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

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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
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.

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.
Data-Driven Automation for IPQI demands fundamental research and development in modeling and control for quality improvements.
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
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• Summary
Stream of Variation Methodologies for Multistage Manufacturing Processes

Multistage Manufacturing System:
Processes with multiple workstations and/or multiple operations

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

Multidisciplinary Research:
- SoV Model-Based Multistage Process Control

The SoV model provides a solid scientific foundation to use system/control theory and advanced statistics in the Multistage process monitoring and diagnostics.
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 \(u_j \equiv 0, j=k+1, k+2, \ldots, N-1\);
- 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

\[
x_k = A_{k-1}x_{k-1} + B_ku_k + w_k
\]
\[
y_k = C_kx_k + v_k
\]

\[
J = \min_{u_k} \hat{y}_{N/k} \cdot Q \cdot \hat{y}_{N/k}^T \\
\text{s.t. } \hat{y}_{N/k} \in [LSL, USL] \\
\text{ } u_{\text{min}} \leq u_{ck} \leq u_{\text{max}} \\
\text{ } u_{ck} = \begin{cases} 
 u_{ck} & \text{if } |u_{ck}| > \Delta u \\
 0 & \text{otherwise} 
\end{cases}
\]


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


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

Advantage:
Reduce flow time; Increase productivity; Achieve high quality; Applicable to all part joins.
Sparse Learning and Model Calibration for Composite Fuselage Shape Control


FEA Simulation Platform and Validation

Material: Carbon fiber & Resin Epoxy

Fabrics -> Stackups -> Sub Laminates

Fabrication Process

ANSYS Workbench: Composite Prepost

Carbon Fiber Orientation

Ten Actuators

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

Field Test: Computer Model v.s. Physical Experiment

Deviations without calibration

- Deviation data for different forces (100 lbf to 600 lbf) with FEA and experiment results compared.
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.

\[
\hat{\theta}_n = \arg\min_{\theta} L(Y^p, Y^s_{\theta}) + \lambda_n \| \theta - \theta_0 \|
\]

\[
= \arg\min_{\theta} (Y^p - Y^s_{\theta})^T (\tau^2 \Phi_{\theta} + \sigma^2 I_n)^{-1} (Y^p - Y^s_{\theta}) + \lambda_n \sum_{i=1}^{m} |\theta_i - \theta^{(0)}_i|
\]

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

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

Problem Formulation

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

Input:
- Initial shape distortion: $\psi \in \mathbb{R}^n$
- Weight matrix: $B \in \mathbb{R}^{n \times n}$

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

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

Sparsity requirement of $F$

Deviations after shape adjustments

Safety requirement

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

s.t. $\|F\|_0 = M$, $F_L \leq F \leq F_Q$
Sparse Learning Modeling and Estimation

\[
\min_F L(F) = (\psi + UF)'B(\psi + UF) + \lambda \|F\|_1, \text{ s.t. } F_L \preceq F \preceq F_Q
\]

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

\[
F^{k+1} = \Pi_C \left( (2U'BU + \rho I)^{-1}(\rho z^k - \rho u^k - 2U'B\psi) \right)
\]

\[
z^{k+1} = S_{\lambda/\rho} (F^{k+1}+u^k)
\]

\[
u^{k+1} = u^k + F^{k+1} - z^{k+1}.
\]

\(I \in R^{m \times m}\) is an identity matrix. \(\Pi_C\) is an Euclidean projection onto the convex set \(C = \{F \in R^m: F_L \preceq F \preceq F_Q\}\), which can be denoted as

\[\Pi_C(\nu) = \arg\min_{F \in C} (\|F - \nu\|_2)\]

\[S_{\lambda/\rho}(\nu) = (\nu - \lambda/\rho)_+ (-\nu - \lambda/\rho)_+\], 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

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

Physics-Driven Machine Learning and Modeling for Multistage Rolling Process

- 50 to 80 roller stations with a 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

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

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)


