Manufacturing Analytics:
Synergies between Engineering and Statistics

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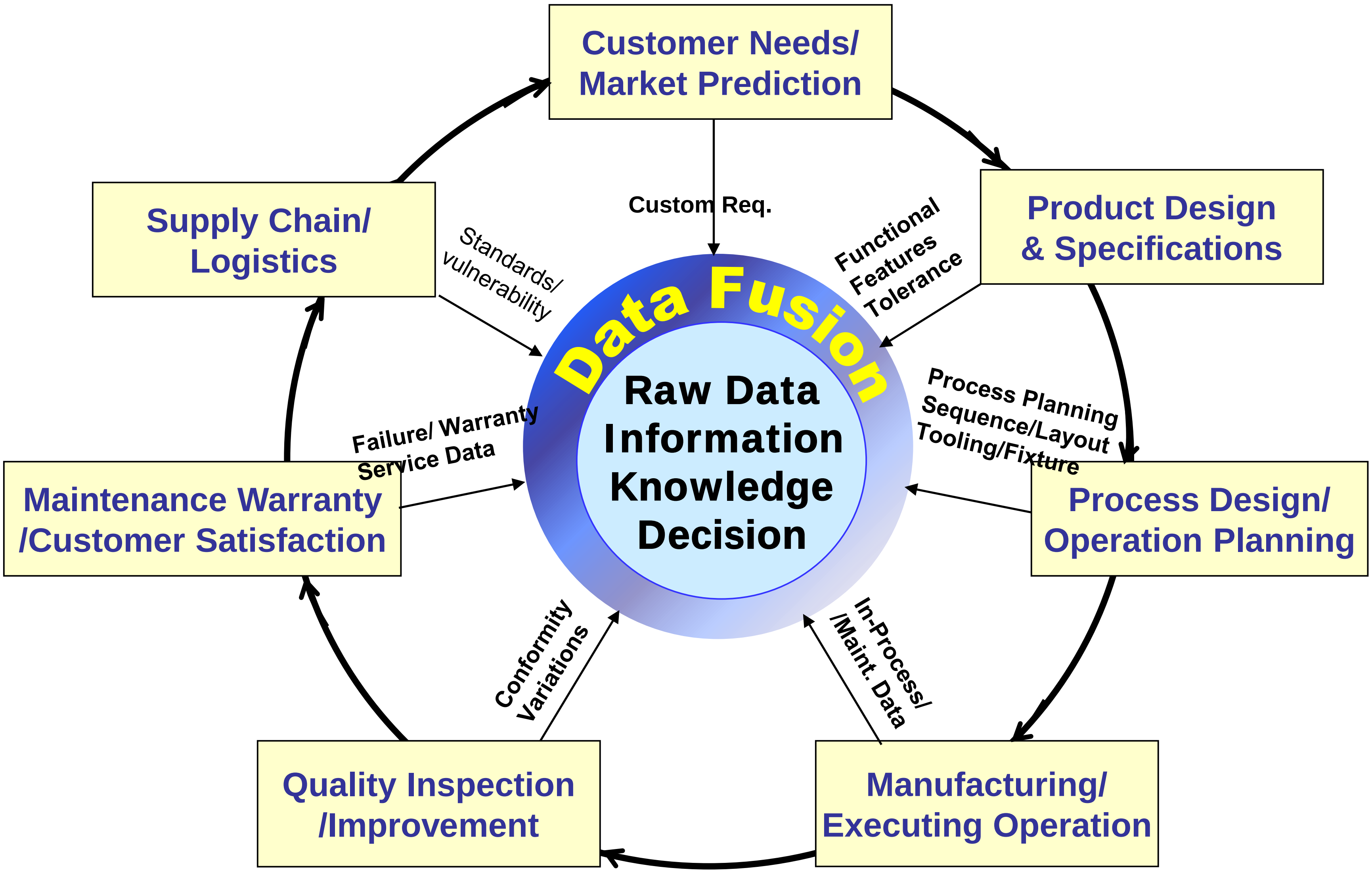
Outline

1. Introduction and Manufacturing Analytics
2. Synergies between Engineering and Statistics
   - Bleeds detection in continuous casting
   - Causation-based process control for rolling
   - Tonnage signature analysis for stamping
   - Nano powder manufacturing scale-up
   - Stream of Variation methodologies for multistage manufacturing processes
3. Summary

Manufacturing System, Product Realization and Big Data



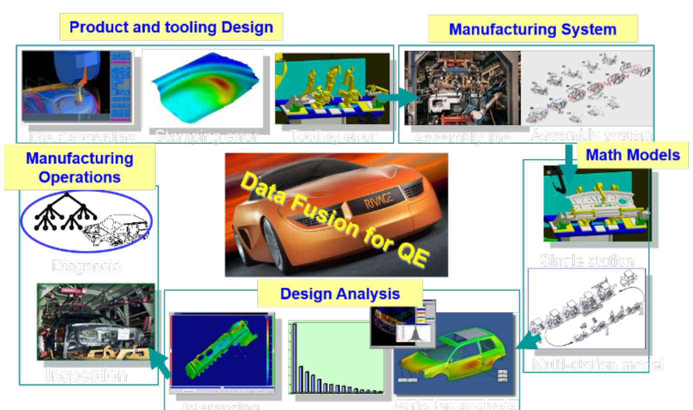
Big Data enables improvements across all stages of the product lifecycle, from product conceptualization, to design, production, service, as well as logistics.

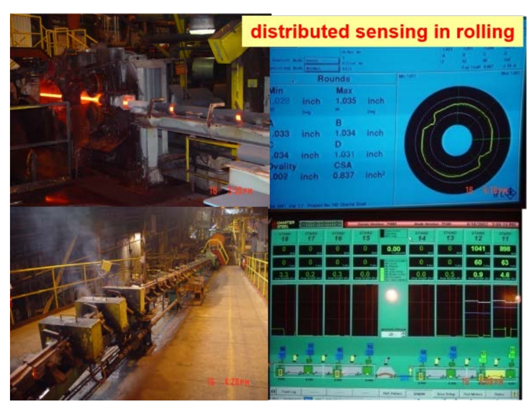
Manufacturing Analytics

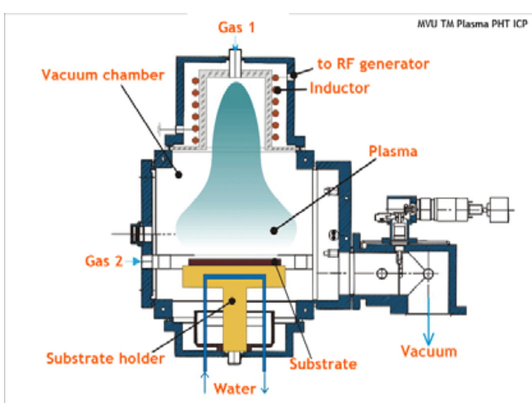
- **Vision:**
  - To achieve “first and every part correct” manufacturing with “minimum cost and lead time” by effectively integrating engineering models, product and process design information, and data analytics tools to drive strategic decisions in design, operations, and control of manufacturing processes.
- **Key Components:**
  - product design, process science, systems informatics, data analytics and visualization, adaptive sensing and metrology, predictive simulation, dynamic data driven optimization

Challenges in Manufacturing Analytics

- Massive manufacturing data: How to get information from massive data in time to make meaningful decisions.
- Data uncertainty and noise: As the size of the data increases exponentially, the amount of "noisy" data that is not valuable also becomes significant.
- Clear engineering objectives: It is essential to find the right information from massive data - majority of value comes from minority of data for a given task.
- The "imbalance" in data availability: Massive normal production data vs. abnormal production data, even more sparse data for a given type of failures.
- Heterogeneous data: How to develop a unified model and strategy to make an informative decision. Complex data structure, data type, and acquisition rate bring more challenges in data fusion and decision making.
- Decision making in data rich environment: Data collection decision such as sensor placement and data driven predictive and proactive maintenance.
- (more challenges…)

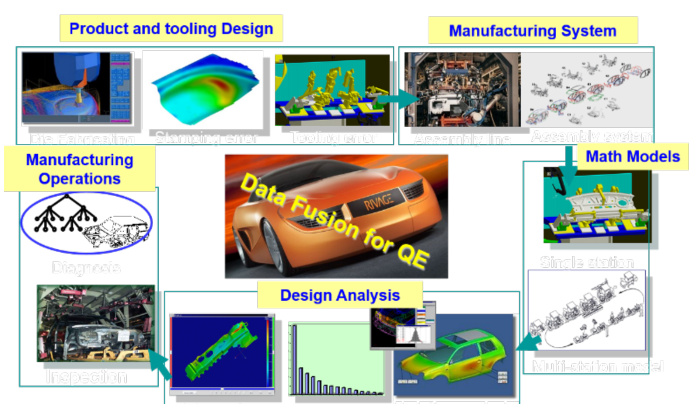


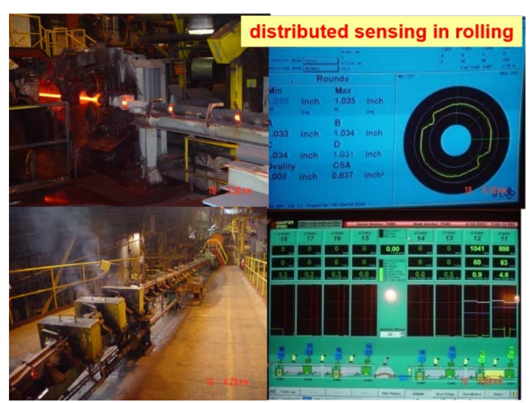


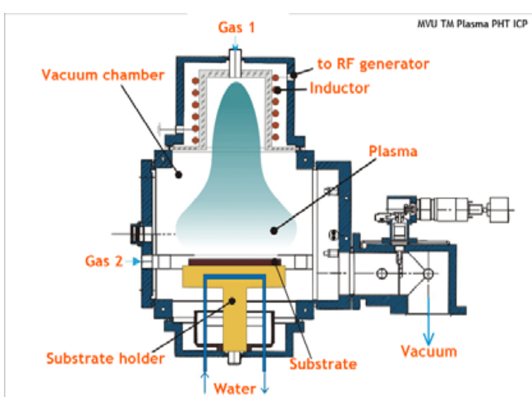


Research Proposition in Mfg Analytics

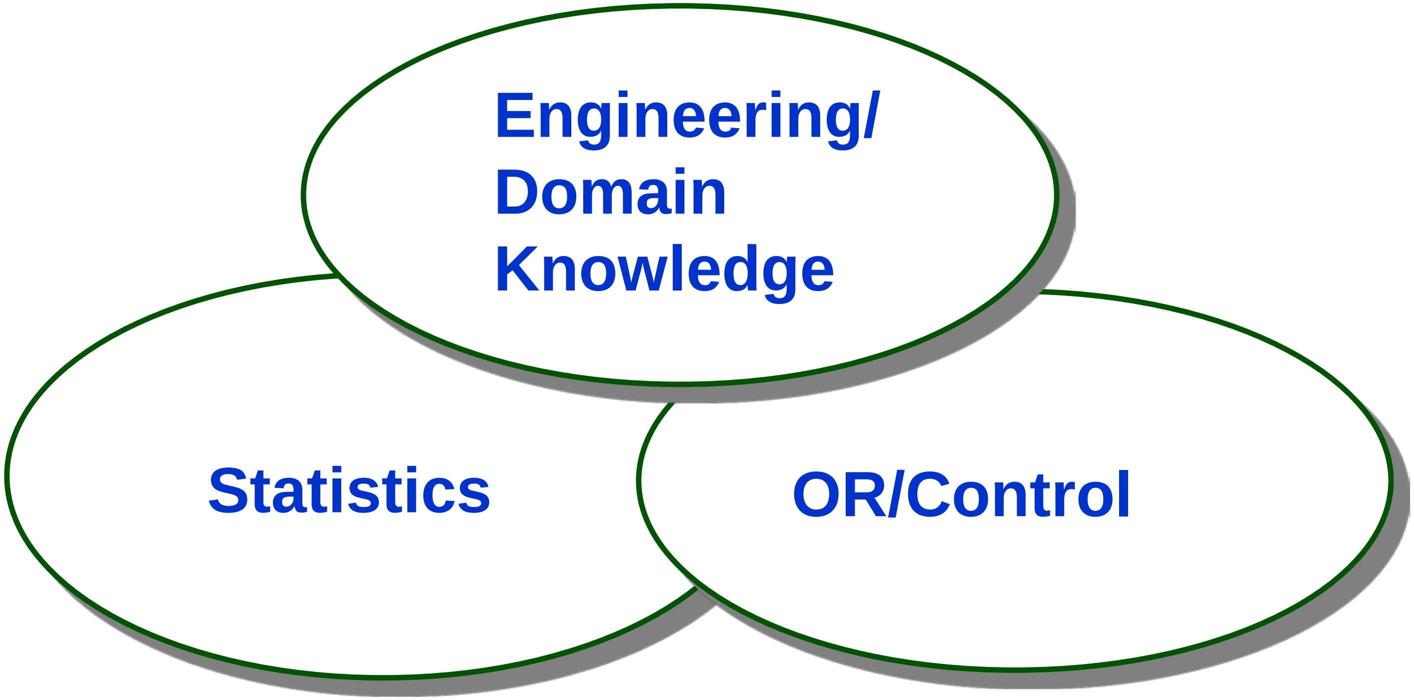
- Engineering models and physics: As an engineered system, there is a good understanding of engineering physics/models for a given product and process.
- System operational data: The operations of a manufacturing system generate massive data that reveals both system functions and unexpected disturbances.
- Two typical ways to model a given system: Physics-based modeling based on the 1st principle, and data-driven modeling based on the operational data.
  - Physics-based modeling performs well in describing a specific device or a machine, but not a real system with various unexpected disturbances;
  - Data-driven modeling works well with data fitting or prediction, but lacking of interpretations and finding inherent system characteristics.
- “Synergies between Engineering and Statistics”: An integration of physics-based modeling with data-driven methods provides new opportunities in manufacturing analytics.







Interdisciplinary Framework: Fusion of Engineering, Statistics, OR/Control

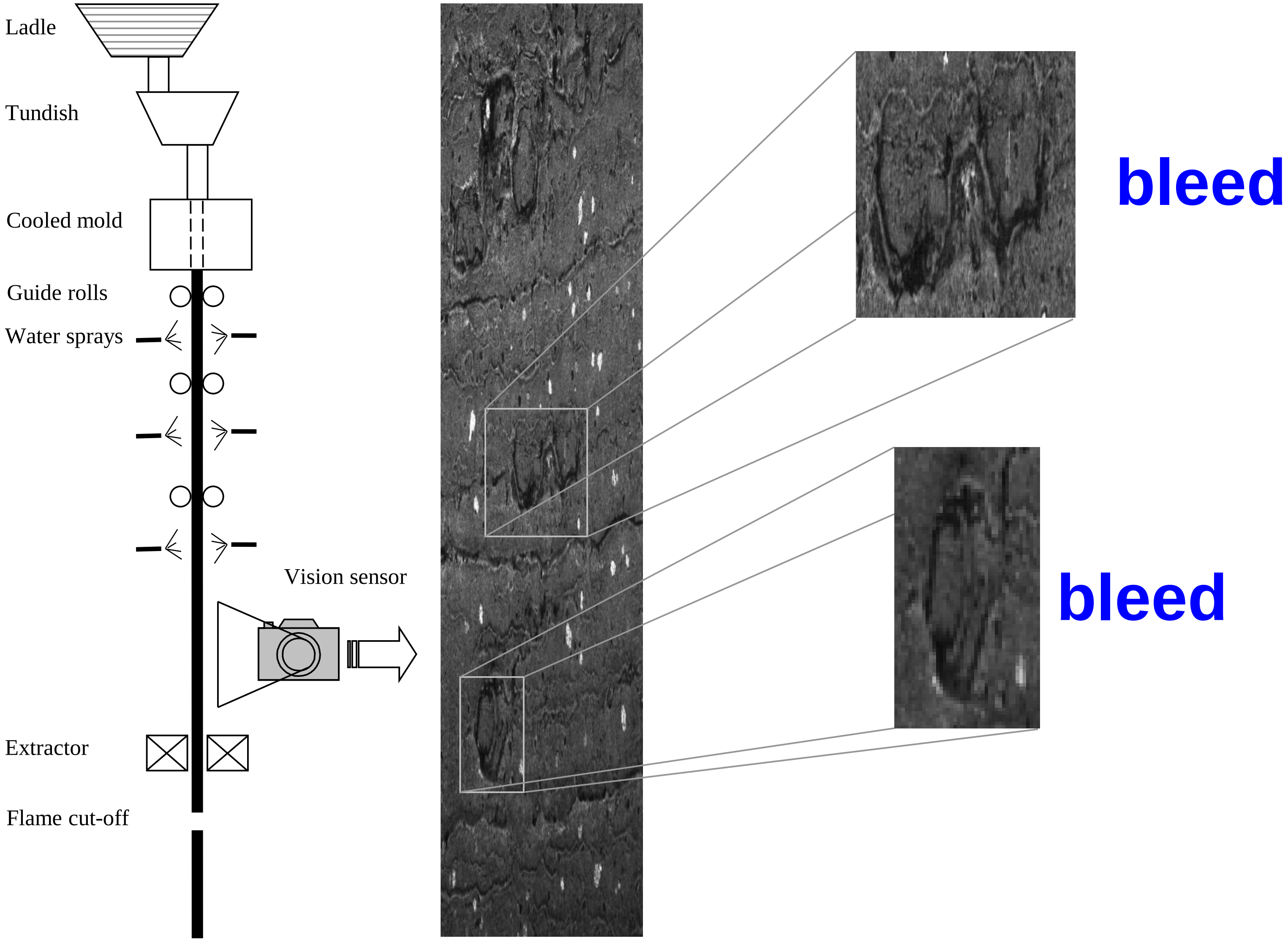


Statistical Methods Driven by Engineering Knowledge

On-line Bleeds Detection in Continuous Casting

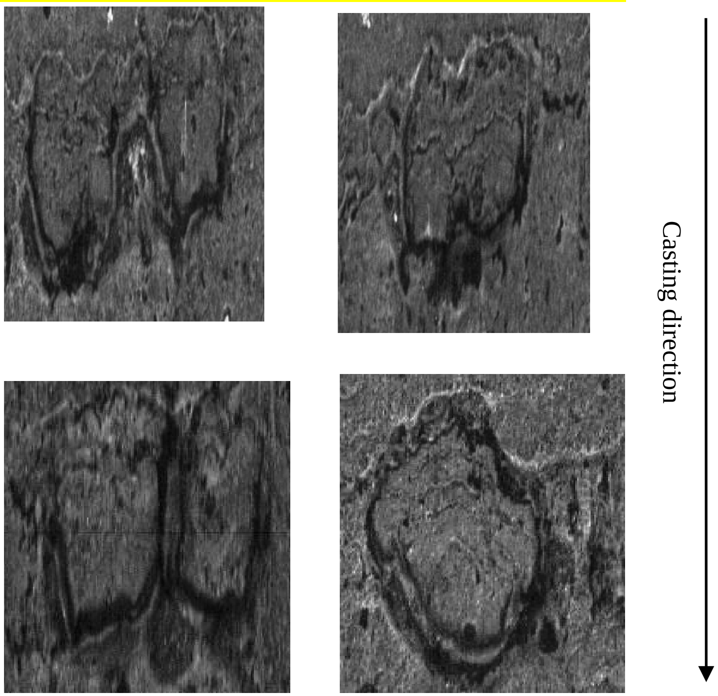
Pan, E., Ye, L., Shi, J., Chang, T., 2009, "On-line bleeds detection in continuous casting processes using engineering-driven rule-based algorithm", *ASME Transactions, J. of Manufacturing Science and Engineering*, Vol. 131, Issue 6.

