



MICHIGAN ENGINEERING
UNIVERSITY OF MICHIGAN



National Science Foundation

Modeling and Analysis of Cyber-Physical Manufacturing Systems for Anomaly Detection

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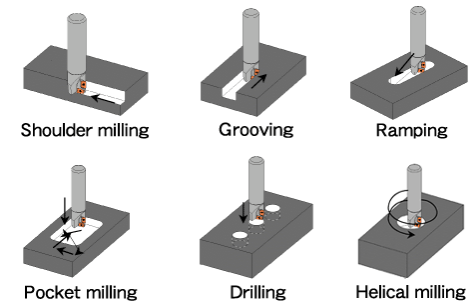
University of Michigan

Dr. Francisco Maturana

Rockwell Automation

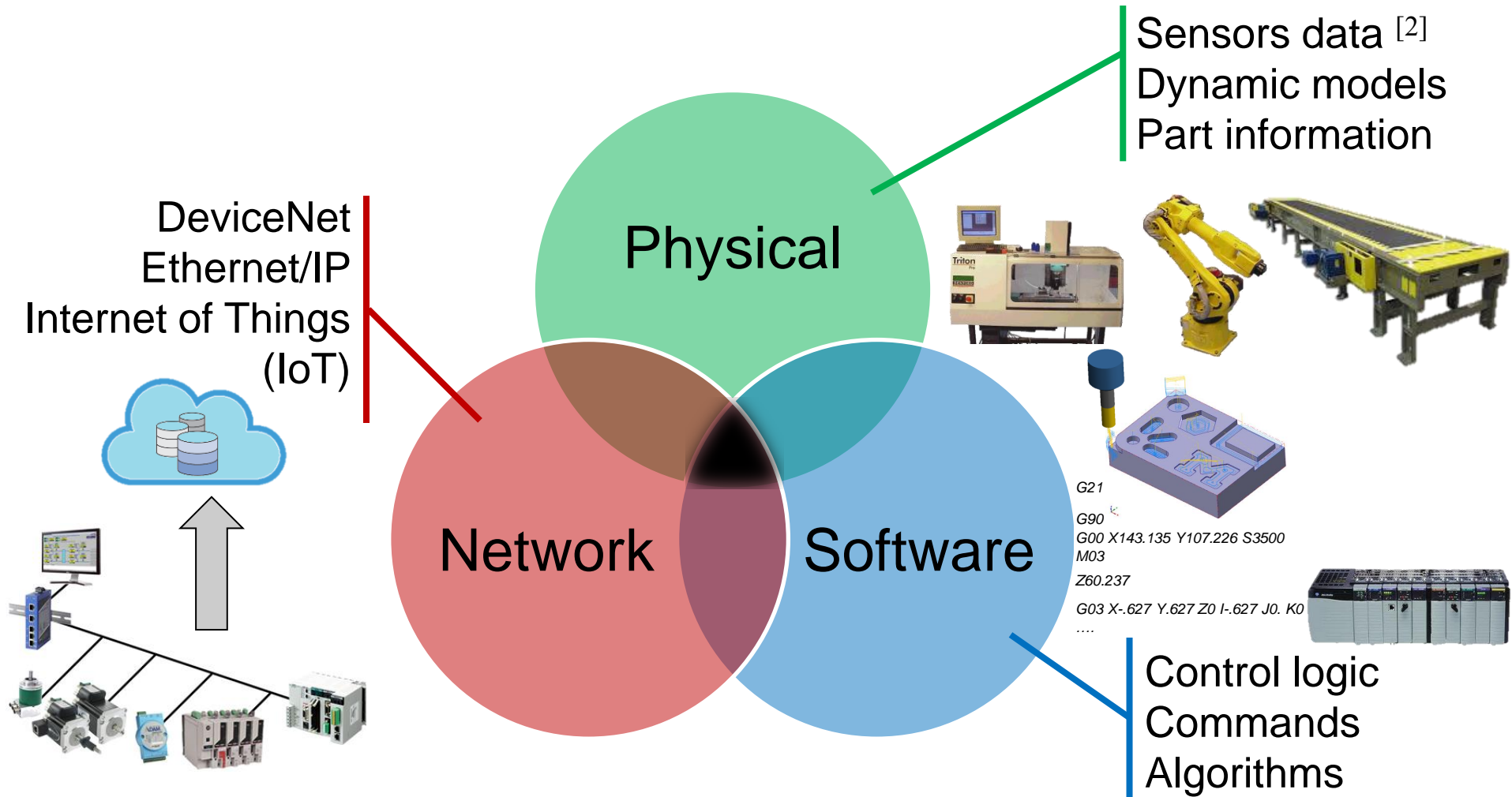
Challenges of anomaly detection

- **Process variability and dynamics:** Combination of transient and steady state operation [1]
- **Part interaction:** Changing loads due to different machine-part interactions
- **Data collection:** Cost and access constraints



MANUFACTURING PROCESSES ARE COMPLEX

Cyber-Physical Manufacturing Systems



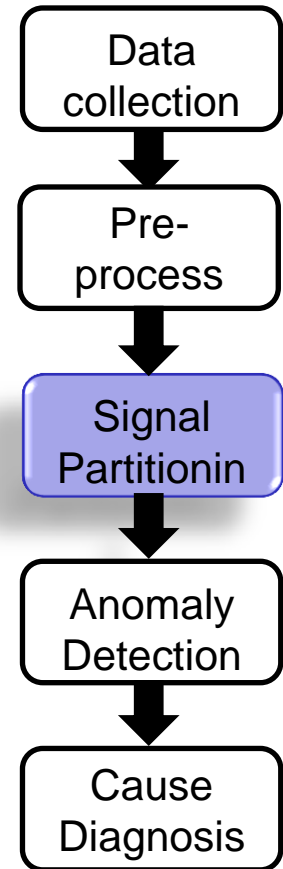
SUPPORT INTEGRATED ANALYSIS OF COMPLEX PROCESSES