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

Online adjust $X$ based on $e$

$y(x,e)$

$\mu_a$ $\mu_b$

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:

\[ y = \beta_0 + \beta_1^T X + \beta_2^T U + \beta_3^T e + \beta_4^T n + X^T B_1 e + U^T B_2 e + X^T B_3 n + U^T B_4 n + \varepsilon \]

Key variables in the model:
- unobservable noise factors \( \mathbf{n} \) and on-line measurable for noise factors \( \mathbf{e} \)
- off-line setting factors \( \mathbf{X} \) and real-time adjustable factors \( \mathbf{U} \)

Control Objective Function:

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

Control Law:

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

Cautious Control Law:

\[ (\mathbf{X}^{c*}, \mathbf{U}^{c*}) = \arg \min_{\|\mathbf{X}\|_\infty \leq 1, \|\mathbf{U}\|_\infty \leq 1} J_{Cautious_{APC}} (\mathbf{X}, \mathbf{U}, \mathbf{\Sigma}_{\beta}, \mathbf{\Sigma}_{\varepsilon}) \]

A Case Study: injection molding process

<table>
<thead>
<tr>
<th>Controllable Factors</th>
<th>Noise Factors</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Off-Line</strong> (x)</td>
<td><strong>On-Line</strong> (v)</td>
</tr>
<tr>
<td>x₁: Mold temperature</td>
<td>u₁: Cycle time</td>
</tr>
<tr>
<td>x₂: Cavity thickness</td>
<td>u₂: Holding pressure</td>
</tr>
<tr>
<td>x₃: Gate size</td>
<td>u₃: Injection speed</td>
</tr>
<tr>
<td></td>
<td>u₄: Holding time</td>
</tr>
</tbody>
</table>

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

$$X^* = \begin{bmatrix} 0.5121 & -0.2817 & 0.5085 \end{bmatrix}^T$$

Control Strategy Evaluation

Cautious control law performs much better than RPD
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)
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 $h_j$,…

Cutting Depth $D_i$, Speed $v_i$
Cutting Depth $D_j$, Speed $v_j$

A set of control variables $\Rightarrow$
Minimize overlay output

A set of control variables $\Rightarrow$
Minimize the deviations from nominal
Objective and Challenges

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

Challenges

❶ High-dimensionality: How to avoid overfitting?
❷ Spatial and temporal correlation structure: How to exploit?
❸ Non-i.i.d Noise: How to model?

Methodology:

Tensor-based time series modeling and control

❶ ❷ ❸
Overview of Image-based Control

Historical control variables

Process model

Control strategy

Controller

Inputs

Historical manufacturing process

Outputs

Novel Tensor time series modeling Technique.

Optimal control variables

Current and previous image output

Control variables

Non-i.i.d Noise

How to learn

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

Process model:

$Y_t = \sum_{j=1}^{p} Y_{t-j} A_j + \sum_{n=1}^{l} X_{t-n} B_n + \delta E_t$

Control Objective function:

$\text{Min}_{x_t} E (\hat{Y}_{t+1|t} (X_t) - T)^2$

closed-form solution for control law $\text{vec}(X_t)$
Methodology: Tensor Basis representation

\[ Y_t = \sum_{j=1}^{p} Y_{t-j} \ast A_j + \sum_{n=1}^{l} X_{t-n} \ast B_n + \delta E_t. \]

Use Tensor Basis representation, we have:

\[ B_n = C_{B_n} \times_1 U_{B_{n1}} \cdots \times_{l} U_{B_{nl}} \times_{l+1} V_{B_{n1}} \times_{l+2} \cdots \times_{l+d} V_{B_{nd}} \]

\[ A_j = C_j \times_1 U_{j1} \times_2 \cdots \times_d U_{jd} \times_{d+1} V_{j1} \times_{d+2} \cdots \times_{2d} V_{jd} \]

When \( C, U, V \) are specified, \( A \) and \( B \) are determined.