The Process and Sensing Signals

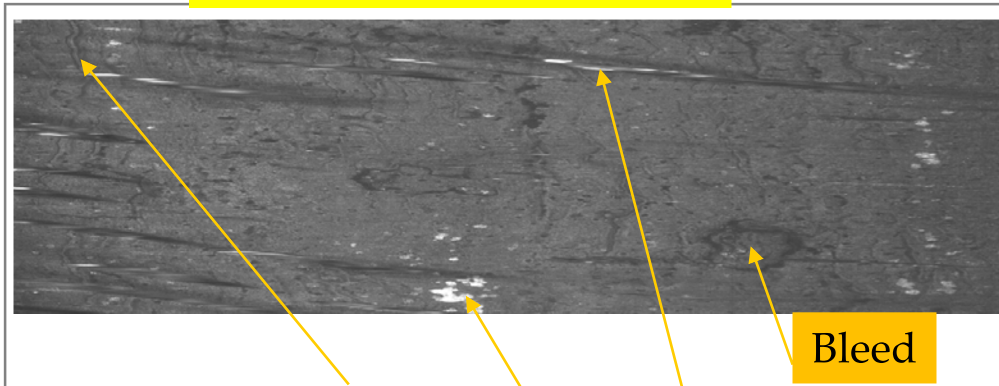


The Challenges in the Bleeds Detection

Irregular shapes

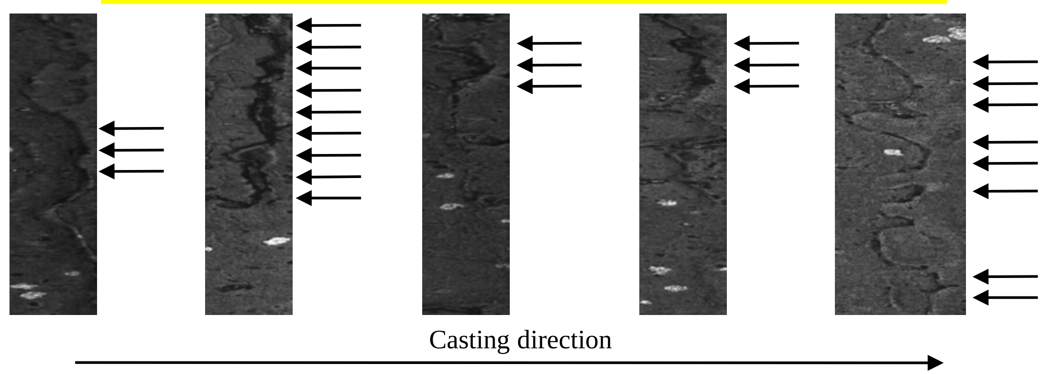


Noisy signals



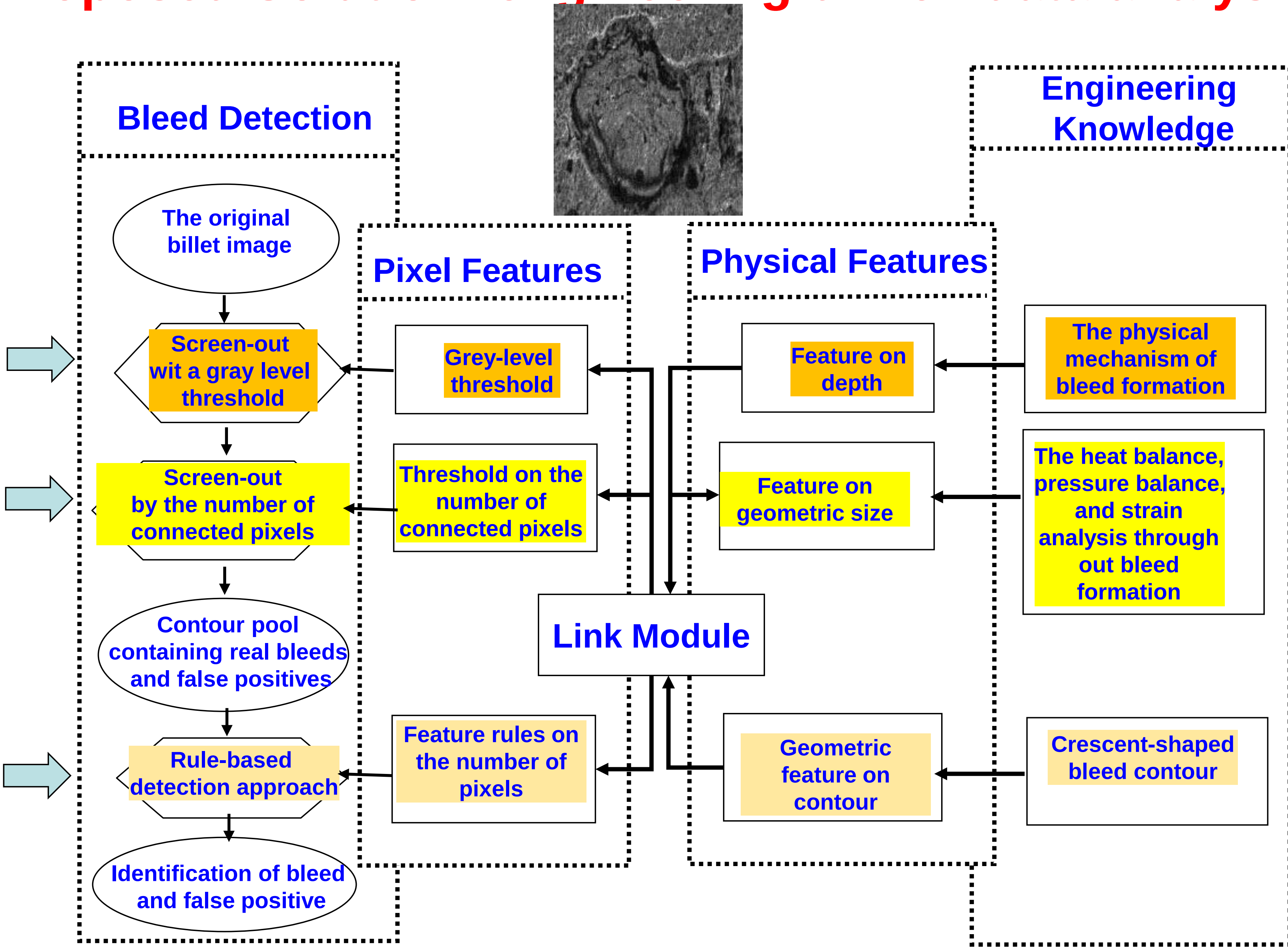
The noises are deep oscillation marks, water vapour, water sprays, steel texture, etc.

False positive signals

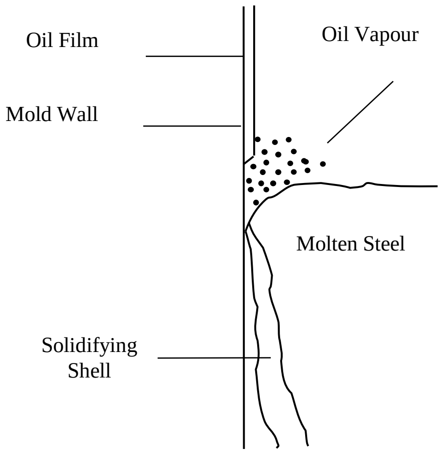


Limited Samples

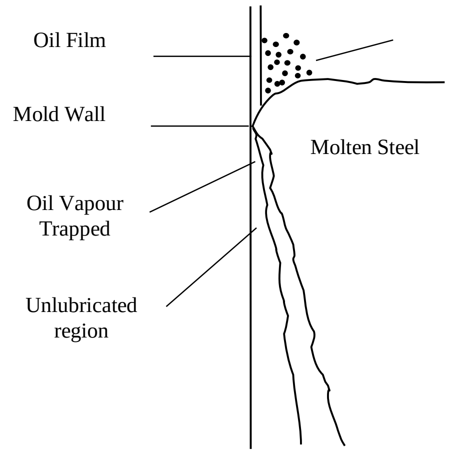
Proposed Solution: engineering-driven data analysis



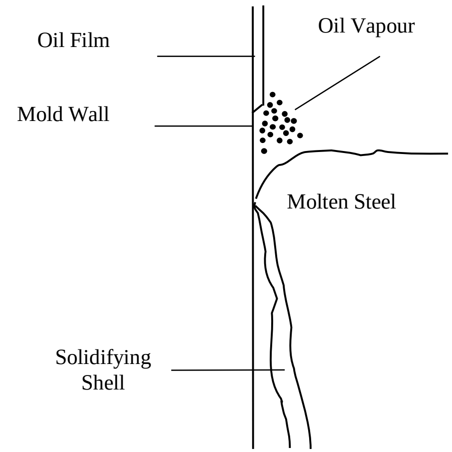
Mechanism of bleed formation



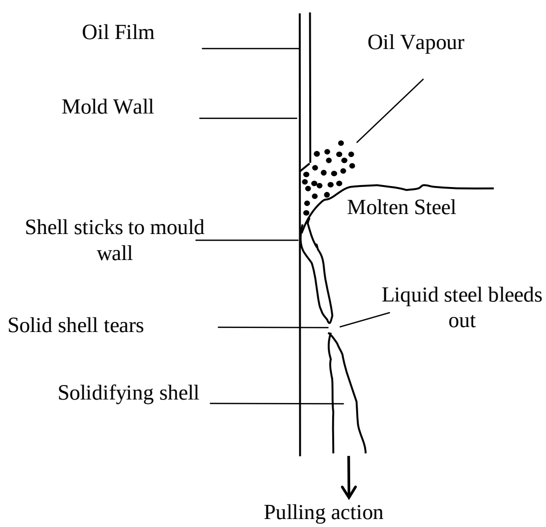
(a)
Metal level stable



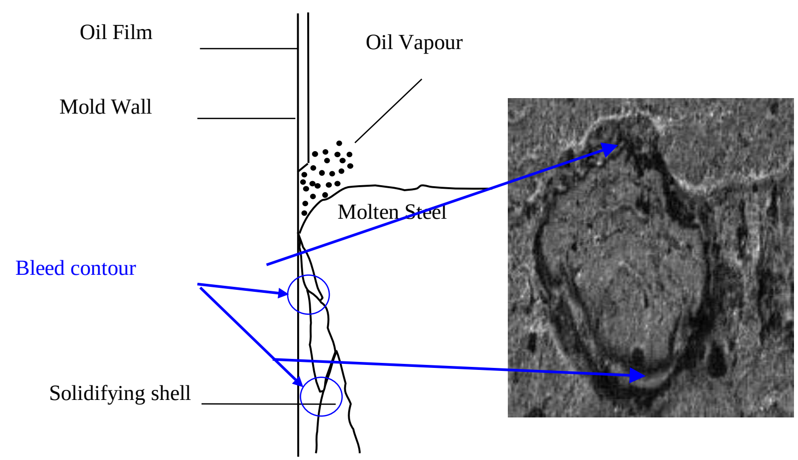
(b)
Metal level rises and evaporates oil on hot face, creating dry, unlubricated regions



(c)
Metal level falls through dry, unlubricated regions on the hot face and sticks to the wall while being pulled by the withdrawal rolls



(d)
Pulling force exerted by the withdrawal rolls causes the thin and weak shell to tear/rupture



(e)
Liquid steel bleeds out and solidifies on the mould wall to create a bleed on the billet surface

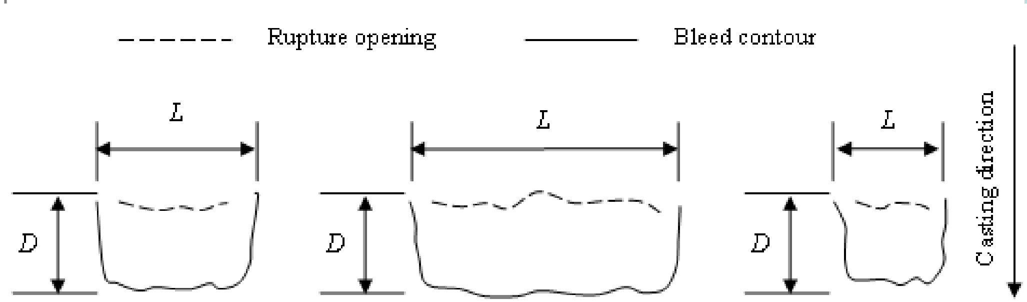
Estimation of the Range of Parameter D based on the Engineering Model

Estimation of geometric size of bleeds using engineering knowledge

$$t_{heal} = \frac{\rho_{liquid} \cdot c_p \cdot \left(T_{Liquid} - T_{solidus}\right)}{h_{gap} \cdot \left(T_{shell} - T_{mold}\right)} \cdot H_{\min} \quad \longrightarrow \quad \hat{D} = \int_{t=0}^{t=t_{heal}} \left\{ v(t) \cdot t \right\} dt$$

$$\text{where, } v(t) = \frac{1}{2\eta} \cdot \rho_{liquid} \cdot g \cdot H_{\min}^2 \left\{ 1 - \frac{32}{\pi^3} \sum_{k=1}^{\infty} \frac{(-1)^{k+1}}{(2k-1)^3} \cdot \exp\left[-\frac{(2k-1)^2 \pi^2}{4H_{\min}^2} \cdot \frac{\eta}{\rho_{liquid}} \cdot t \right] \right\}$$

Illustration of geometric size of bleed contours



L is a random variable, whose estimated range is needed in KRD algorithm.

D is estimated using the equations shown above

Screen-out with the number of connected pixels

The link module for transferring physical feature into pixel feature

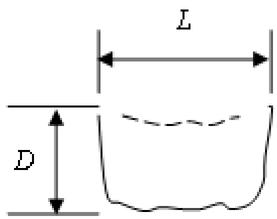
$\hat{D}$

$\hat{L}_{\min}$ $\hat{L}_{\max}$

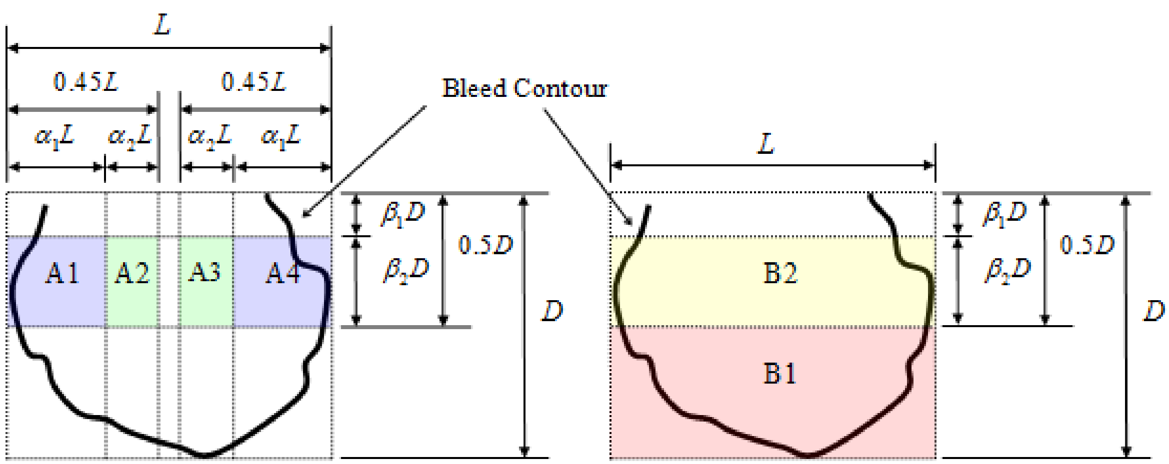
$$G(\hat{P}) = 260 \cdot \left(2 \cdot \hat{D}\right) + 160 \cdot \hat{L}$$

$\hat{\psi}_{\min}$

$\hat{\psi}_{\max}$



Link function coefficients determined by sensor settings, sensing condition, image scale, etc.

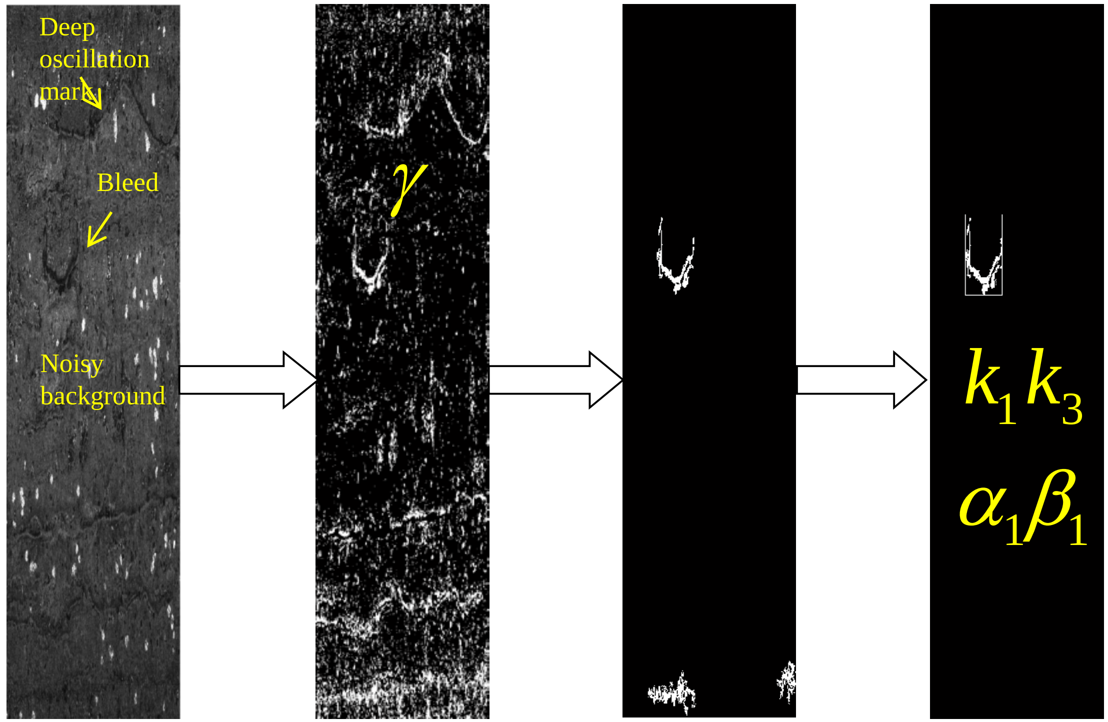


k_1 k_3 α_1 β_1

Key features are optimized through DOE with constraints given by physical models

Illustration of effectiveness

An illustrative sample showing how an original image is processed using KRD algorithm