Objective

Improve anomaly detection and diagnosis in manufacturing processes

Solution:^[3]

- ✓ Model Cyber-Physical Systems considering **both, Cyber and Physical** domains
- ✓ **Context-specific** analysis of manufacturing operation merging multiple models

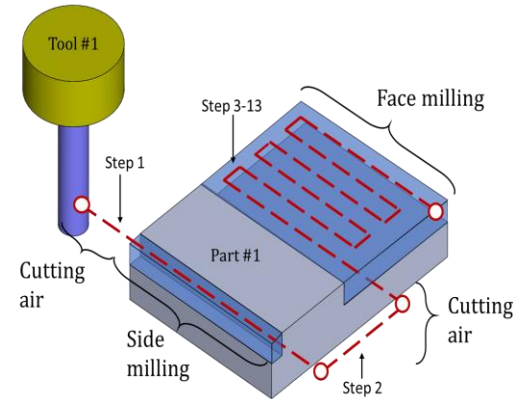


MERGE DATA AND INFORMATION WITH EXPERT KNOWLEDGE

Identify Operational Context

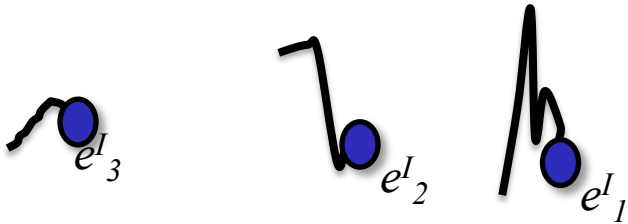
Global Operational State (GOS):

- **Functional:** Reduced controller model
- **Dynamic:** States describing machine dynamics
- **Interactive:** Describe the operations in the part
- **Information:** Explicit process descriptors