**Advantage:**

\[ A \in \mathbb{R}^{256 \times 256 \times 256 \times 256} \quad \rightarrow \quad 4.3 \times 10^9 \text{ unknown parameters.} \]

\[ C \in \mathbb{R}^{3 \times 3 \times 3 \times 3}; \quad U_1, U_2 \in \mathbb{R}^{256 \times 3}; \quad V_1, V_2 \in \mathbb{R}^{256 \times 3}; \quad \rightarrow \quad 3153 \text{ unknown parameters.} \]
Methodology--- Coefficients Learning

Learn the input span basis $U$ from the input data.

We assume $\Sigma$s are known.

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

Loop until converge

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

Block Coordinate Descent (BCD) algorithm is exploited.

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

Minimizing the negative log likelihood function.
Optimal Image-based control law

Control Objective function (Quadratic Loss function):

$$ \text{Min}_{X_t} E \left( \hat{Y}_{t+1}(X_t) - T \right)^2 $$ (3)

**Proposition 3 (Optimal Image-based control law)**

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

$$ E\hat{Y}_{t+1}(X_t) = T, \quad (4) $$

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

$$ \text{vec}(X_t) = (U_{B1} \otimes ... \otimes U_{B1}) C_B^{-1} (V_{Bd} \otimes ... V_{B2} \otimes V_{B1})^T \text{vec}(R_{Bt}) $$

$$ = C_B^{-1} (V_{Bd} \otimes ... V_{B2} \otimes V_{B1})^T \text{vec}(R_{Bt}) \quad (5) $$

Where the $C_B \in R^{\bar{P} \times \bar{Q}}$ is an unfolding of the core tensor $C_B$ with $\bar{P} = \Pi_{j=1}^l \bar{p}_j$ and $\bar{Q} = \Pi_{j=1}^d \bar{q}_j$ and $R_{Bt} = T - \Sigma_{j=1}^p Y_{t+1-j} \star A_j$.

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

Data Generation:

\[ Y(t + 1) = \mathcal{A}_1 \ast Y(t) + \mathcal{A}_2 \ast Y(t - 1) + \mathcal{B}_1 \ast X(t) + \delta E_t \]

- **\( X(t) \in \mathbb{R}^{2 \times 1} \):** Each element randomly generated from \( N(0,1) \).
- **\( \mathcal{A}_k = C_k \times_1 V_1 \times_2 V_2 \times_3 V_1 \times_4 V_2 \) & **\( \mathcal{B}_1 = C_B \times_1 V_1 \times_2 V_2 \)**

**Random tensor** & **Fourier Basis**

- **\( \delta E_t \sim N(0, \Sigma_1, \Sigma_2, \Sigma_3) \)**

**Setting 1:** \( \theta = 0.001 \)

Strong spatial correlation

**Setting 2:** \( \theta = 10000 \)

Weak spatial correlation

- **Spatial covariance matrices:**
  \[ \Sigma_{1|i_1,i_2} = \Sigma_{2|i_1,i_2} = e^{-\theta \|r_{i_1} - r_{i_2}\|^2} \]

- **Temporal covariance matrix:** \( \Sigma_3 \) 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:

\[
\frac{\sum_{i=1}^{N} \|Y_{after control} - T\|_F^2}{\sum_{i=1}^{N} \|Y_{before control} - T\|_F^2}
\]

<table>
<thead>
<tr>
<th>Proposed method</th>
<th>Univariate control</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \Theta = 10000 )</td>
<td>0.7959</td>
</tr>
<tr>
<td>( \Theta = 0.001 )</td>
<td>0.9355</td>
</tr>
</tbody>
</table>

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.

* Arrows indicate the direction of movement.
Case Study: Result

Mean square control error:

\[ \frac{\sum_{i=1}^{N} \|Y_{after\ control} - T\|_F^2}{\sum_{i=1}^{N} \|Y_{before\ control} - T\|_F^2} = 1.51 \times 10^{-11} \]
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 need 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!