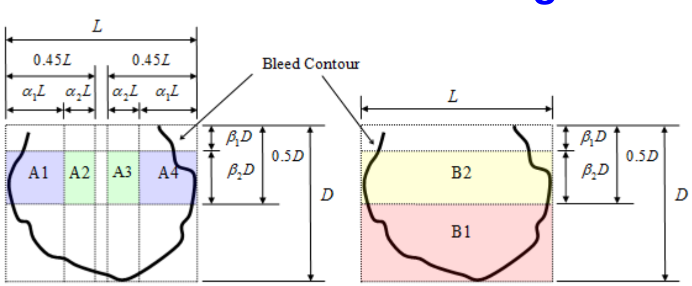


(a) Original Image

(b) Image processed by gray-level threshold

(c) Image processed by the number of connected pixels

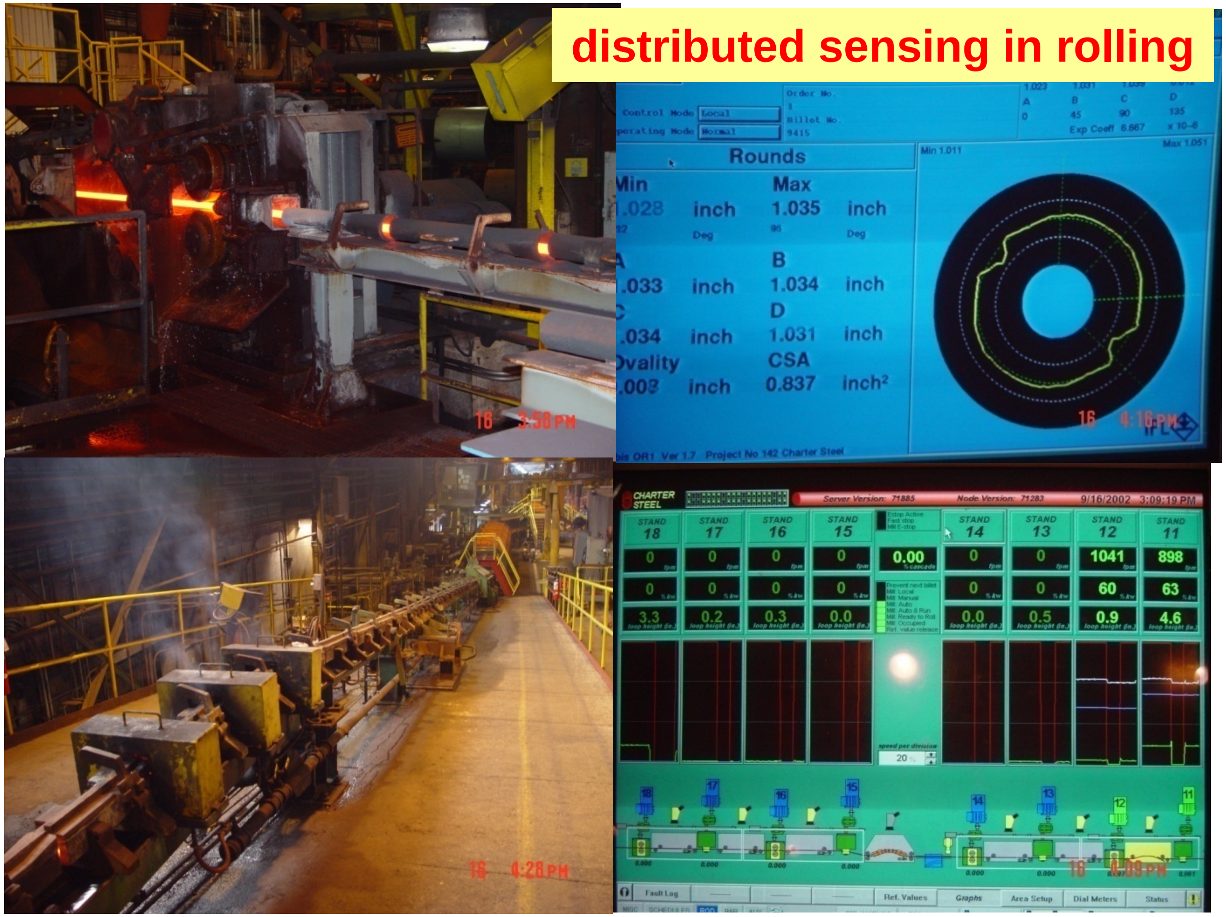
(d) Image processed by designed rules



Causation-based Quality Control

- Li, J., Jin, J., and Shi, J., 2008, "Causation-based T^2 Decomposition for Multivariate Process Monitoring and Diagnosis," *Journal of Quality Technology*, Vol. 40, No. 1, pp. 46-58
- 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*, 45, 630–643.
- Liu, K., Zhang, X. and Shi, J., 2013, "Adaptive Sensor Allocation Strategy for Process Monitoring and Diagnosis in a Bayesian Network", (in press) *IEEE Transactions on Automation Science and Engineering*. (This paper received Best Student Paper Award in the Industrial and Systems Engineering Research Conference (ISERC) 2013)

Massive Data Generated from Complex Mfg System

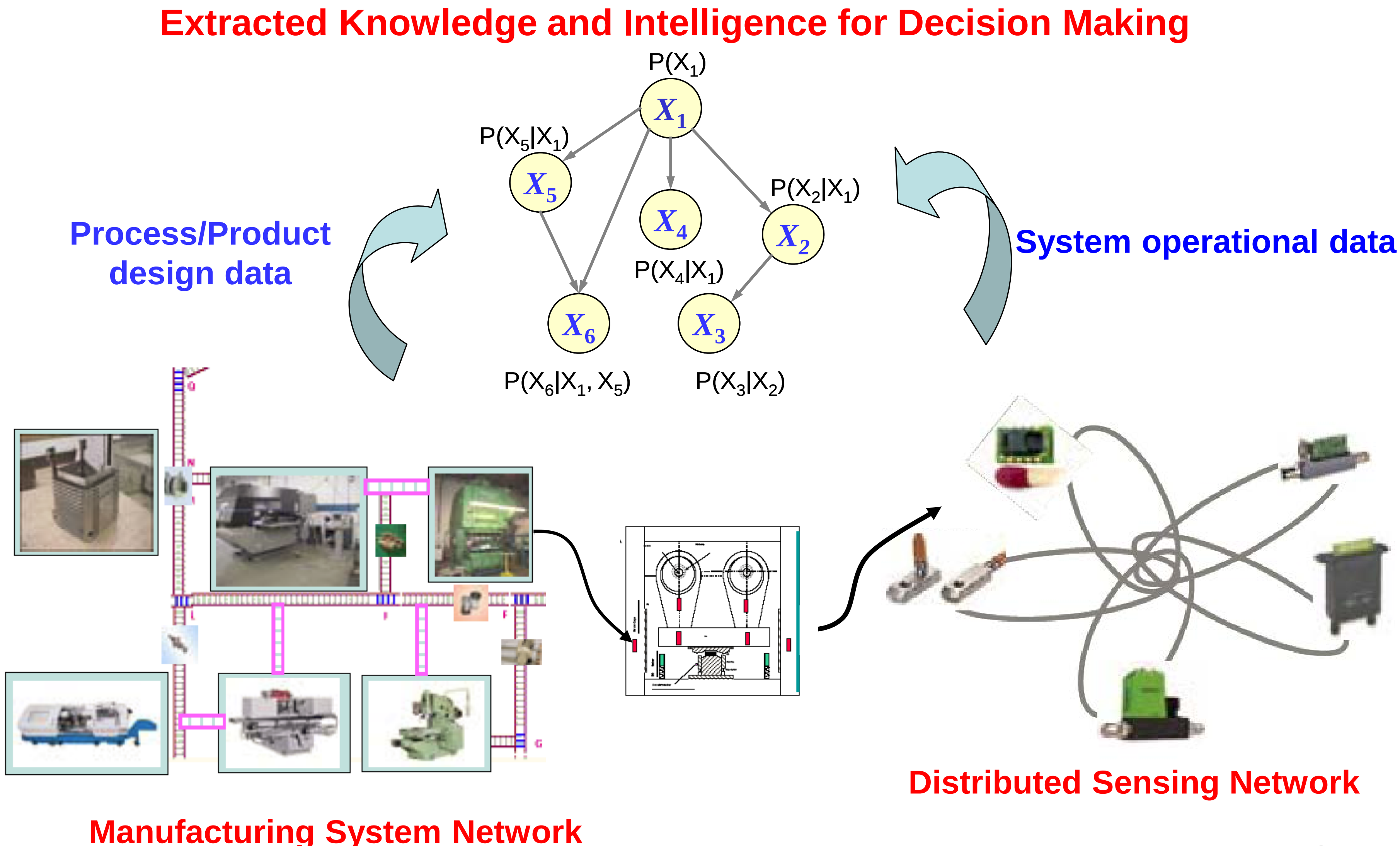


- 30 to 50 roller stations
- Each station has more than 10 typical variables (speed, temp, force, lub, etc…)
- Multiple data types with different level of uncertainties
- Complex interactions among the variables
- Multiple products produced in the same production systems
- Cost of quality/defects are HIGH!!!

Q1: How to model and analyze the multi-type, high dimension data with complex relationships?

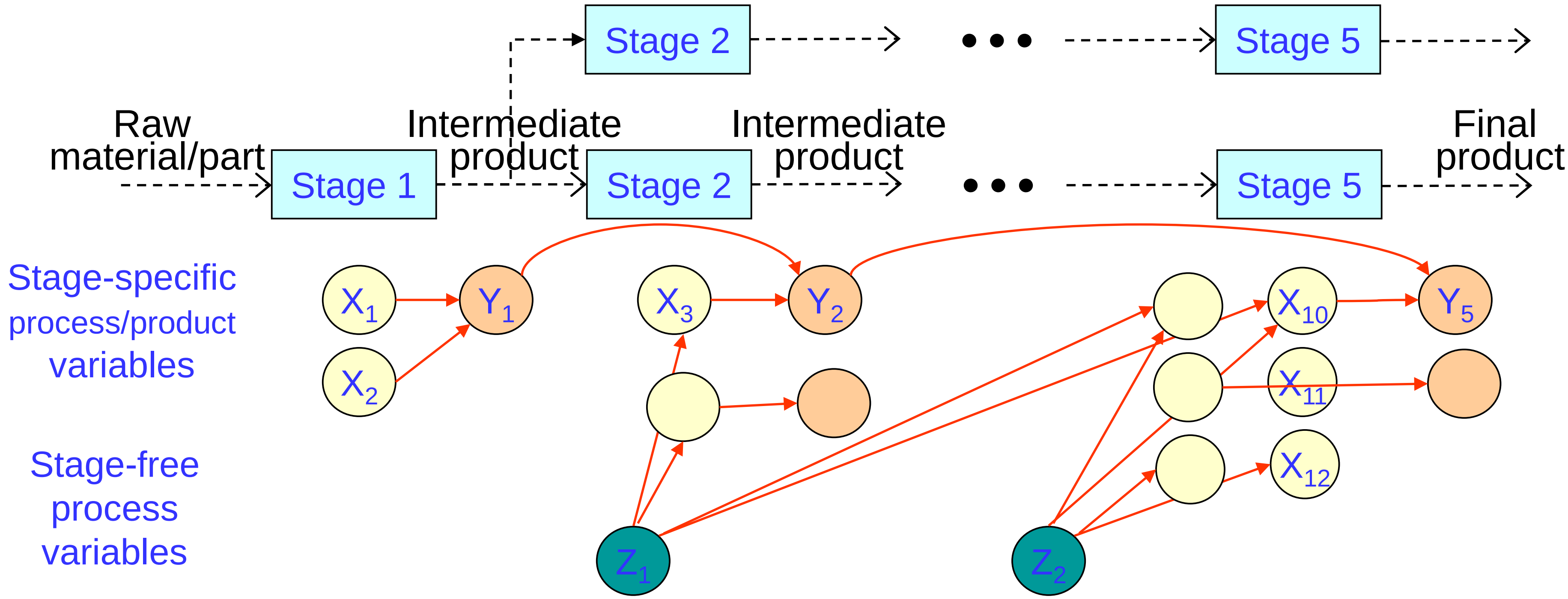
Q2: How to conduct effective process monitoring, root cause diagnosis and proactive control for quality improvements?

VISION: Three interrelated layers of networks:
- system, sensing, and decision making



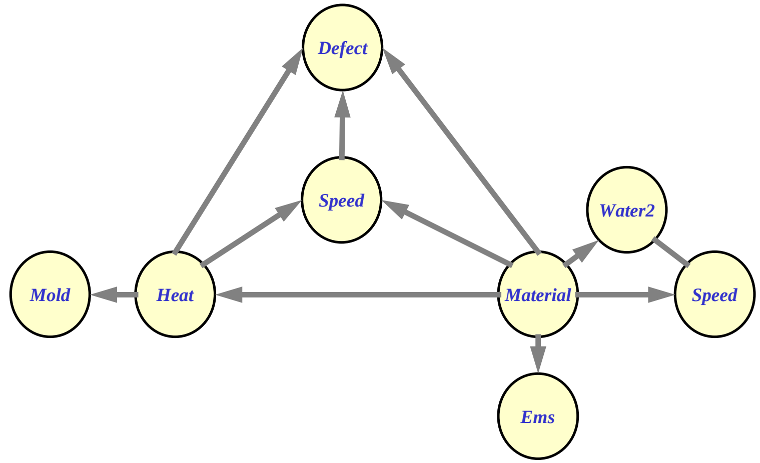
An illustrative example of multistage manufacturing process

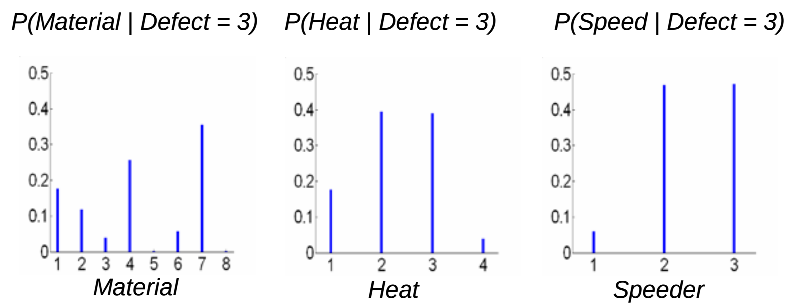
- A complex manufacturing system with
  - Numerous process/quality variables measured
  - Intricate relationships among them



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.

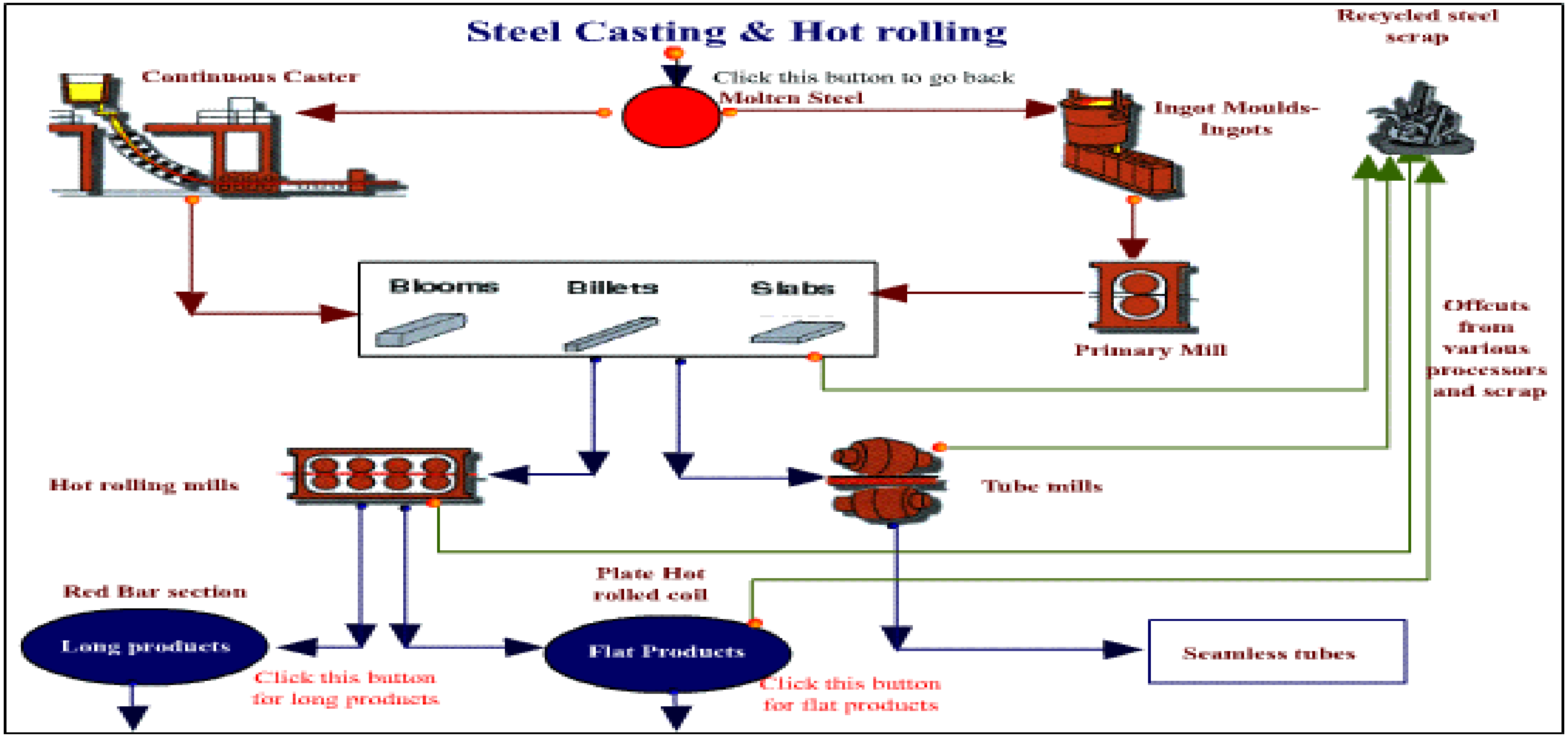
Li, J., Jin, J., and Shi, J., 2008, "Causation-based T^2 Decomposition for Multivariate Process Monitoring and Diagnosis," *Journal of Quality Technology*, Vol. 40, No. 1, pp. 46-58

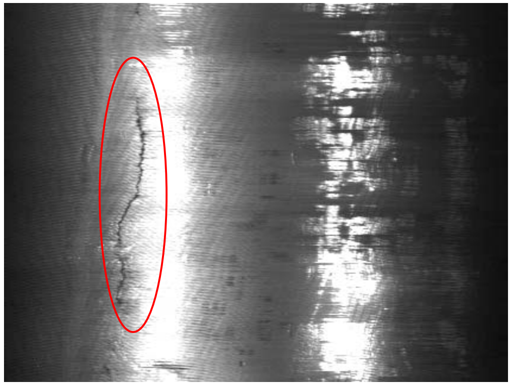
On-line Root Cause Diagnosis for Repeating Defect Pattern in Rolling

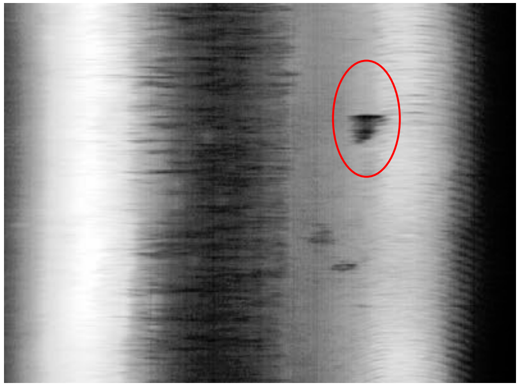
H. Jia and J. Shi, "On-line repeating fault pattern detection and its root cause diagnosis in hot rolling processes", *Technical Report, OGT, 2005*.