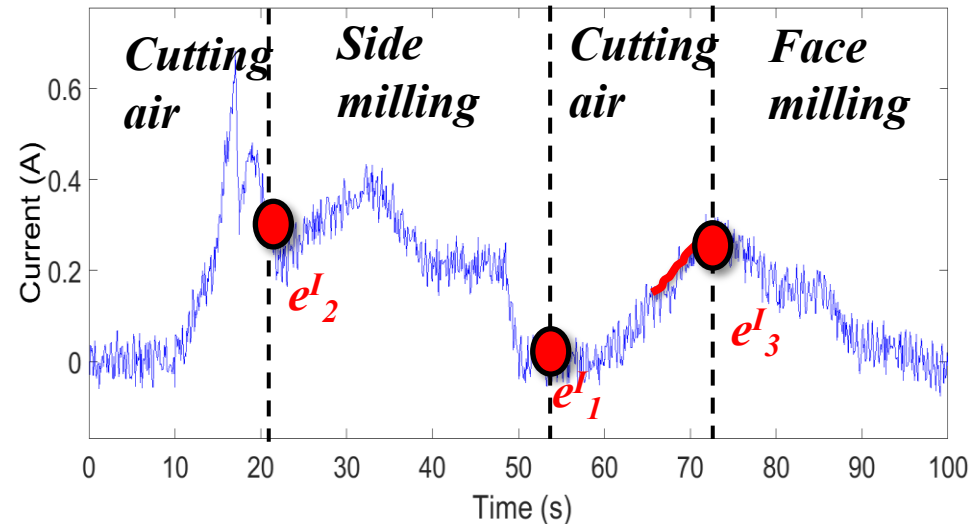


$$G = [Y(1) \dots Y(m)]^T$$

$$e^I = [Y_{ref}(1) \dots Y_{ref}(n)]^T$$



$$\min(DTW(e^I, G))$$



UNDERSTAND THE MACHINE OPERATION AND INTERACTION

Define Context-Specific Model

- Multi-model Specification:[4]**

$$M = (GOS, U, X, Y, F, H)$$

GOS: Global Operational State

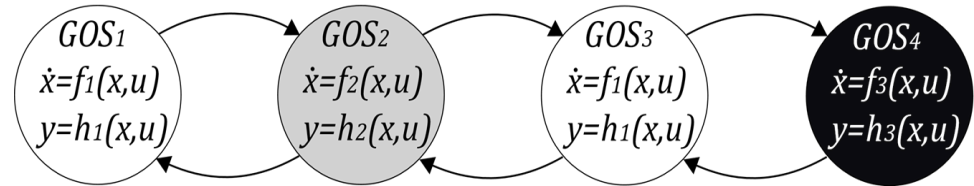
U: Continuous inputs

X: State variables

Y: Output variables

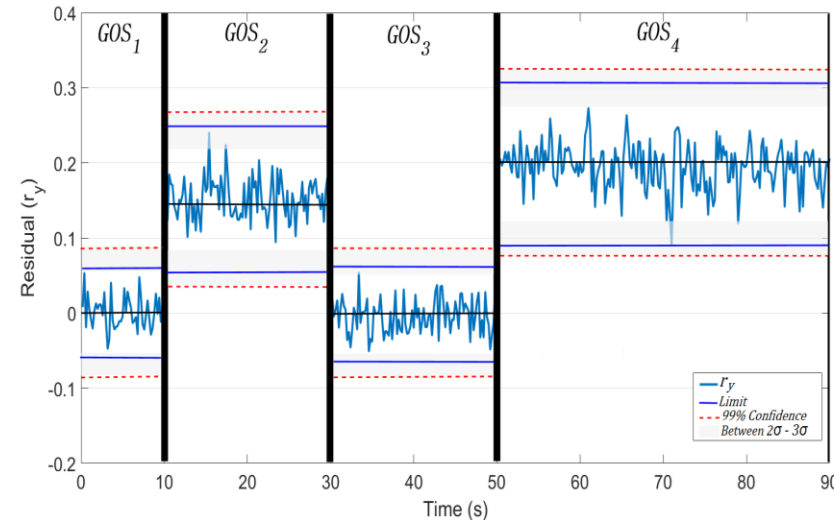
F: Mapping of state variable functions

H: Mapping of output variable functions

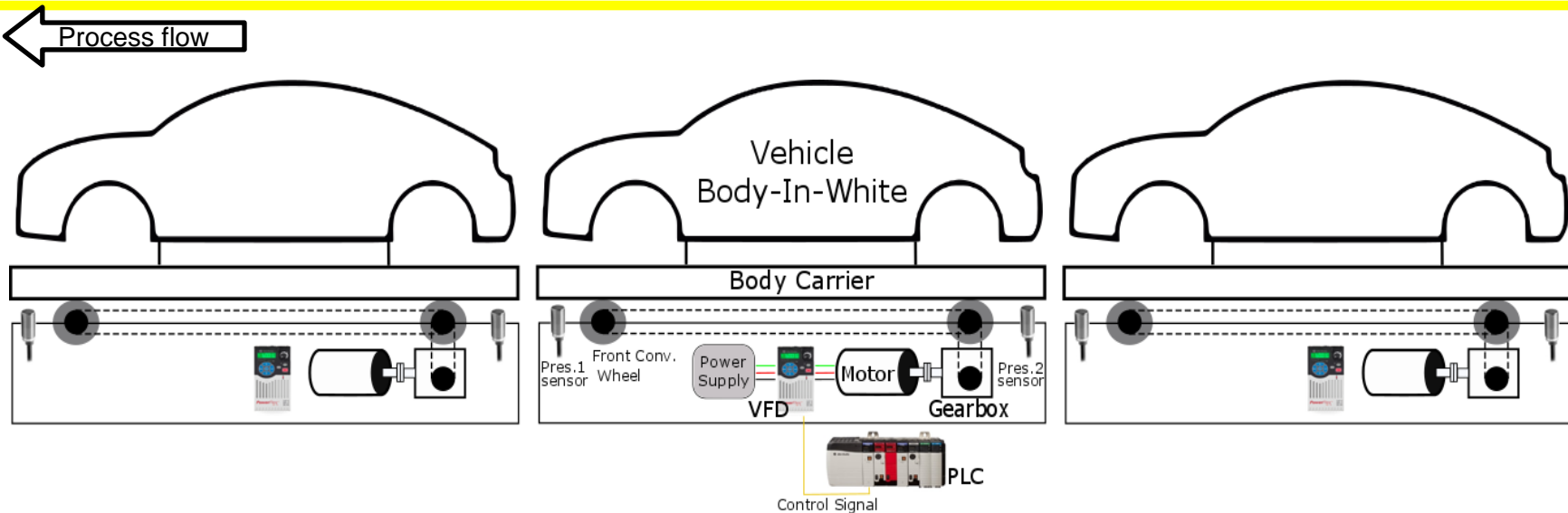


- Adaptive Threshold Limits:**

$$\Delta r_{GOS} = \mu \pm \psi_R Z \sigma$$



Case Study: Conveyor



- Available controller data

