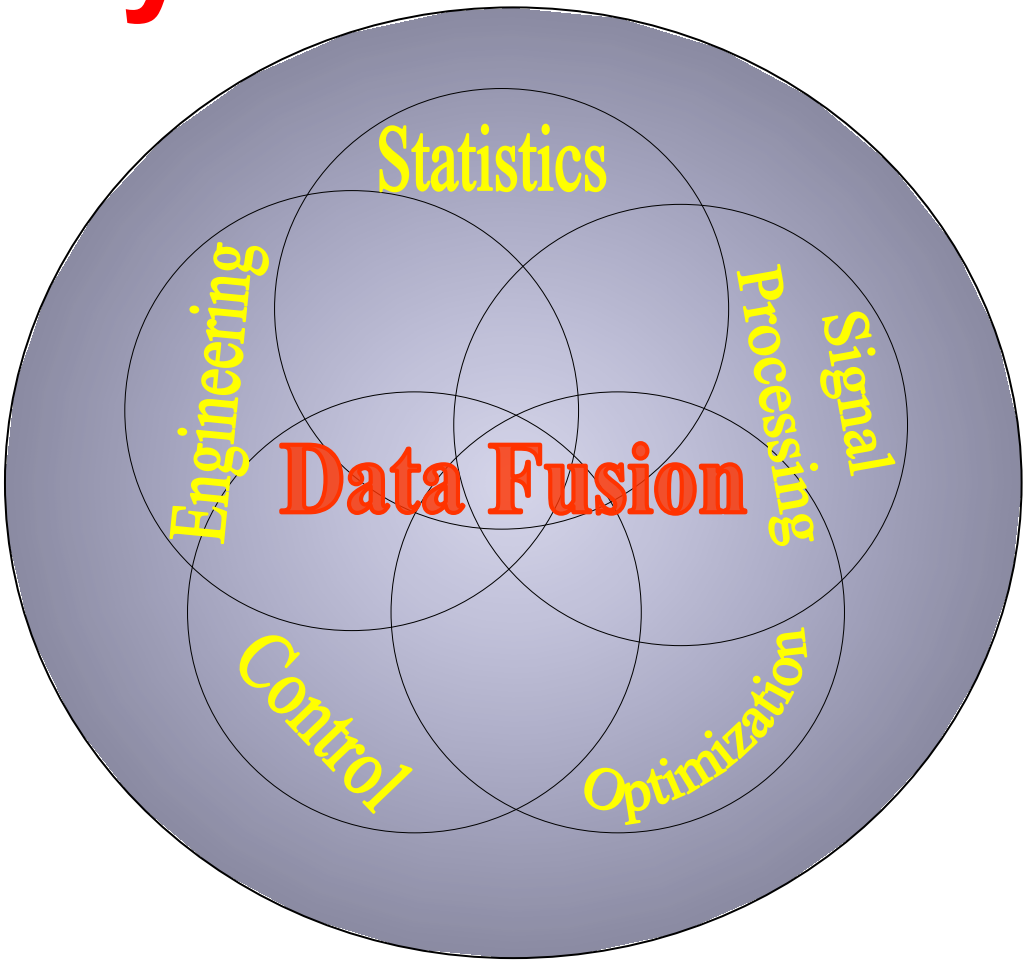
$$\frac{\Sigma_{i=1}^{N}\left\|Y_{aftercontrol}-T\right\|_F^2}{\Sigma_{i=1}^{N}\left\|Y_{beforecontrol}-T\right\|_F^2} = 1.51 \times 10^{-11}$$

Summary

- **Data-driven automation is effective for in-process quality improvements.**
- **New modeling and control methodologies are required to link the product quality with the process control variables.**
- **Numerous challenges needs to be addressed to handle hydrogenous data, high/low dimensional data, time-varying sampling data, etc.**
- **Several control algorithms, including SOV-based control, causation-based control, machine learning enabled control, DOE-based APC, and image-based control, are introduced in this talk.**
- **There are much more research and implementation opportunities for IPQI using data-drive automation in smart manufacturing systems.**



Thank you!


Statistics
Engineering
Signal Processing
Data Fusion
Control
Optimization