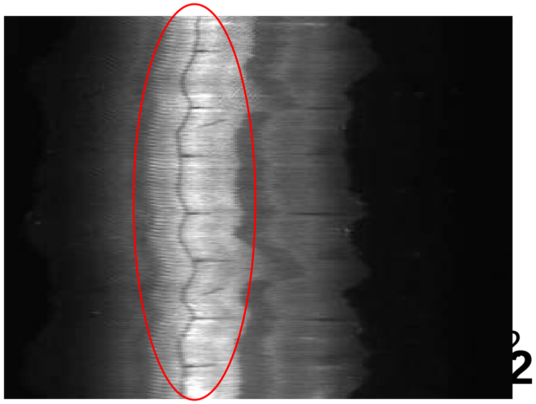
Hot Rolling Process and Surface Defect Images

(OGT and MacSteel)

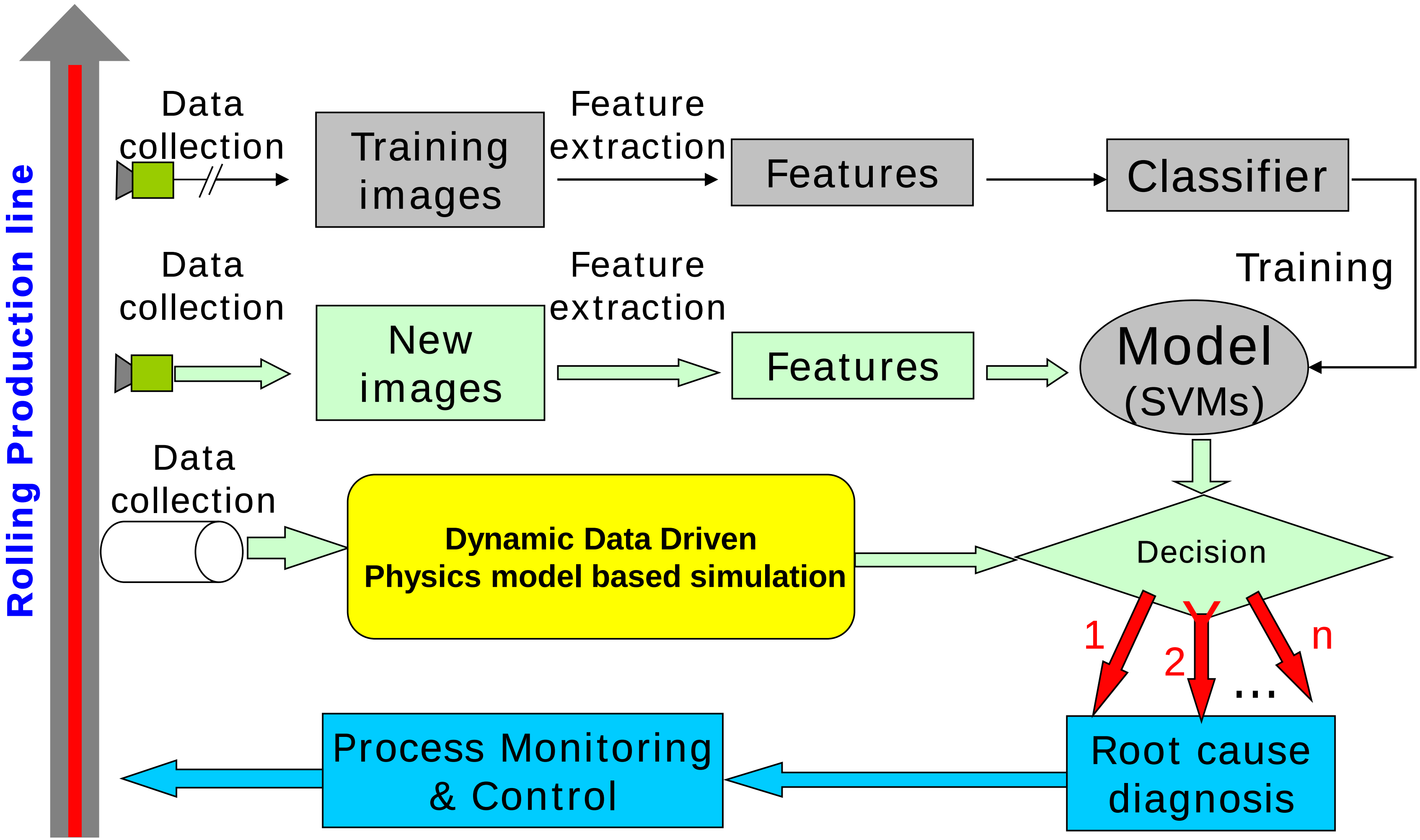








Overview of System Structure



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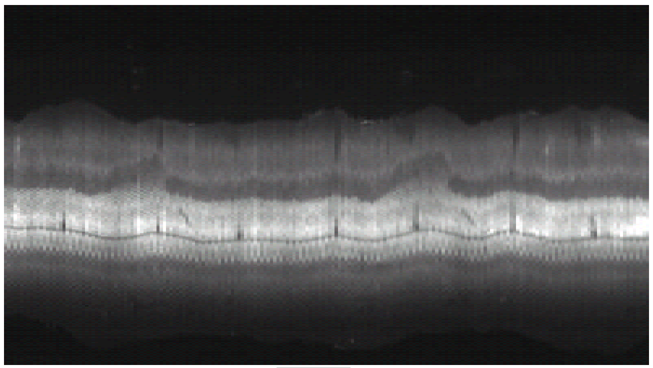
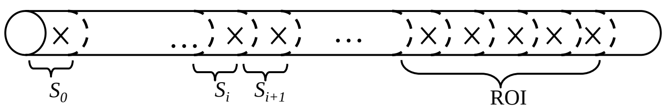
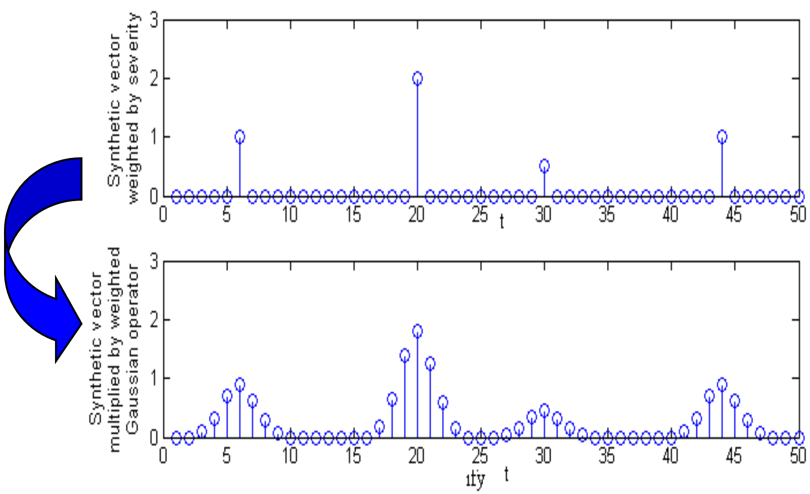
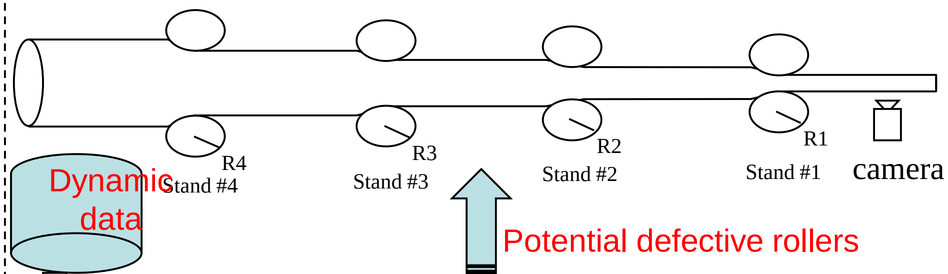
Real-time Dynamic Data Driven Simulation for Repeating Defect Pattern Detection





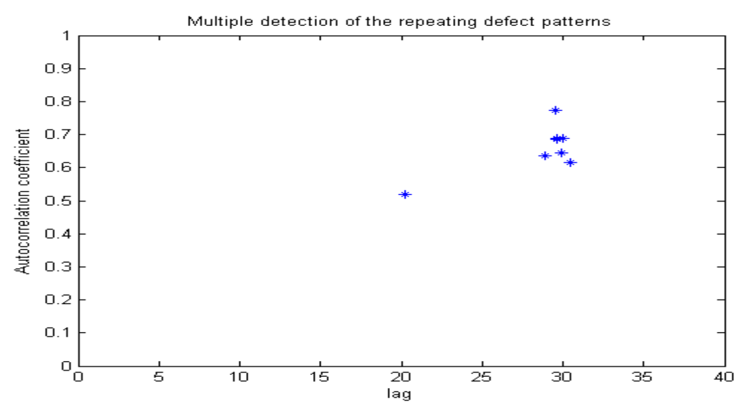




Potential defective rollers

Rolling compression Model

$$P = 2\pi R_i \prod_{k=i}^{N} (1 + ReductionRatio_i)$$



$$r_k = \frac{\sum_{i=1}^{n-k} (Y_i - \bar{Y})(Y_{i+k} - \bar{Y})}{\sum_{i=1}^{n} (Y_i - \bar{Y})^2}$$

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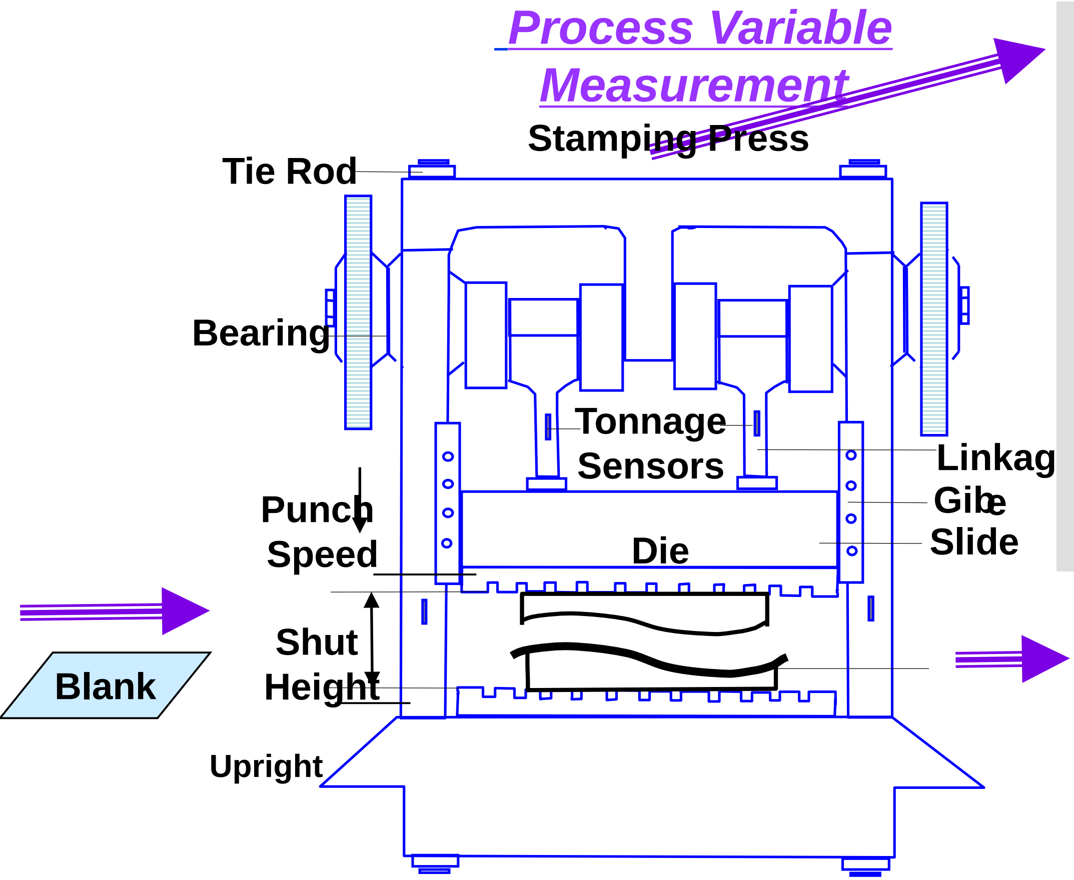
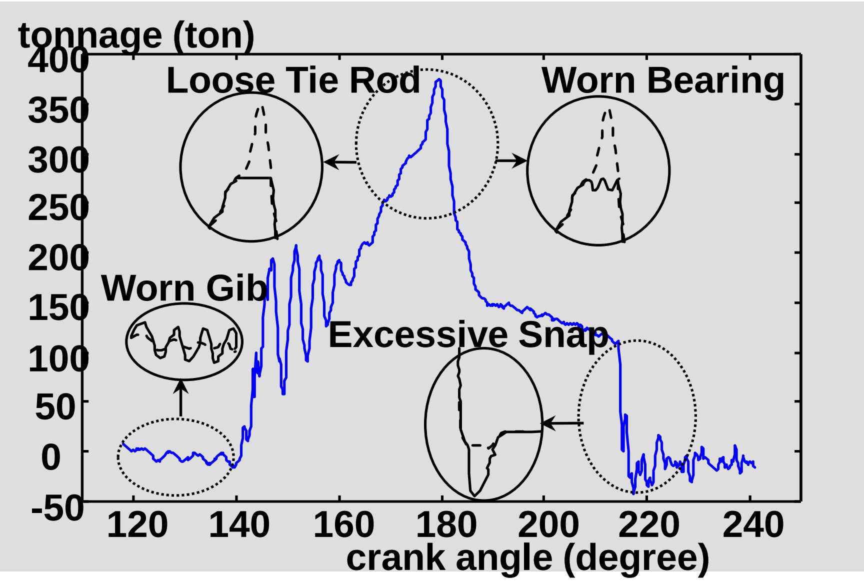
Signature Analysis for
On-line Cyclic Waveform Signals

1. *Koh, C.*, Shi, J. and Williams, W., 1995, "Tonnage Signature Analysis Using the Orthogonal (Harr) Transforms", NAMRI/SME Transactions, Vol. 23, pp229-234.
2. *Koh, C.*, Shi, J., and Black, J., 1996, "Tonnage Signature Attribute Analysis for Stamping Process", NAMRI/SME Transactions, Vol. 23, pp193-198.
3. *Koh, C.*, Shi, J., Williams, W., Ni, J., 1999, "Multiple Fault Detection and Isolation Using the Haar Transform - Part 1: Theory", ASME Transactions, Journal of Manufacturing Science and Engineering, Vol. 121, No.2, pp290-294.
4. *Koh, C.* , Shi, J., Williams, W., Ni, J., 1999, "Multiple Fault Detection and Isolation Using the Haar Transform - Part 2: Application to the Stamping Process", ASME Transactions, Journal of Manufacturing Science and Engineering, Vol. 121, No.2, pp295-299.
5. Jin, J. and Shi, J., 1999 "Feature-Preserving Data Compression of Stamping Tonnage Information Using Wavelets", Technometrics, Nov. 1999, Vol. 41, No.4, pp 327-339.
6. Jin, J., and Shi, J., 2000, "Diagnostic Feature Extraction from Stamping Tonnage Signals Based on Design of Experiment," ASME Transactions, Journal of Manufacturing Science and Engineering, Vol. 122, No. 2, pp.360-369.
7. Jin, J., and Shi, J., 2005, "Press Tonnage Signal Decomposition and Validation Analysis For Transfer or Progressive Die Processes", *ASME Transactions, Journal of Manufacturing Science and Engineering*, Vol. 127(1), pp. 231-235.
8. Jin, J. and Shi, J., 2001, "Automatic Feature Extraction of Waveform Signals for In-process Diagnostic Performance Improvement", Journal of Intelligent Manufacturing, Vol. 12, pp267-268.
9. Kim, J., Huang,Q., and Shi, J., 2008, "Latent Variable-based Key Process Variable Identification and Process Monitoring for Forging", *SME Transactions Journal of Manufacturing Systems.*Vol. 26, No. 1, pp53- 61.
10. Zhou, S., Sun, B., Shi, J., 2006, "An SPC Monitoring System for Cycle-Based Waveform Signals Using Haar Transform", *IEEE Transactions on Automation Science and Engineering*, Vol. 3(1), pp. 60-72.
11. Kim, J., Huang, Q., Shi, J., and Chang, T.-S., 2006, "Online Multi-Channel Forging Tonnage Monitoring and Fault Pattern Discrimination Using Principal Curve," *Transactions of the ASME, Journal of Manufacturing Science and Engineering*, Vol. 128, pp944-950, 2006.

Tonnage Signature Analysis for Stamping

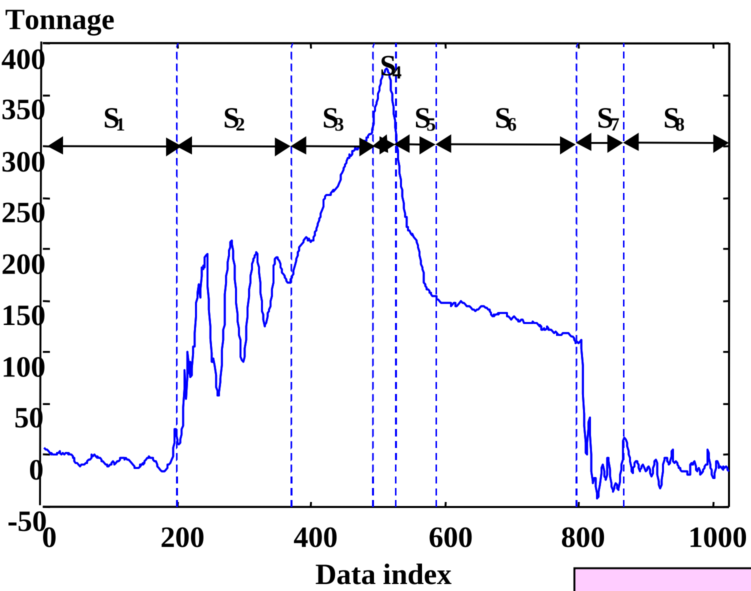




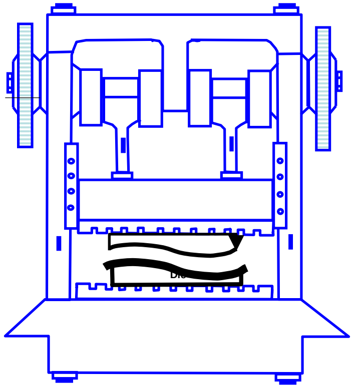
- High production rates (50 to 500 parts/minutes)
- Low throughput in part measurement and inspection
- Complex mfg process (40+ variables impact on quality)
- Lots of sensors installed in dies and presses for automation and die/press protection

Engineering-Driven Feature Extraction

Tonnage Data



Design Data



Domain Knowledge Data

Segment S_r	Crank Angle [Data Range]	Potential Process Faults	Fault Signal Characteristics	Resolution of Interest J_r (s=3)	P_r %
S_1: slide goes down	118.12°-141.76° [1,198]	gib chatter due to the excessive clearance	dominant low frequency component	J=6,5	5
S_2: blank hold & draw bid forming	141.88°-162.40° [199,370]	excessive dynamic interaction dependent on the nitrogen cushion system, working speed	1. transient rising edge dependent on the shut height and material thickness; 2. dominant frequency components dependent on the process dynamic characteristics; 3. signal mean value dependent on the nitrogen pressure setting, working speed	J=3,4,5,6,7	10
S_3: part drawing	162.52°-176.20° [371,485]	forming force sensitive to the material thickness	signal slope and curvature	J=3,4,5,6	5
S_4: slide close to bottom	176.32°-182.20° [486,535]	force change due to loose tie rod, worn bearing, shut height change, die worn-out;	shape and peak value change	J=3,4,5,6	2
S_5: slide leaving away from lower die	182.32°-188.20° [536,585]	force change sensitive to blank material properties (spring back)	signal slope and curvature	J=3,4,5,6	5
S_6: slide contacting lower binder	188.32°-213.40° [586,795]	force variation due to the nitrogen pressure change	no obvious periodic component, the mean value representing the nitrogen pressure.	J=3,4	5
S_7: slide leaving away from lower binder	213.52°-221.80° [796,865]	excessive snap due to the negative force generated by the die bounce at the time of nitrogen cushion released	the transient dropping edge sensitive to the shut height and material thickness, and the area of the negative force sensitive to die bounce degree	J=3,4,5,6,7	10
S_8: slide continuously going up	221.92°-240.88° [866,1024]	gib chatter	dominant low frequency component	J=5,6	5

$$C = WY \qquad Y = W^T C$$

$$Y(y_1, y_2, \ldots, y_n) \longrightarrow S_1\ S_2, \ldots, S_8$$

?

$$C\ (c_{00}, c_{10}, \ldots\ c_{n-1,2^{n-1}-1})$$

Feature Preserving Data Compression

Wavelets Analysis

Wavelet coefficients thresholding rules

Quantitative relationships between the wavelet thresholds and the detection power change in process monitoring

Data Fusion

Quantitative relationships between engineering specifications and the thresholds in wavelet domain

System Domain Knowledge

Signal feature specifications:
- time domain
  profile natural variability
- frequency domain
  characteristic freq. range