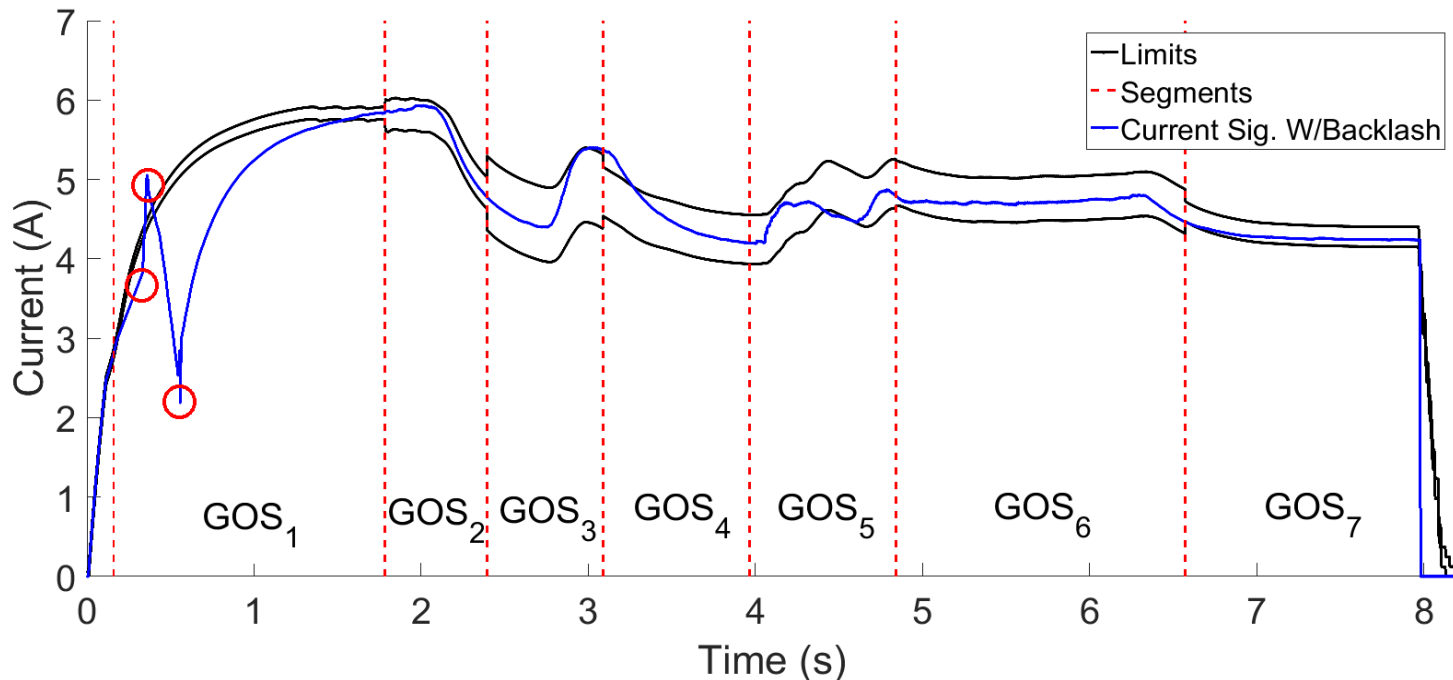
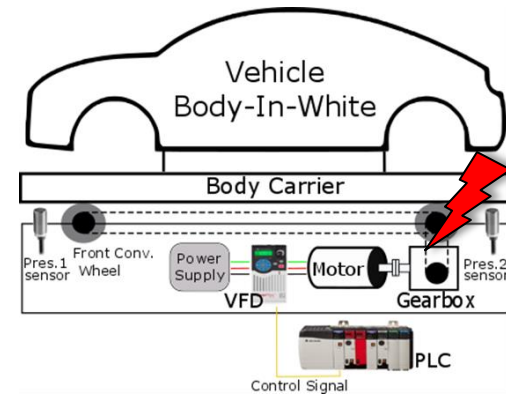
Type	Variables
Categorical	Vehicle model
Functional state	Ready, Processing, Down
State-space	Velocity, Torque
Energy	Current, Voltage, Frequency

Case Study: Conveyor

Anomaly detection: Adaptive threshold limits
(*Snapshot measurements*)

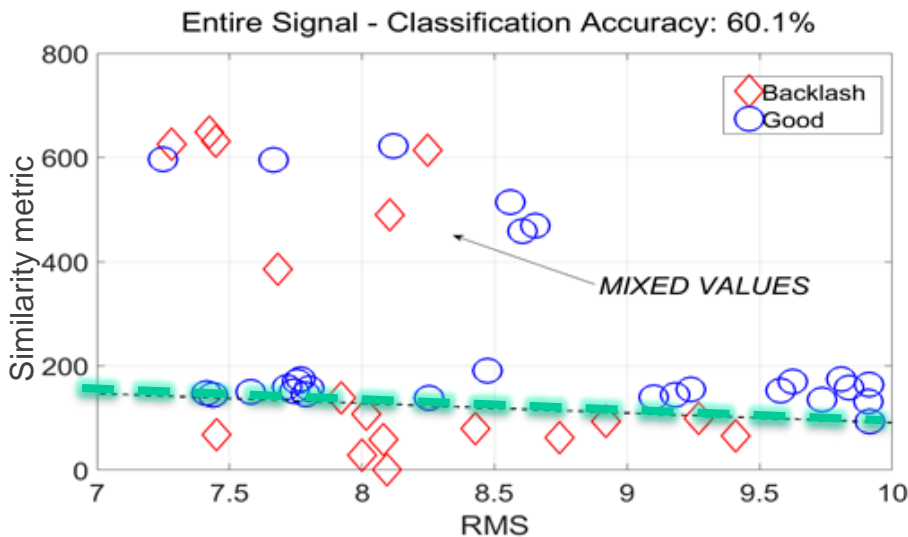
State	GOS ₁	GOS ₂	GOS ₃	GOS ₄	GOS ₅
Functional	Proc	Proc	Proc	Proc	Proc
Dynamic	Accel	Accel	Const	Const	Const
Interactive	Part.Out Front/Rear	Part.Out Front	Part.Out Front	Part.In Rear	Part.In Front

...

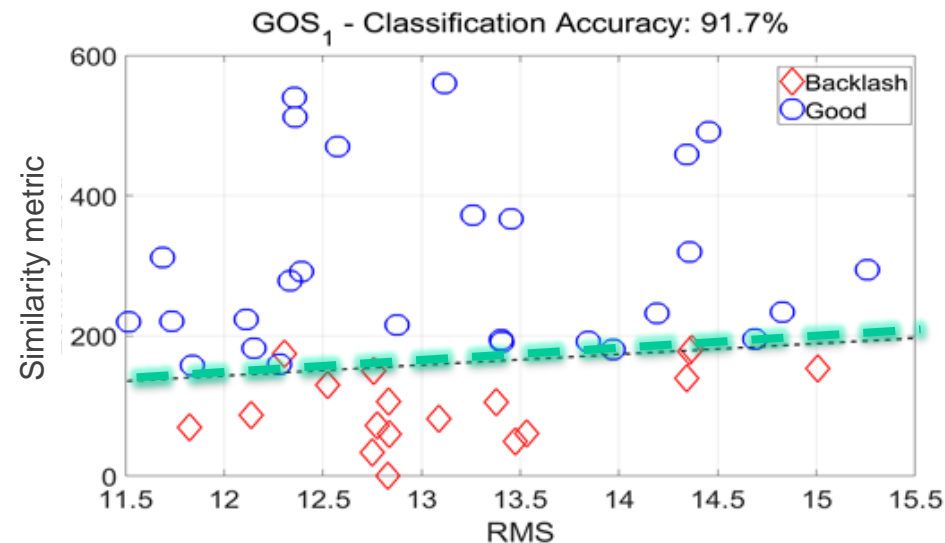


Case Study: Conveyor

Anomaly diagnosis: Supervised learning (SVM) to separate **Backlash** from **Good**



Entire signal: 60%



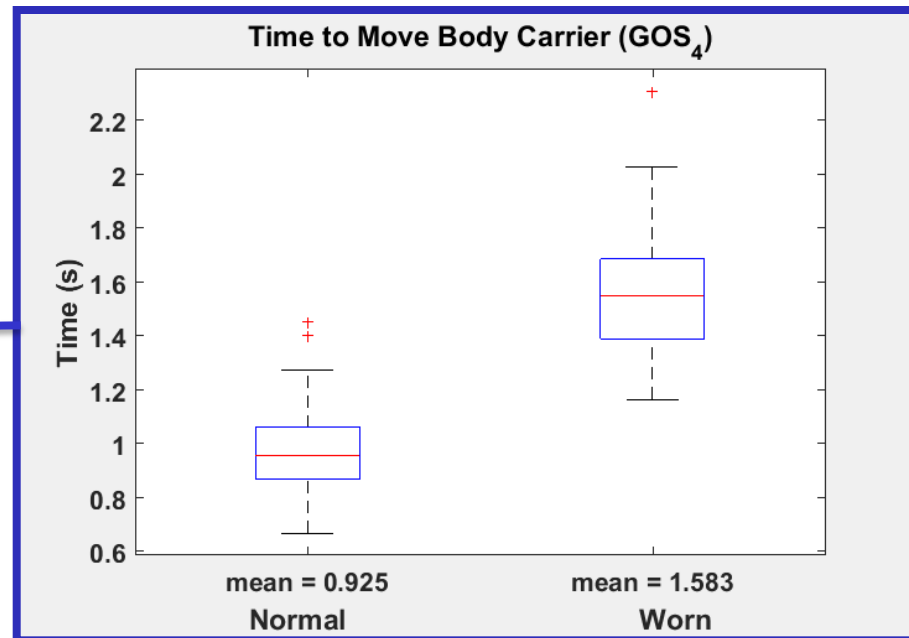
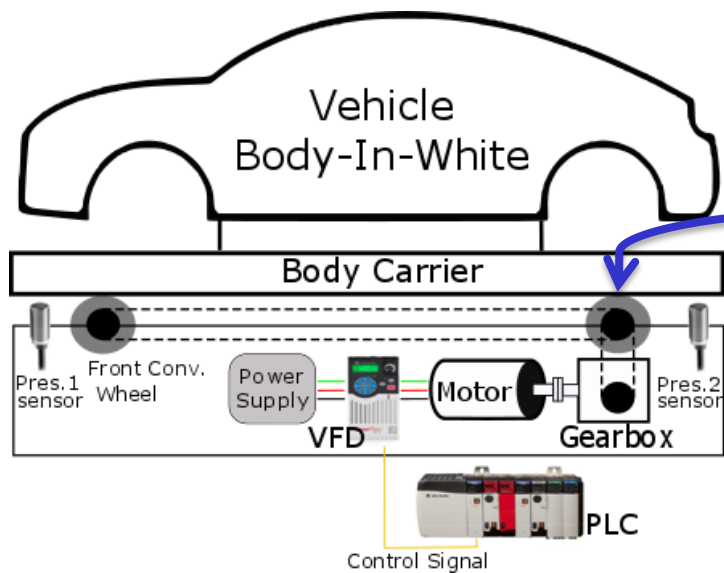
Only GOS₁: 92%

32% IMPROVEMENT IN ROOT CAUSE DIAGNOSIS

Case Study: Conveyor

Productivity analysis: Monitoring time of sub-tasks

Mean increase in time in GOS_4 when wheels are worn



DETECT 0.6 SEC INCREASE IN SUB-TASKS TIME

Case Study: CNC Machine

- Merge sensor data and context information

Process
step

+

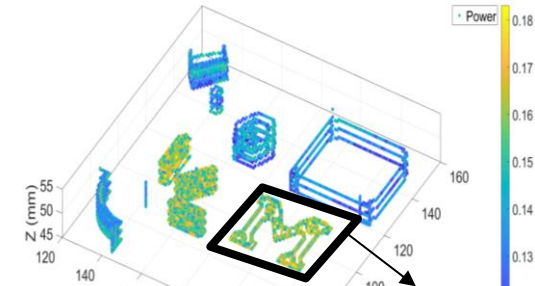
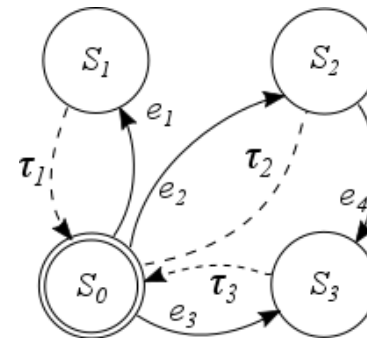
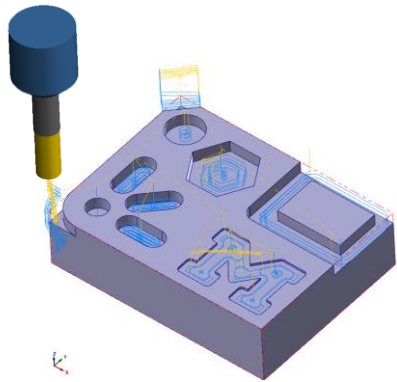
Artificial
vision