Detection Power Loss Analysis

$$\Delta D = \sqrt{n}\left(g(L - K\sqrt{n}) - g(-L - K\sqrt{n})\right) \cdot \Delta K$$

$$\Delta K = \Delta\mu / \sigma \qquad \Delta\mu = -\int_{-\lambda}^{\lambda} x g(x) dx$$

mapping thresholds

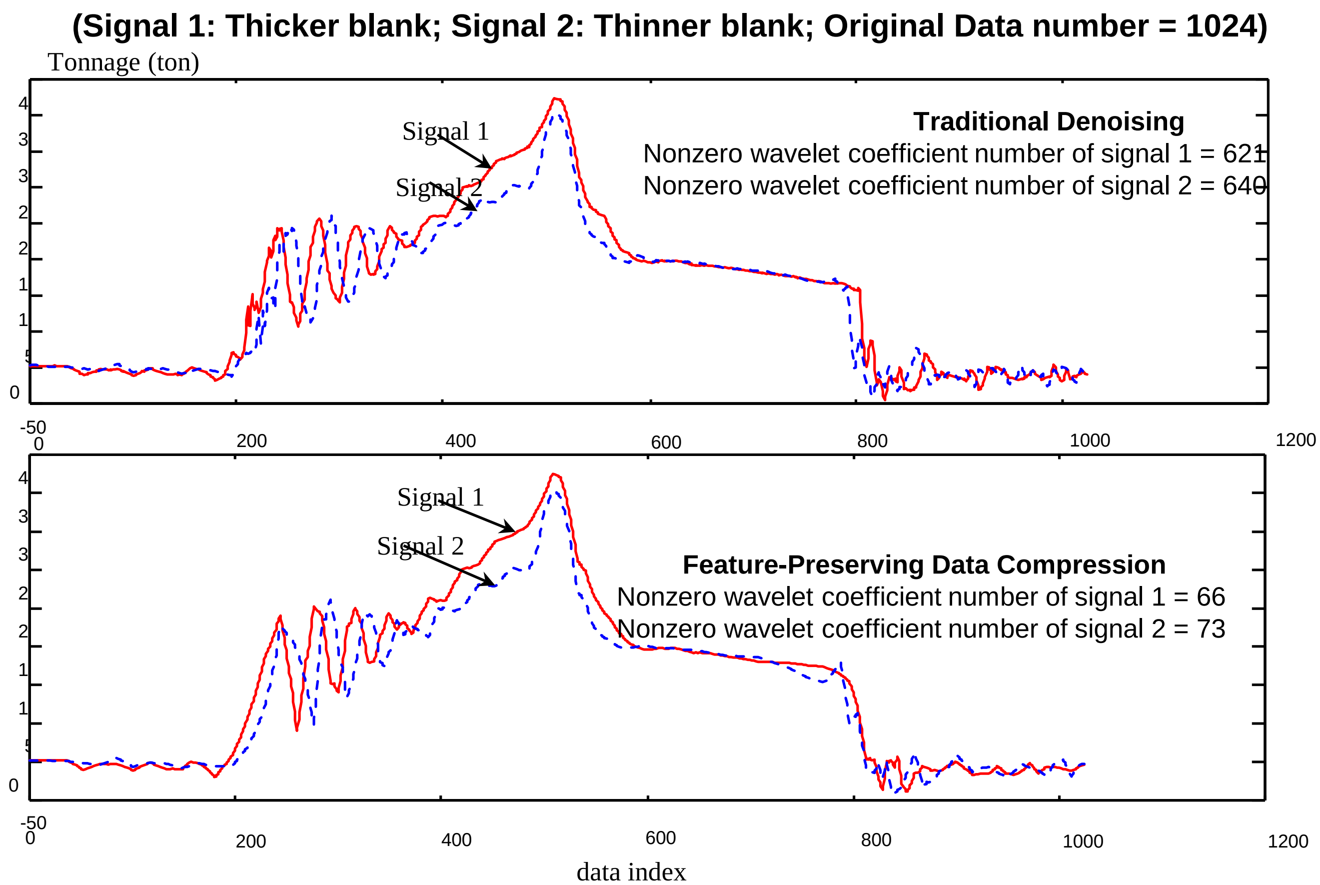
$$T^E = \begin{cases} c_{jk}, & \text{if } |c_{jk}| > \lambda^E \\ 0, & \text{if } |c_{jk}| \le \lambda^E \end{cases}$$

$$\lambda^E = \sup\left\{ \lambda \le \left[\frac{P \cdot \|\mathbf{C}^I\|^2}{n_z} \right]^{1/2} \right\}$$

$$P = \frac{\text{energy loss}}{\text{total energy}} = \frac{\|\mathbf{F}^I - \mathbf{F}^A\|^2}{\|\mathbf{F}^I\|^2} \times 100\%$$

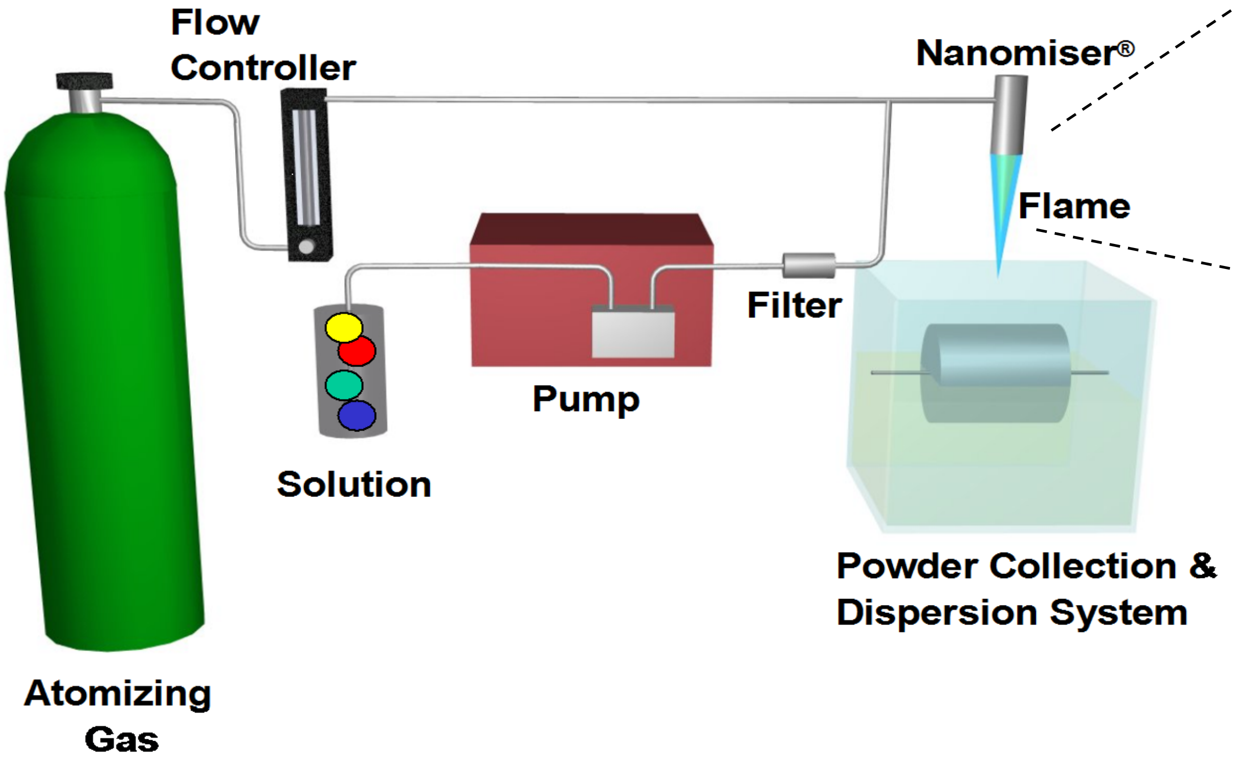
Jin and Shi, "Feature-Preserving Data Compression of Stamping Tonnage Information Using Wavelets," *Technometrics*, Nov.1999, Vol.41, No.4, pp.327-339.

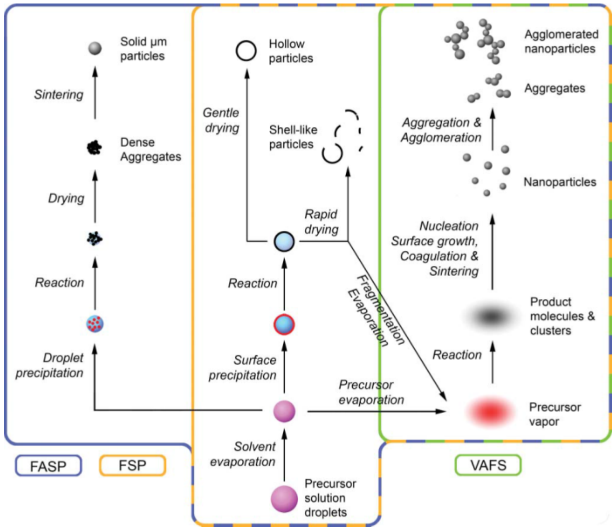
Feature Preserving Data Compression: Results



The detection power loss is 0.91% with and without feature-preserving data compression.

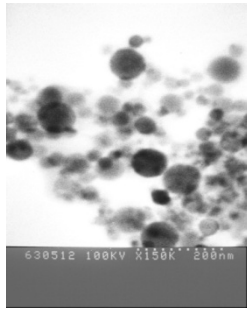
Nanopowder Manufacturing Process Control

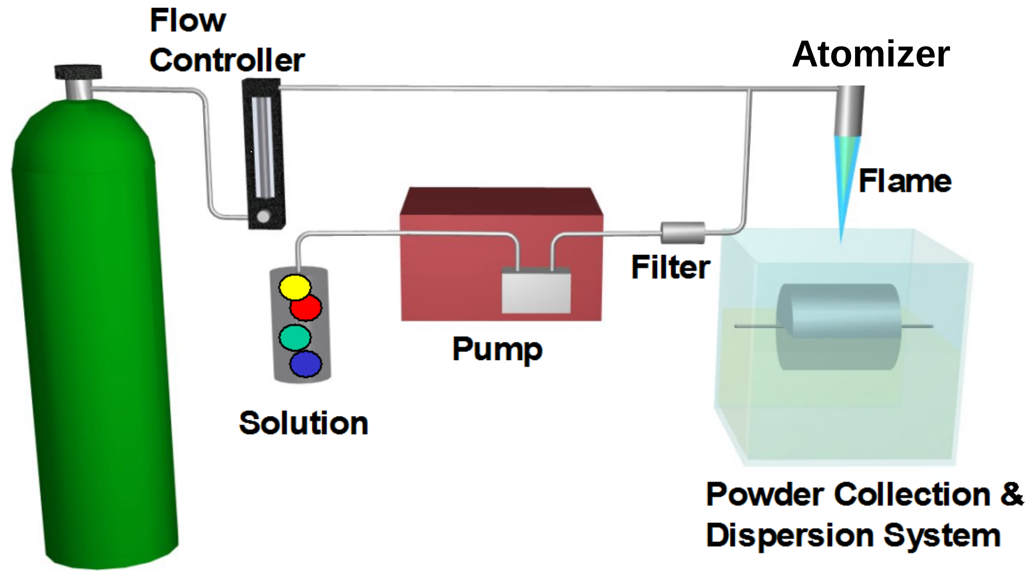




*Reference: Oljaca, M. et al. (2002), Flame synthesis of nanopowders via combustion chemical vapor deposition, Journal of materials science letters, 21, 621– 626.

Nanopowder Manufacturing Scale-up





Goal: 1kg/day to 1000kg/day

Challenges:

- Nano-metrology analysis for process control
- Variation propagation in multi-stage manufacturing process
- Process control capability

Engineering knowledge → Predictive Model Development

Data → **Statistical Model Calibration**

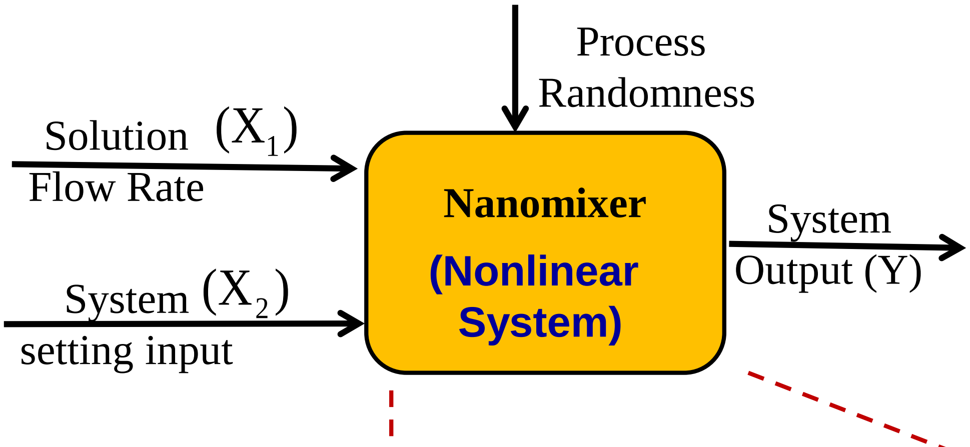
Control cost → Control & Evaluation

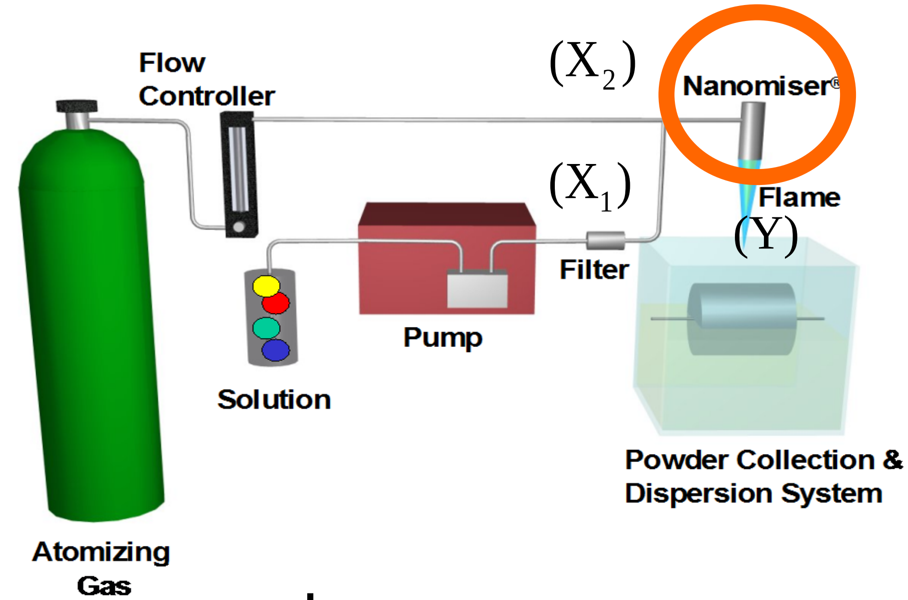
Quality Indices

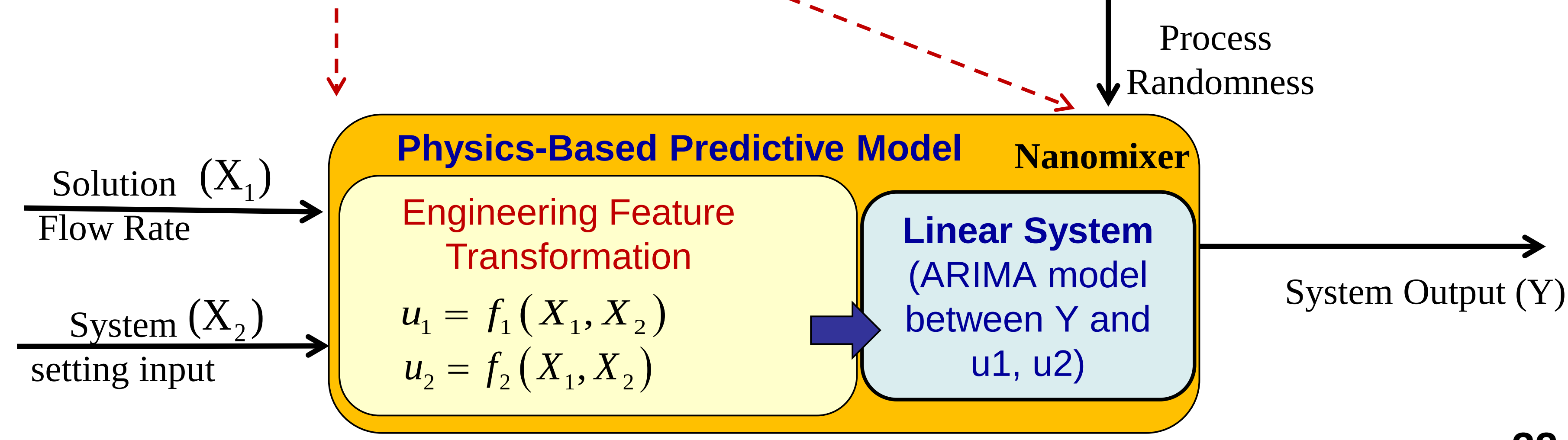
Chang, C. -J., Plumlee, M., Shi, J., 2011, "A predictive Model of Nanomiser Energy And Its Application In System Monitoring", Technical Report to Department of Energy and nGimat Company

Physics-based Feature Extraction & Predictive Model

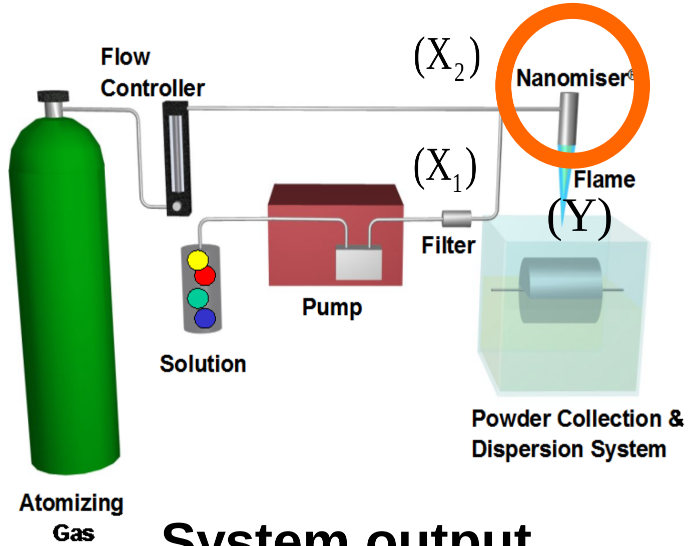
- **Objective: Translate and re-define the nonlinear dynamic system into linear model**



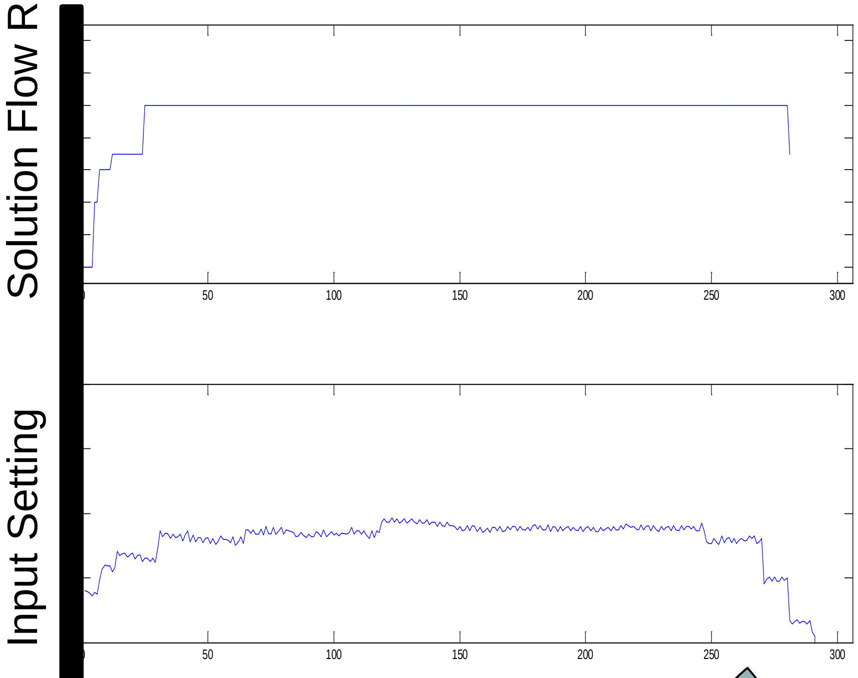




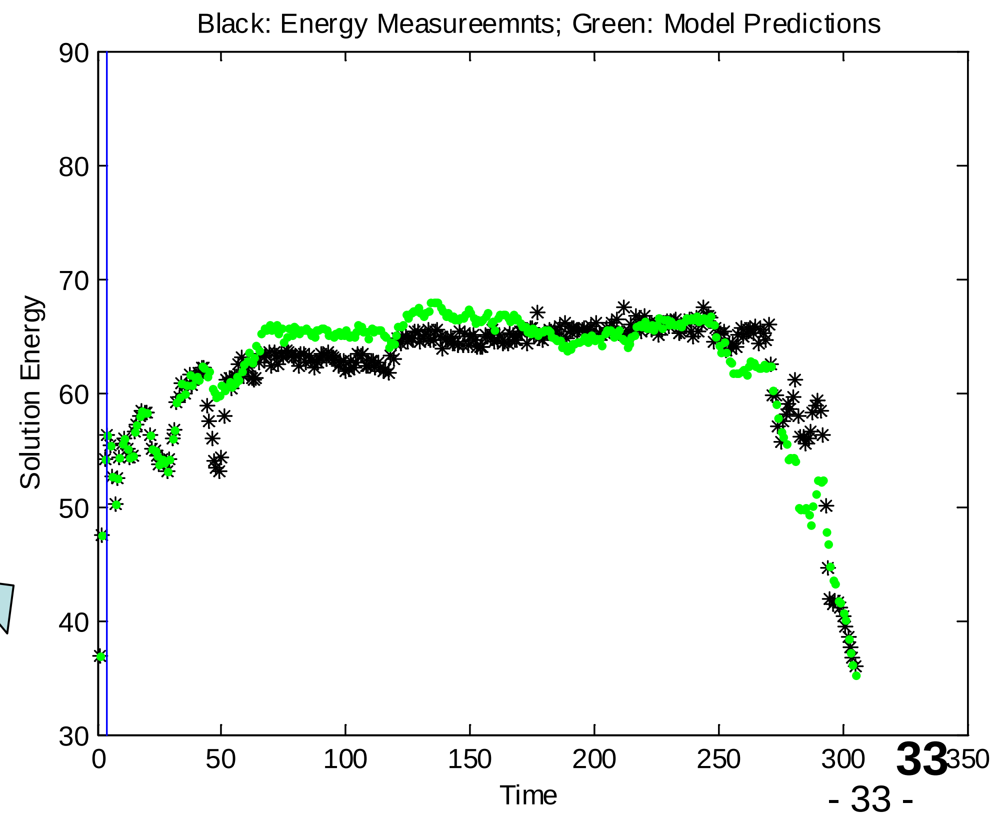
Physics-based Data-Driven Model Model Validation



System inputs



System output

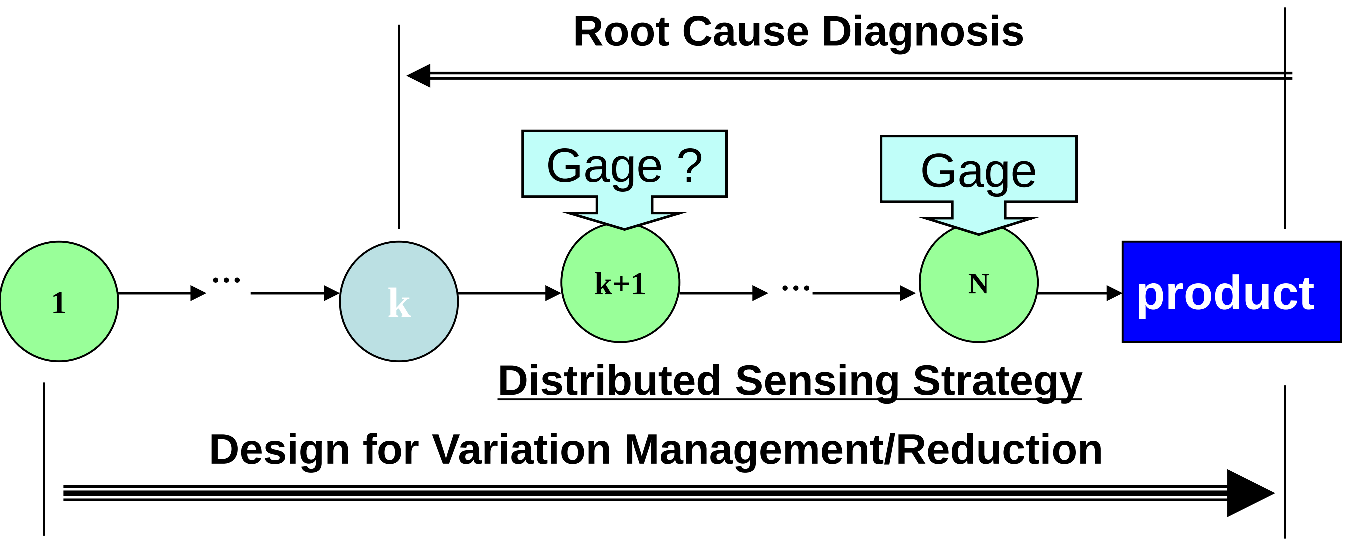


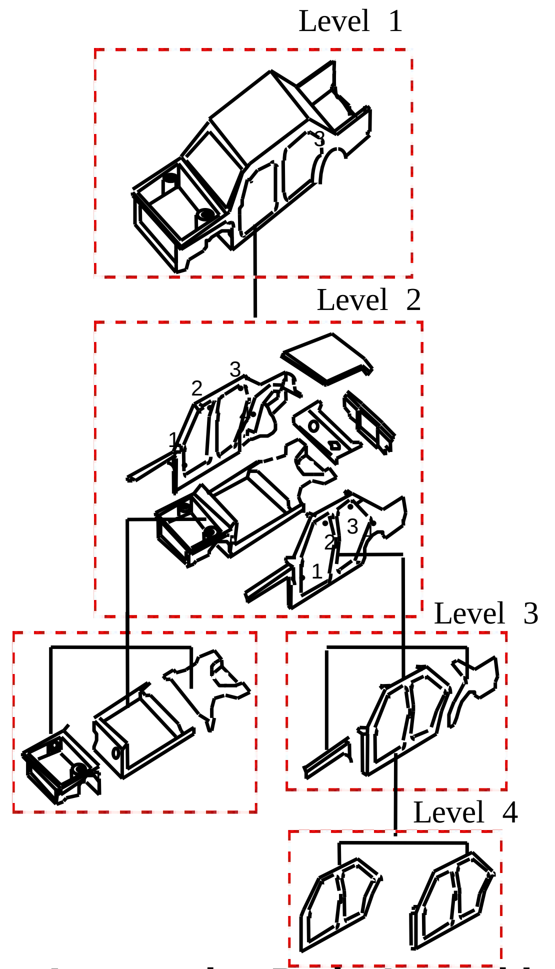
Stream of Variation Methodologies
for
Multistage Manufacturing Processes (MMP)

Shi, J. ***"Stream of Variation Modeling and Analysis for Multistage Manufacturing Processes***", CRC Press, 2006. 469pp.

Shi, J. and Zhou, S., 2009, "Quality Control and Improvement for Multistage Systems: A Survey", *IIE Transactions on Quality and Reliability Engineering*, Vol. 41, pp744-753.

Multistage System and Its Common Characteristics

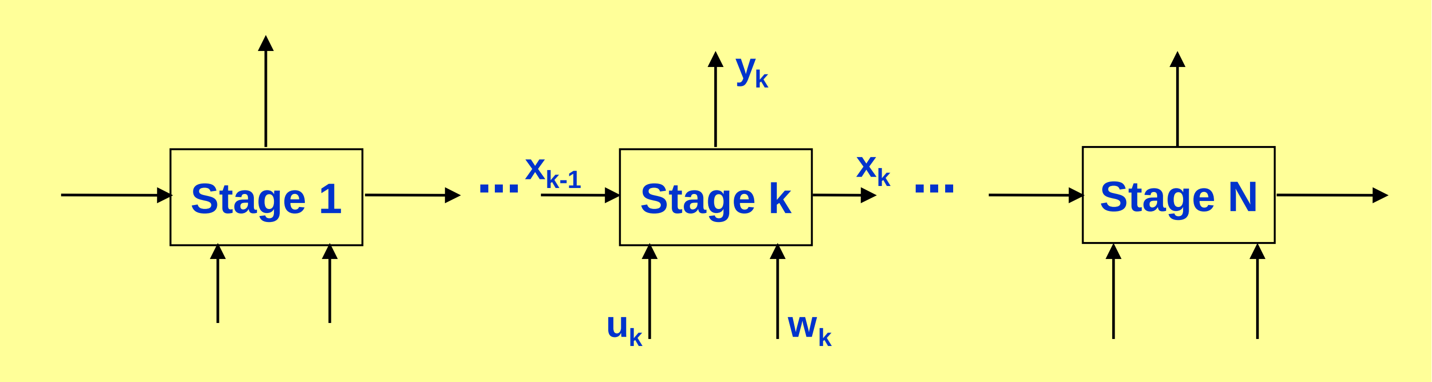




Automotive Body Assembly

- SoV Modeling: model variation and its propagation for MMPs
- Tolerance Synthesis: Allocate optimal tol. given final quality spcs.
- Root cause diagnosis: Find causes of product variability
- Distributed sensing: Select where and what to measure in a process
- Automatic compensation: Adjust tooling to ensure quality
- Optimal process design: design tooling and stages to minimize Var.

Basic Engineering Modeling Approach



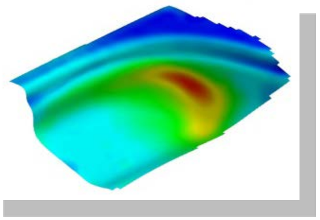
- **Variation Propagation Model**
  - System Equation: $x_k = A_{k-1}\, x_{k-1} + B_k\, u_k + w_k$ (k=1,2,…N)
  - Observation Equation: $y_k = C_k\, x_k + v_k$

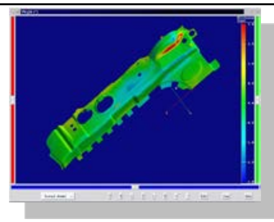
- **State Space Modeling:**
  - The variation propagation can be modeled as a state-space linear system where a machining stage plays the role of time

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, Nov. 1999, pp756-762.

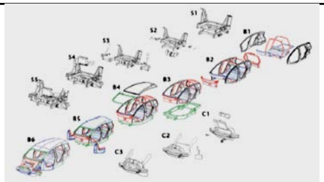
SoV Modeling for Multistage Mfg Processes

Product Design:
- Quality representation
- Critical features





Process Design:
- Relationship between workpiece and tooling
- Machine layout
- Process sequences



1 : Datum Error $\quad \mathbf{x}_{k-1} \xrightarrow{\mathbf{A}_{k-1}} \mathbf{x}_k$

2 : Fixture Error

3 : Machine Error $\quad \mathbf{u}_k \xrightarrow{\mathbf{B}_k} \mathbf{x}_k$

4 : Overall Error $\quad \mathbf{x}_k = \mathbf{A}_{k-1}\mathbf{x}_{k-1} + \mathbf{B}_k\mathbf{u}_k + \mathbf{w}_k$

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

Huang, Q., Zhou, S., Shi, J., 2002, "Diagnosis of Multi-Operational Machining Processes by Using Virtual Machining", Robotics and Computer Integrated Manufacturing, 18, pp.233 –239.

Zhou, S., Huang, Q., Shi, J., 2003, "State Space Modeling of Dimensional Variation Propagation in MMP Using Differential Motion Vectors", IEEE Transactions on R&A. 19(2),pp296-309.

Multidisciplinary Research:
- SoV Model-Based Multistage Process Control

System and Control Theory

Multivariate Statistical Analysis

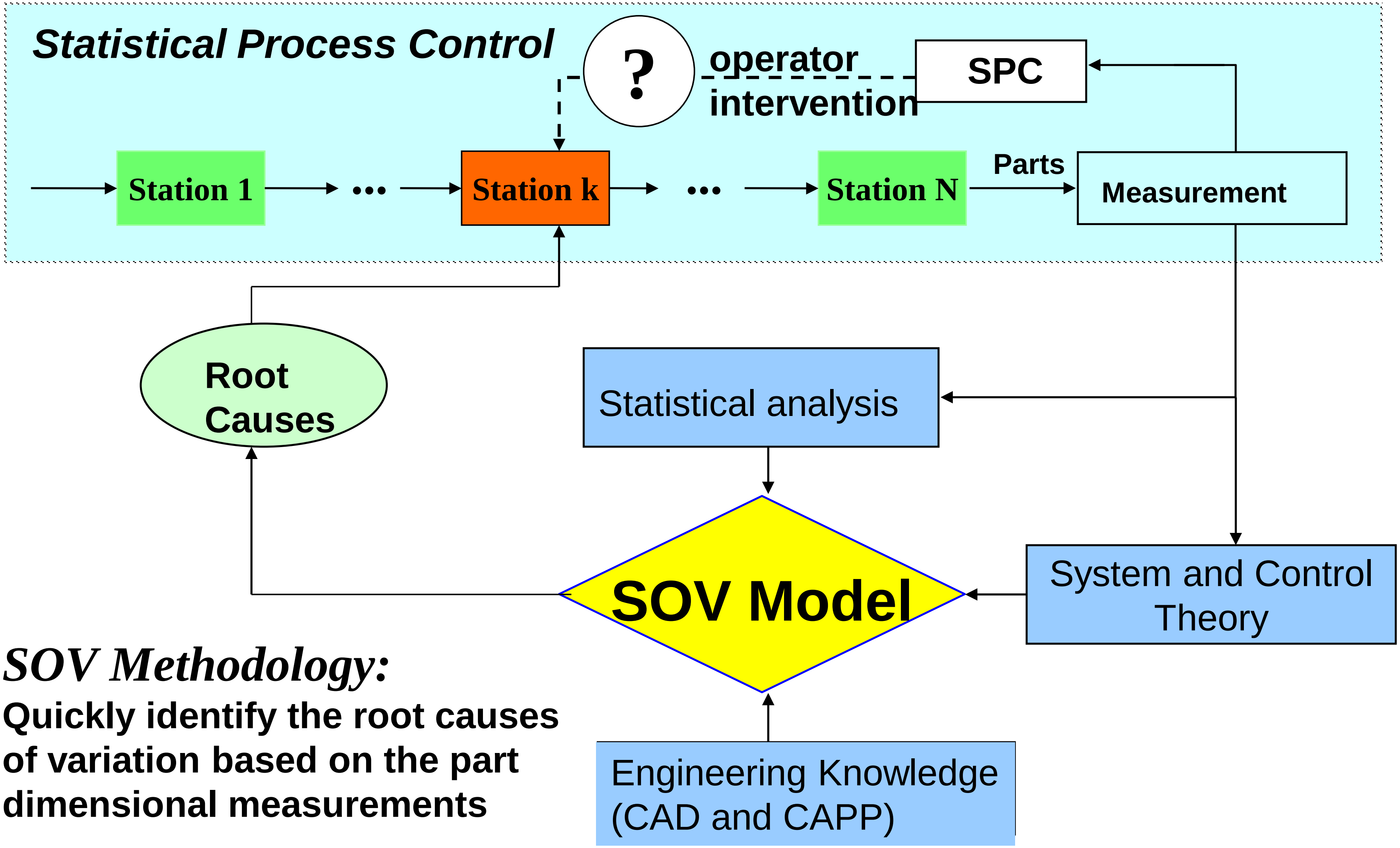
SoV-State Space Model

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

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.

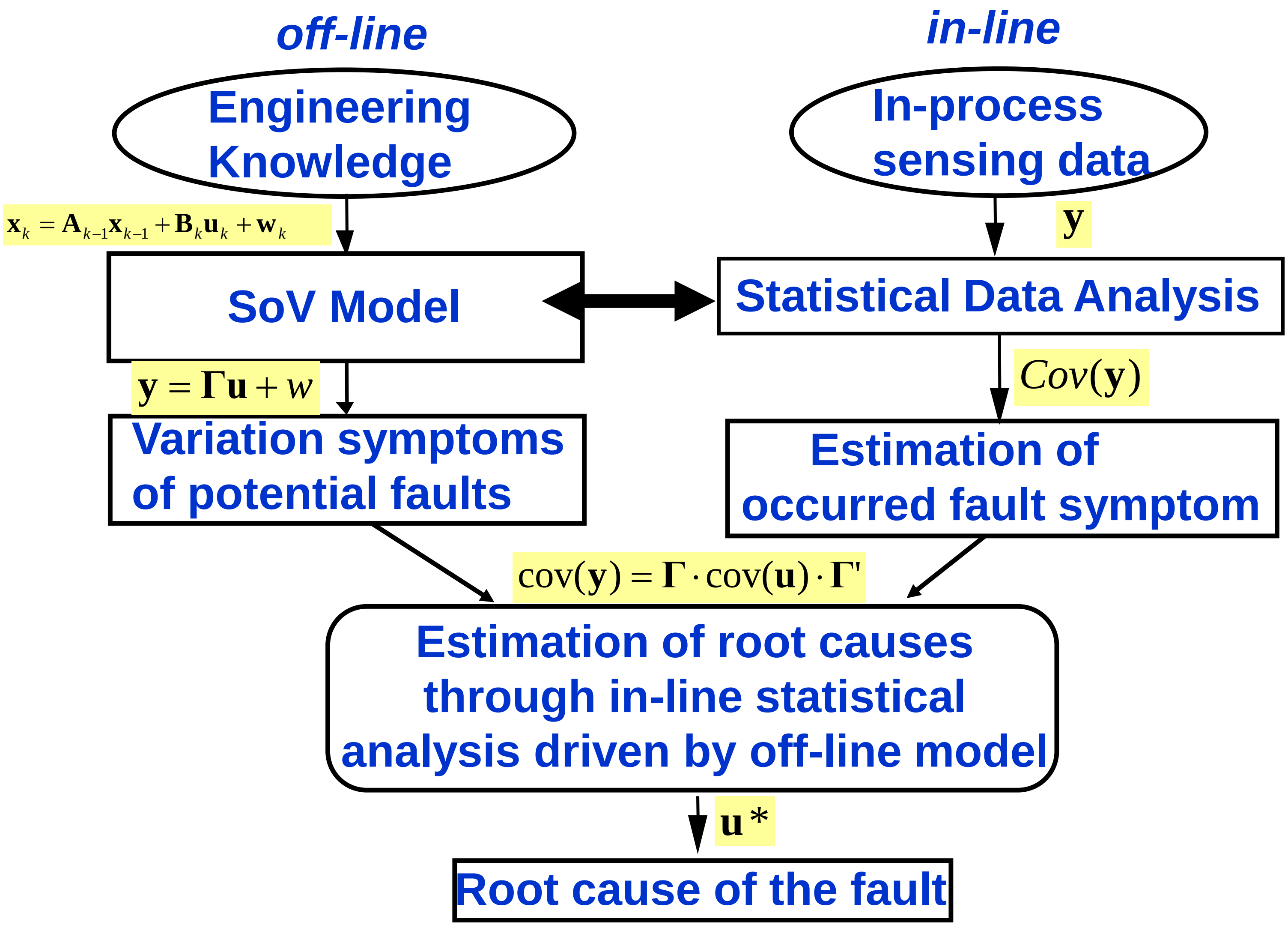
SPC vs. SOV – Based Diagnosis



SOV Methodology:

Quickly identify the root causes of variation based on the part dimensional measurements

Variation Pattern Based Diagnosis



Ding, Y., Ceglarek, D., and Shi, J. (2002), "Fault diagnosis of Multi-station Manufacturing Processes by Using State Space Approach," ASME Transactions, Journal of Manufacturing Science and Engineering, 124(2), pp. 313-322.