+

Controller
model

+

Energy
signature



G21

G90

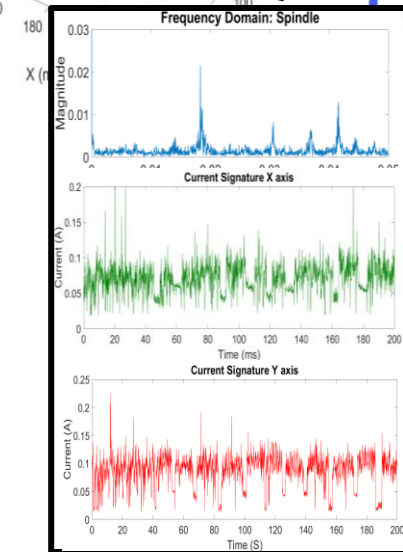
G00 X143.135 Y107.226 S3500 M03

Z60.237

G03 X-.627 Y.627 Z0 I-.627 J0. K0.

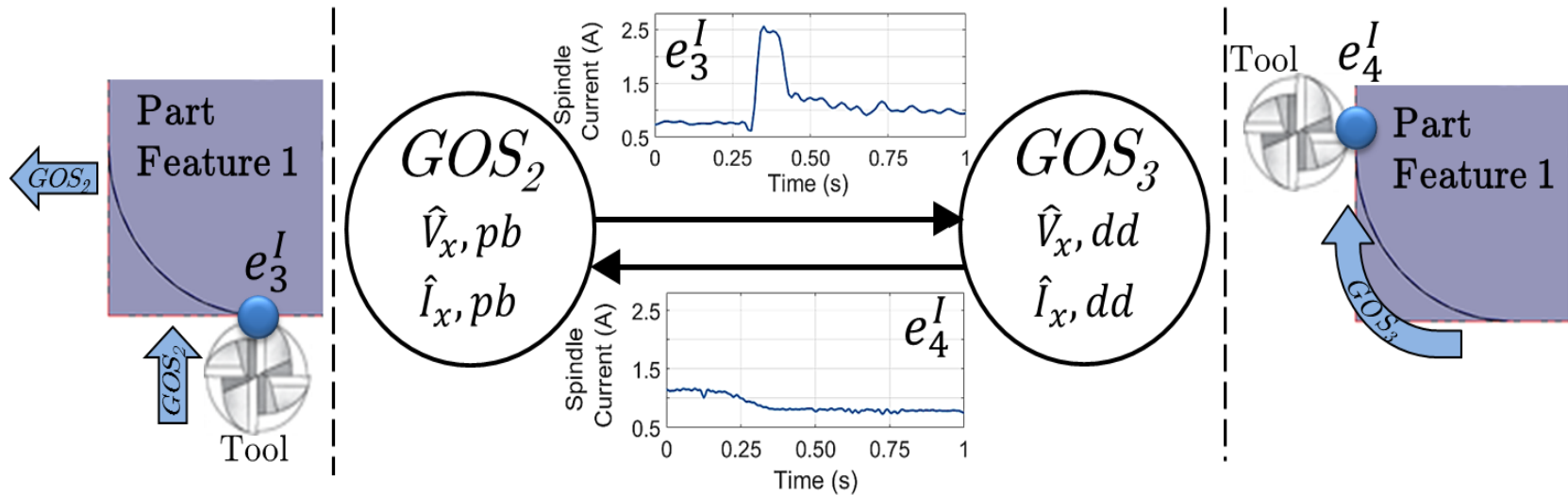
G00 X155 Y108.54

...



Case Study: CNC Machine

Multi-Model Framework:



Single Mass dynamic model

$$\hat{I} = Jq + M_{F1}\dot{q} + M_{F0} \sin(\dot{q}) / \psi$$

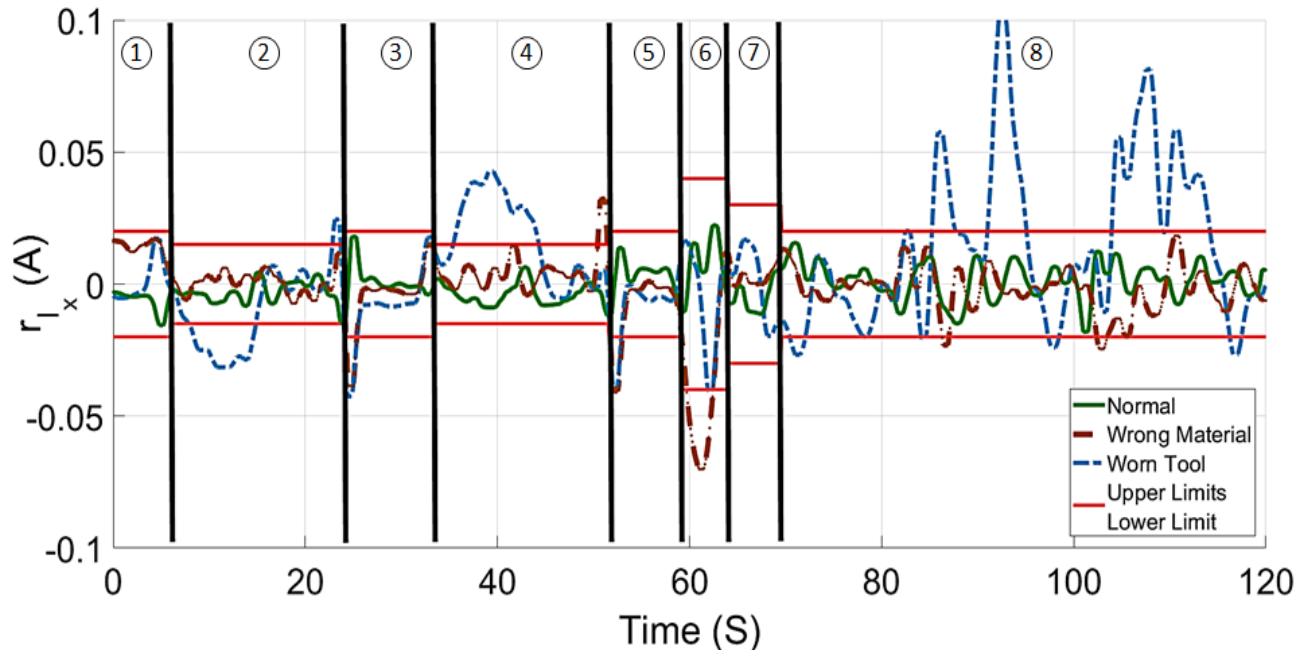
Autoregressive model

$$\phi_I(B)\hat{I} = \phi_{I1}(B)q + \phi_{I2}(B)\dot{q} + \varepsilon$$

Case Study: CNC Machine

- Multi-Model Framework:

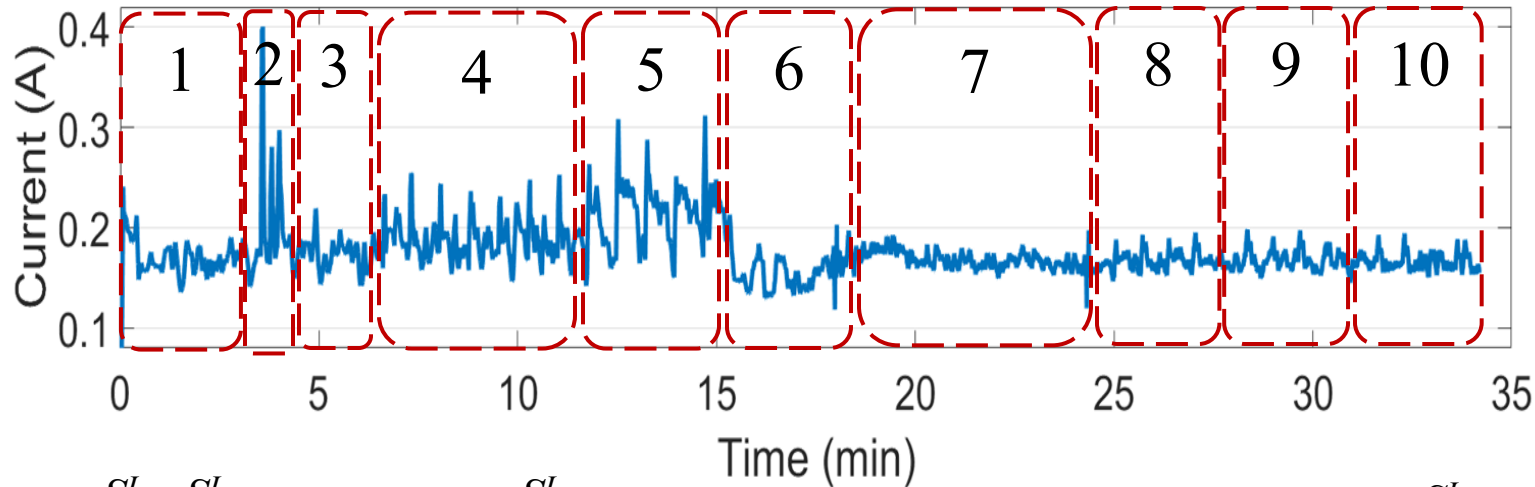
State	GOS 1	GOS 2	GOS 3	GOS 4	GOS 5	GOS 6	GOS 7	GOS 8
<i>Functional</i>	Proc.	Proc.	Proc.	Proc.	Proc.	Proc.	Proc.	Proc.
<i>Dynamic</i>	2 in/sec	5 in/sec	50 in/sec	2 in/sec	2 in/sec	2 in/sec	50 in/sec	5 in/sec
<i>Interactive</i>	No Int.	Side Int.	No Int.	Side Int.	No Int.	End Int.	No Int.	Side Int.