Estimation Based Root Cause Diagnosis

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

System and Control Theory

Input-Output Model:
$$\mathbf{y}_k = \sum_{j=1}^{k} \gamma_{kj}\boldsymbol{\mu}_j + \sum_{j=1}^{k} \gamma_{kj}\tilde{\mathbf{u}}_j + \sum_{j=1}^{k} \boldsymbol{\beta}_{kj}\mathbf{w}_j + \mathbf{v}_k$$
$$\text{where } \boldsymbol{\beta}_{kj} = \mathbf{C}_k\boldsymbol{\Phi}_{k,j},\ \gamma_{kj} = \mathbf{C}_k\boldsymbol{\Phi}_{k,j}\mathbf{B}_j$$

Linear Fault - Quality Model for Statistical Analysis:
$$\mathbf{Y}_i = \boldsymbol{\Gamma}\mathbf{U} + \boldsymbol{\Gamma}\tilde{\mathbf{U}}_i + \boldsymbol{\Psi}\mathbf{W}_i + \mathbf{V}_i$$

U: unknown constants, $\tilde{\mathbf{U}}_i$, $\mathbf{W}_i$, and $\mathbf{V}_i$ are zero mean independent random variables
Γ, Ψ are known constant matrices.

Zhou, S., Chen, Y., and Shi, J., 2004, "Root Cause Estimation and Statistical Testing for Quality Improvement of MMP", *IEEE Transactions on Automation Science and Engineering*, 1(1), pp73-83.

Ding, Y., Zhou, S., and Chen, Y., 2005, "A Comparison of Process Variation Estimators for In-Process Dimensional Measurements and Control", *ASME Transactions, Journal of Dynamic Systems, Measurement and Control,* 127, pp69-79.

Diagnosability study and distributed sensing

Consider the model $\mathbf{y} = \boldsymbol{\Gamma} \cdot \boldsymbol{\mu} + \boldsymbol{\Gamma} \cdot \tilde{\mathbf{u}} + \boldsymbol{\Psi} \cdot \mathbf{w} + \mathbf{v}$

Define the range space of a matrix as R(.), and D=[Γ Ψ]. For the mixed linear model

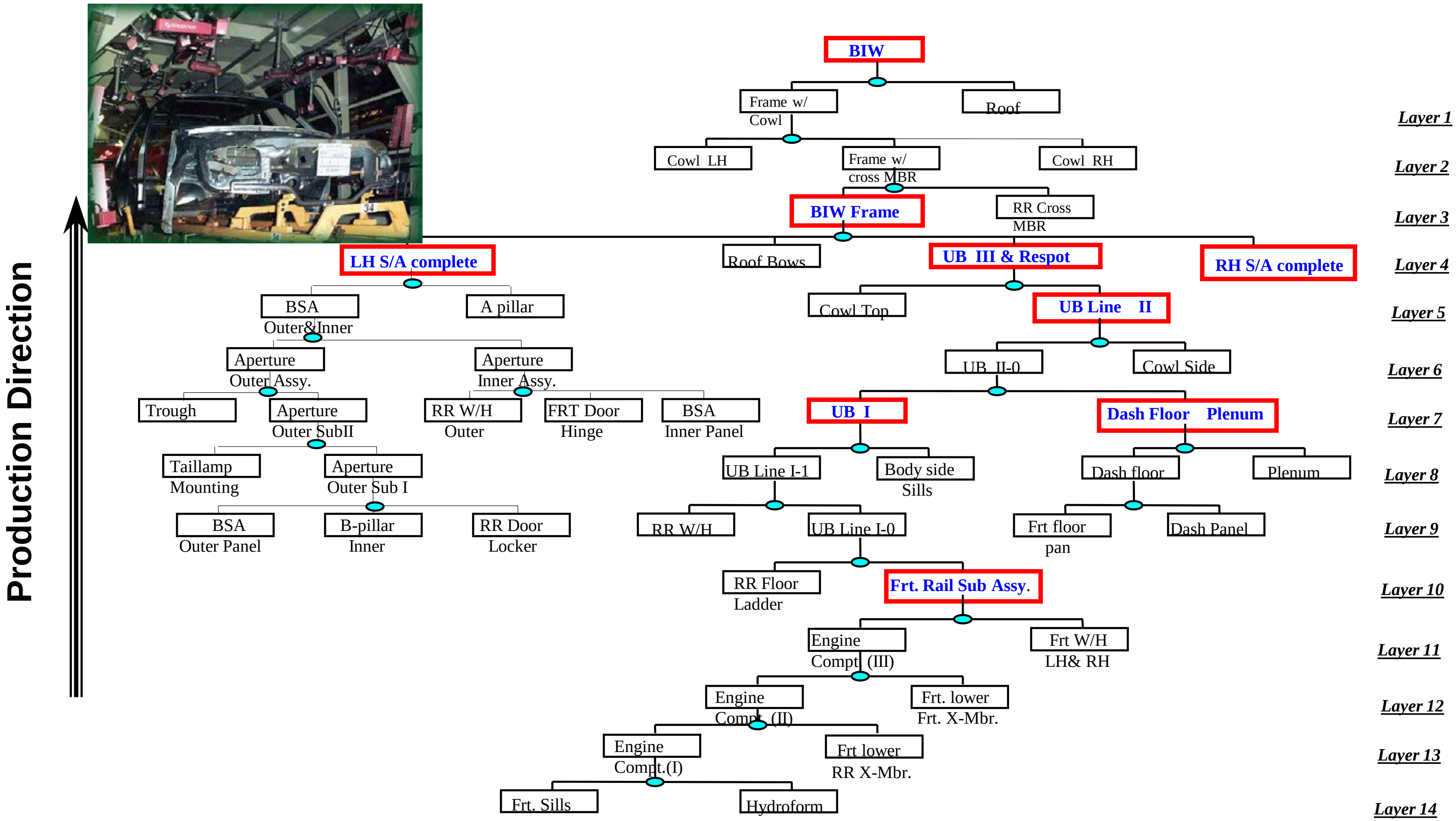
- $p^T\alpha$ is diagnosable if and only if $p \in R(\Gamma^T)$
- $f^T\theta$ is diagnosable if and only if $f \in R(H)$, where H is symmetric and given as

$$\mathbf{H} = \begin{bmatrix} (\mathbf{D}_{:1}^T\mathbf{D}_{:1})^2 & \cdots & (\mathbf{D}_{:1}^T\mathbf{D}_{:i})^2 & \cdots & (\mathbf{D}_{:1}^T\mathbf{D}_{:(P+Q)})^2 & \mathbf{D}_{:1}^T\mathbf{D}_{:1} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ (\mathbf{D}_{:i}^T\mathbf{D}_{:1})^2 & \cdots & (\mathbf{D}_{:i}^T\mathbf{D}_{:i})^2 & \cdots & (\mathbf{D}_{:i}^T\mathbf{D}_{:(P+Q)})^2 & \mathbf{D}_{:i}^T\mathbf{D}_{:i} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ (\mathbf{D}_{:(P+Q)}^T\mathbf{D}_{:1})^2 & \cdots & (\mathbf{D}_{:(P+Q)}^T\mathbf{D}_{:i})^2 & \cdots & (\mathbf{D}_{:(P+Q)}^T\mathbf{D}_{:(P+Q)})^2 & \mathbf{D}_{:(P+Q)}^T\mathbf{D}_{:(P+Q)} \\ \mathbf{D}_{:1}^T\mathbf{D}_{:1} & \cdots & \mathbf{D}_{:i}^T\mathbf{D}_{:i} & \cdots & \mathbf{D}_{:(P+Q)}^T\mathbf{D}_{:(P+Q)} & \mathbf{N} \end{bmatrix}$$

where N is the number of replicated samples

Zhou, S., Ding, Y, Chen, Y., Shi, J., "Diagnosability Study of Multistage Manufacturing Processes Based on Linear Mixed-effects Models", *Technometrics.* 2003. Vol. 45, No.4, pp 312-325.

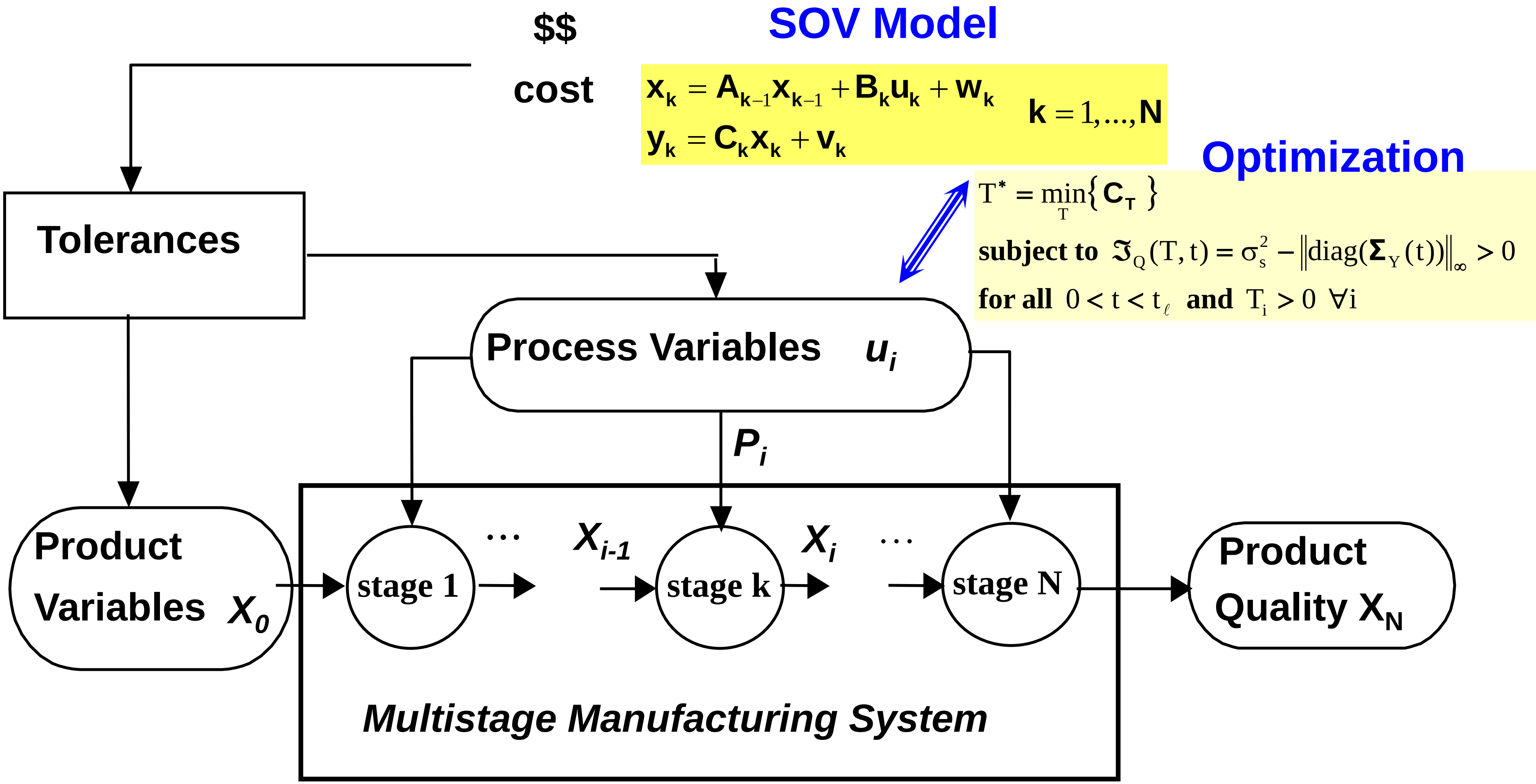
Distributed Sensing Strategy and Evaluation



Total 9 OCMM stations, 375 sensors

Ding, Y., Shi, J., and Ceglarek, D. (2002), "Diagnosability Analysis of Multi-station Manufacturing Processes," ASME Transactions, Journal of Dynamic Systems, Measurement, and Control, 124 (1), pp. 1-13.

Process-oriented Tolerancing Synthesis

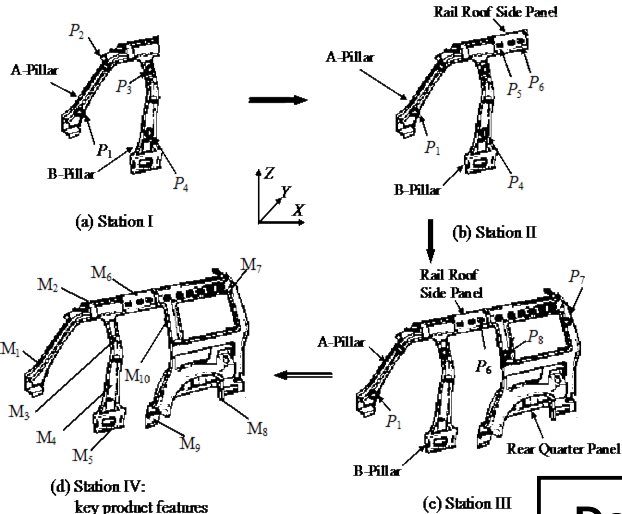


Ding, Y., Jin, J., Ceglarek, D., and Shi, J., (2005), "Process-oriented Tolerancing for Multi-station Assembly Systems," *IIE Transactions*, 37(6), pp. 493-508. (also Proceedings of IMEAC, 2000)

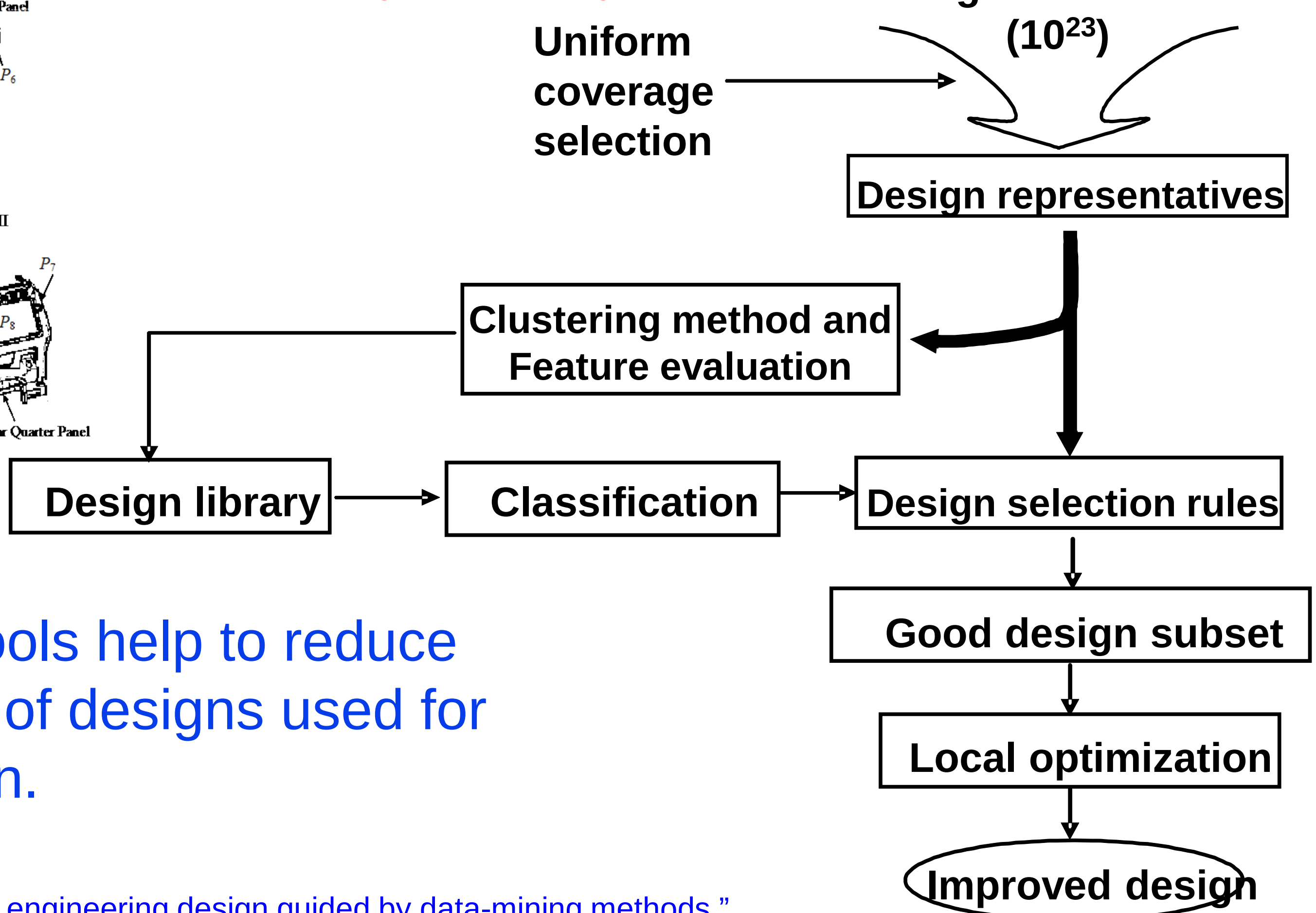
Huang, Q., Shi, J., 2003, "Simultaneous Tolerance Synthesis through Variation Propagation Modeling of Multistage Manufacturing Processes," *NAMRI/SME Transactions*, 31, pp. 515-522.

Data-mining Aided Design for Fixture Layout Optimization

Problem: Fixture Layout Optimization



Proposed Solution:
Data Mining Aided Design



- Statistical tools help to reduce the number of designs used for classification.

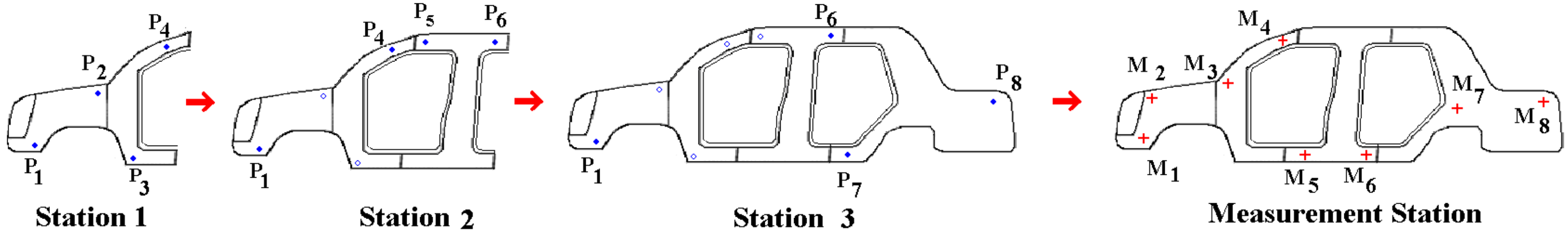
Kim, P. and Ding, Y., 2005, “Optimal engineering design guided by data-mining methods,” *Technometrics*, Vol. 47(3), pp. 336-348

Ding, Y., Ceglarek, D., and Shi, J. (2002), “Design Evaluation of Multi-station Manufacturing Processes by Using State Space Approach,” *ASME Transactions, Journal of Mechanical Design*, 124(4), pp. 408 –418.

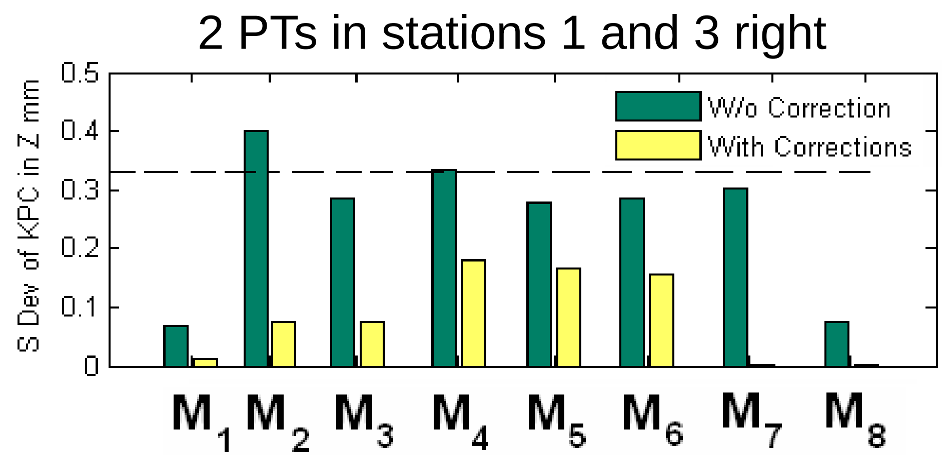
Active Control and Compensation in MMP

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

- Assemble 4 parts in 3 stations



$$J = \min_{\mathbf{u}_k} \ \hat{\mathbf{y}}_{N/k} \cdot \mathbf{Q} \cdot \hat{\mathbf{y}}_{N/k}^T$$
$$\text{s.t.} \quad \hat{\mathbf{y}}_{N/k} \in [LSL, \mathrm{USL}]$$
$$\mathbf{u}_{\min} \le \mathbf{u}_{ck} \le \mathbf{u}_{\max}$$
$$\mathbf{u}_{ck} = \begin{cases} \mathbf{u}_{ck} & \text{if } |\mathbf{u}_{ck}| > \Delta_u \\ 0 & \text{otherwise} \end{cases}$$



Eduardo Izquierdo, J. Zhong, J. Shi, J. Hu, (2004) "Adaptive Control of Assembly Quality Using Programmable Tooling", GM CRL Workshop

Wang, H., and **Huang, Q**., 2005, "Error Cancellation Modeling and Its Application in Machining Process Control," *Accepted by IIE Transactions on Quality and Reliability.*

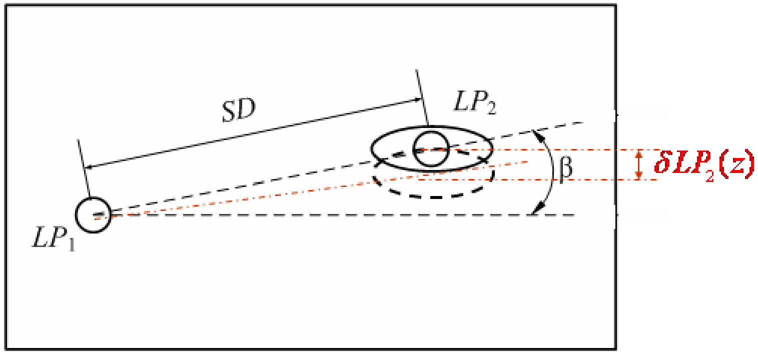
Cautious control strategy considering modeling error

$$J_k^* = \min_{\mathbf{u}_k} J_k = \min_{\mathbf{u}_k} E\left[\mathbf{y}_{N/k}^T \mathbf{Q}_N \mathbf{y}_{N/k} + \mathbf{u}_k^T \mathbf{R}_k \mathbf{u}_k\right]$$

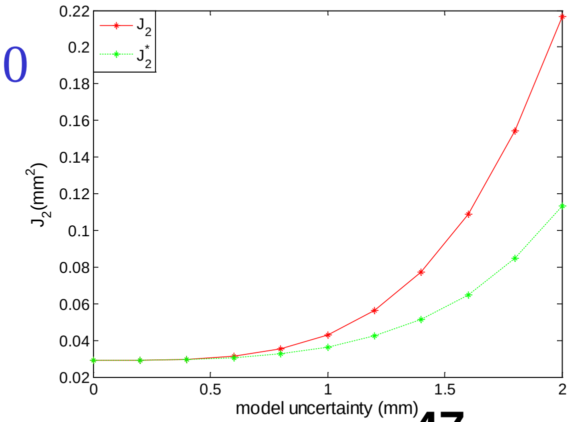
$$s.t.\ \mathbf{u}_{k+i} = 0,\ 1 < i < N-k$$

- **SoV model with uncertainty**

$$\begin{cases} \mathbf{x}_k = \left(\mathbf{A}_{k-1} + \tilde{\mathbf{A}}_{k-1}\right)\mathbf{x}_{k-1} + \left(\mathbf{B}_k + \tilde{\mathbf{B}}_k\right)\mathbf{u}_k + \mathbf{w}_k \\ \mathbf{y}_k = \left(\mathbf{C}_k + \tilde{\mathbf{C}}_k\right)\mathbf{x}_k + \mathbf{v}_k \end{cases}$$



- **Cautious control strategy**
  - **Minimum should be achieved at** $\dfrac{dJ_k}{d\mathbf{u}_k} = 0$
  - **Solution:** $\mathbf{u}_k = f\left(\mathbf{\Gamma}_i, \mathbf{u}_i, \mathbf{x}_s, \mathrm{var}\left(LP_i\right)\right),\quad i \le k$
- **Case study performance**



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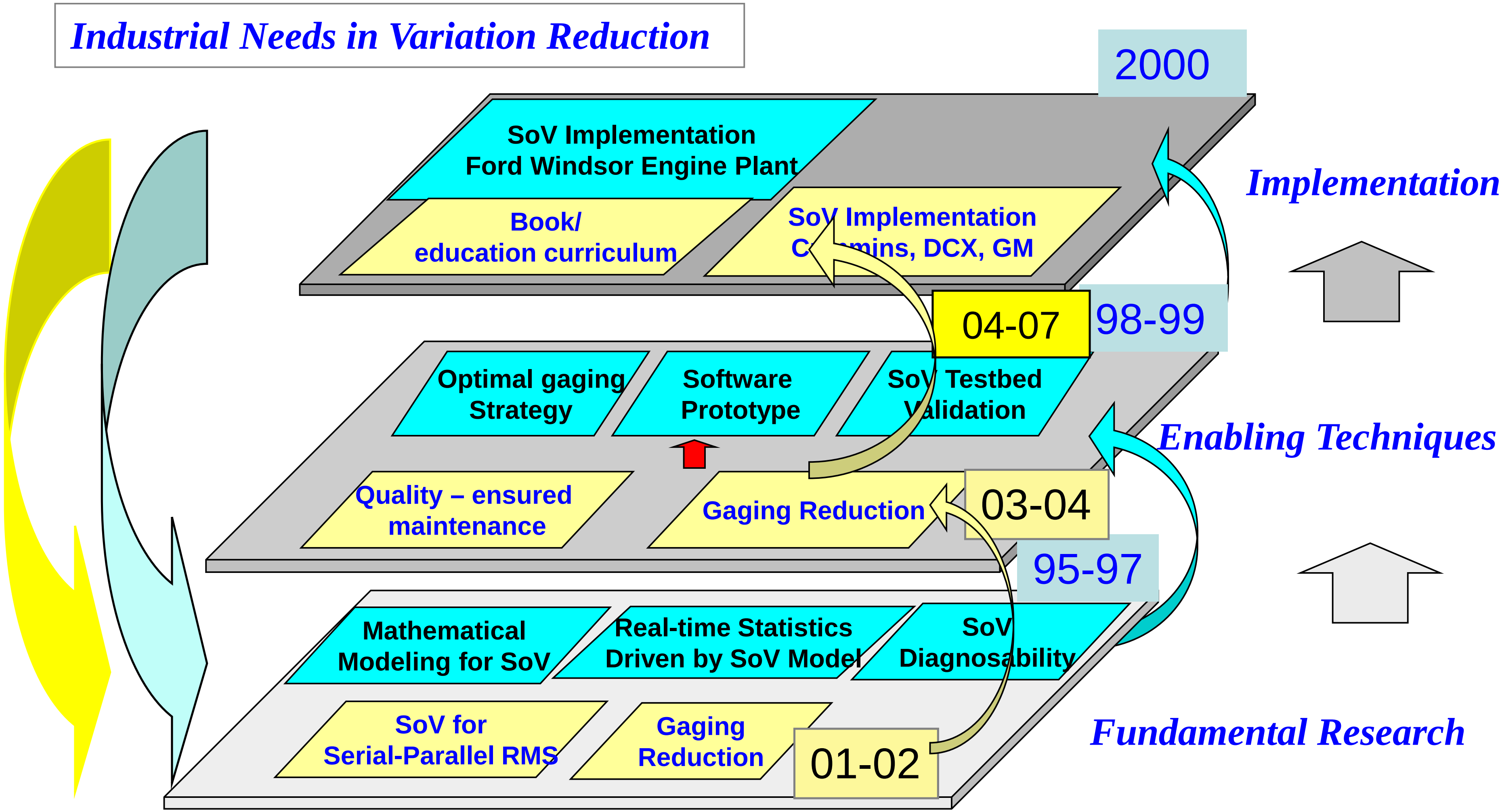
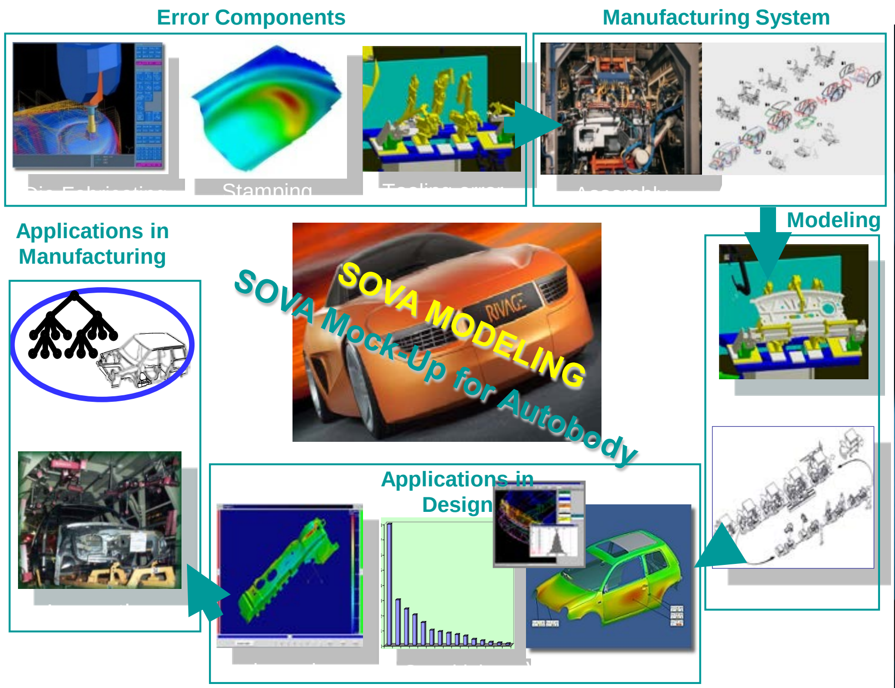
SoV R&D Strategy and Timelines

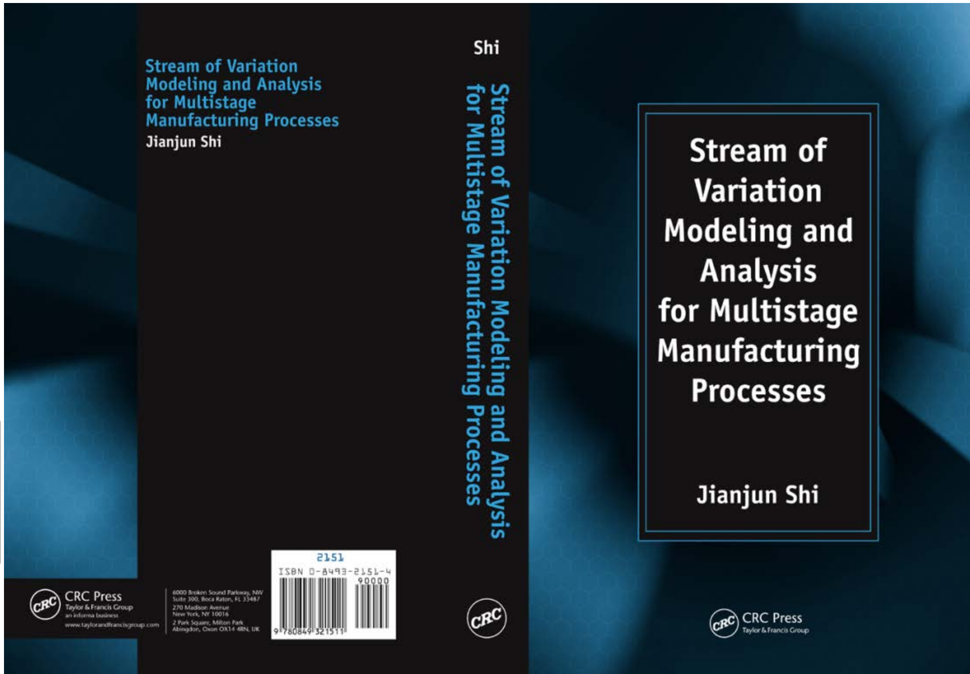


Stream of Variation Theory and Applications

Methodology Development: 50+ papers with best paper awards from ASME, IIE, INFORMS, IEEE
Education: A graduate course was developed and adopted by multiple universities;
Industrial Impacts: SoV theory has been implemented in auto and aerospace and their supplies companies

DCS SOVA Product for modeling, analysis and partial of the diagnosis and test at auto and aero industry



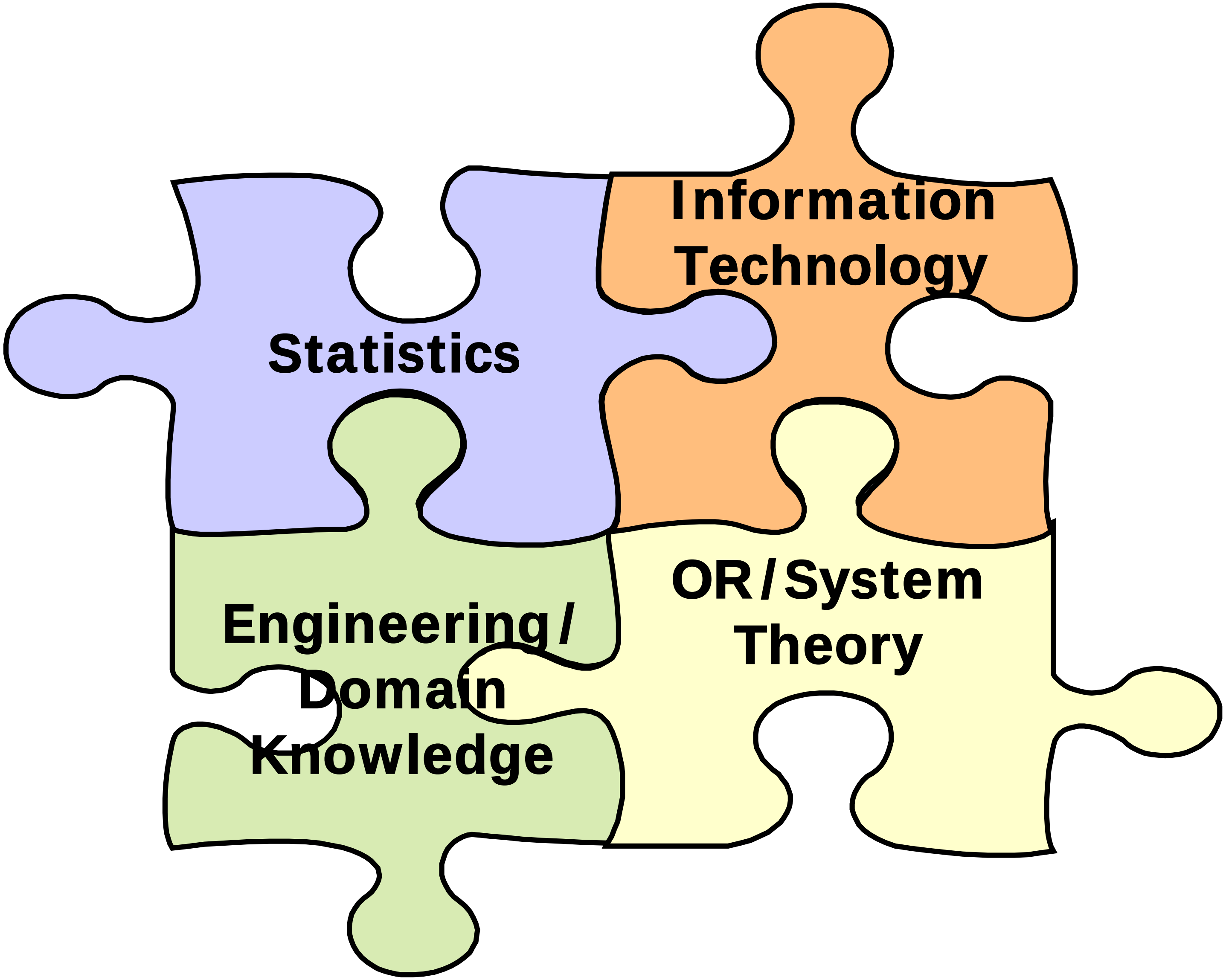


Summary

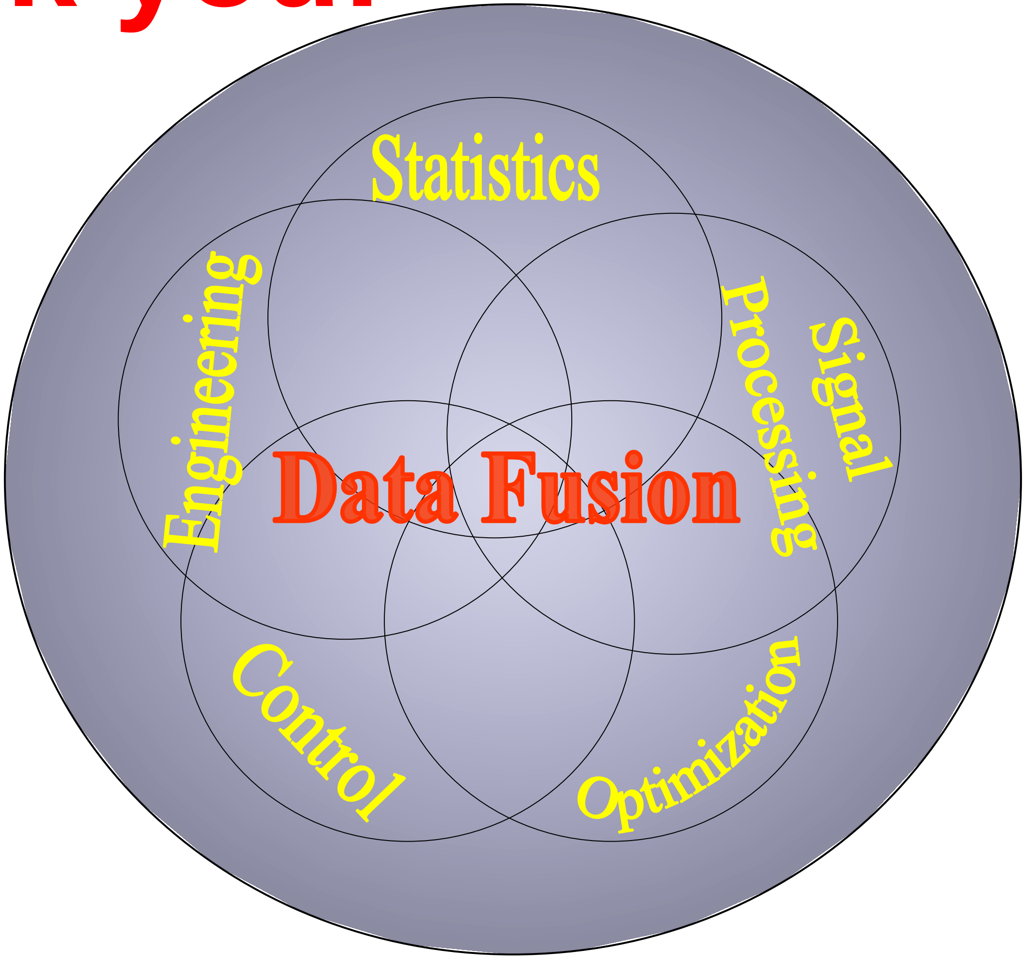
- Manufacturing Analytics is an emerging research area, which provides opportunities, as well as challenges, for performance improvement throughout the life cycle of a manufacturing system.
- Manufacturing Analytics R&D requires multidisciplinary efforts including engineering knowledge, statistics, and decision making.
- Some initial efforts in manufacturing analytics R&D have been made and demonstrated in both methodological developments and industrial applications.
- More collaborative efforts are required in both research and education.

Summary:

Key to Success - Multidisciplinary Research and Education



Thank you!


Statistics
Engineering
Signal Processing
Data Fusion
Control
Optimization

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  - D. Apley (NWU)
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  - X. Yue

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