DEFINE CONTEXT-SENSITIVE ADAPTIVE THRESHOLD LIMITS

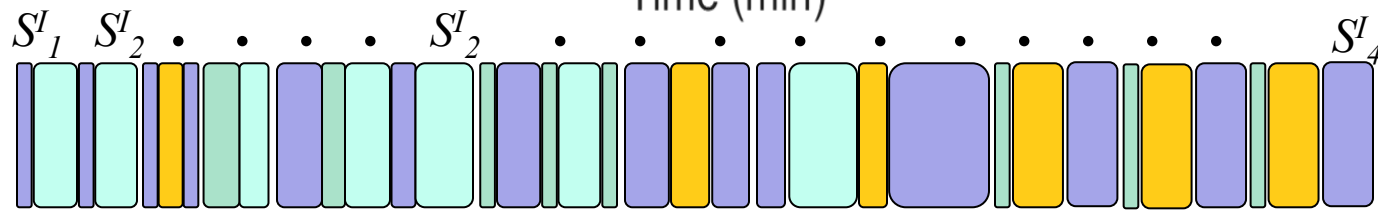
Case Study: CNC Machine

Collect
Raw data

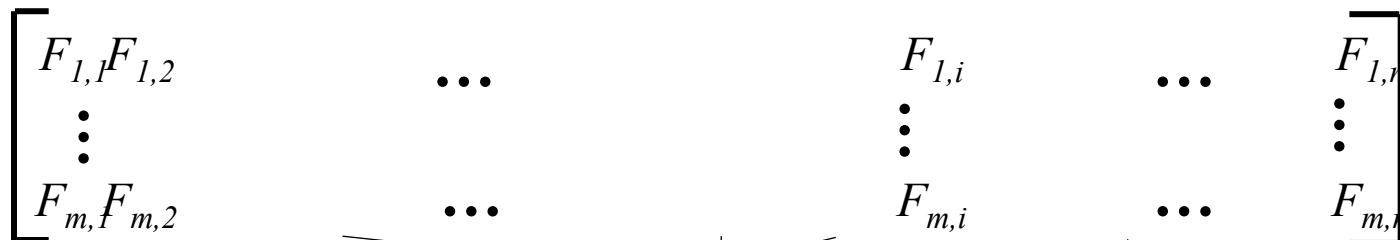


Partition by
part feature

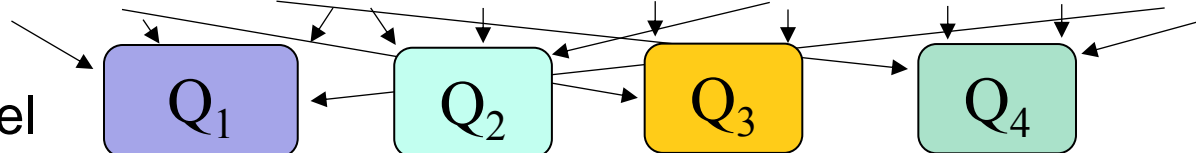
Partition by
Interaction



Extract
Signal features

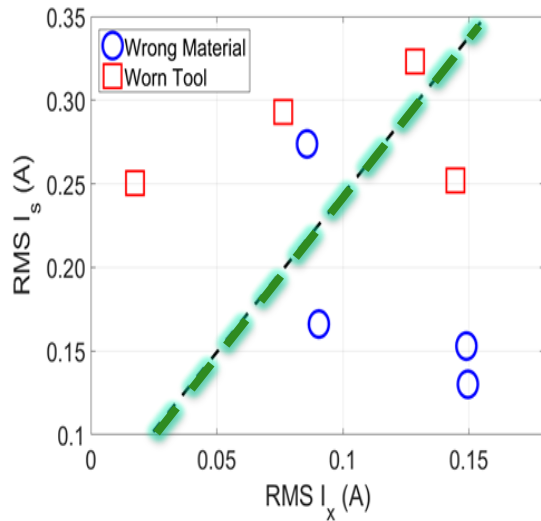


Context-Specific
Classification Model

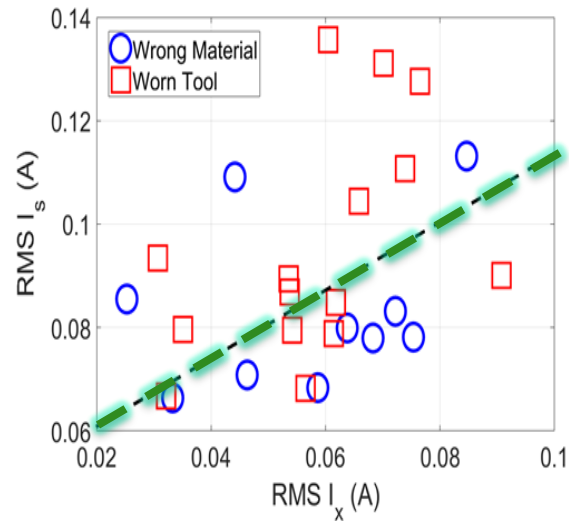


Case Study: CNC Machine

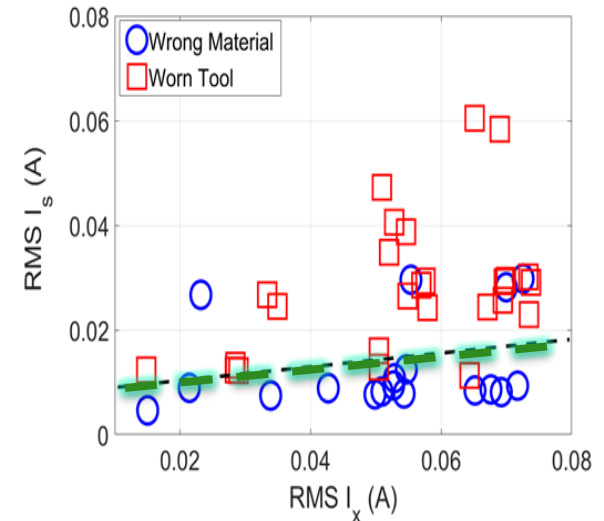
Use supervised learning (SVM) to separate **worn tool** from **wrong material**



**Entire signal:
75%**



**Partition by
part feature: 81.2%**



**Partition by
part feature
and GOS: 93.6%**

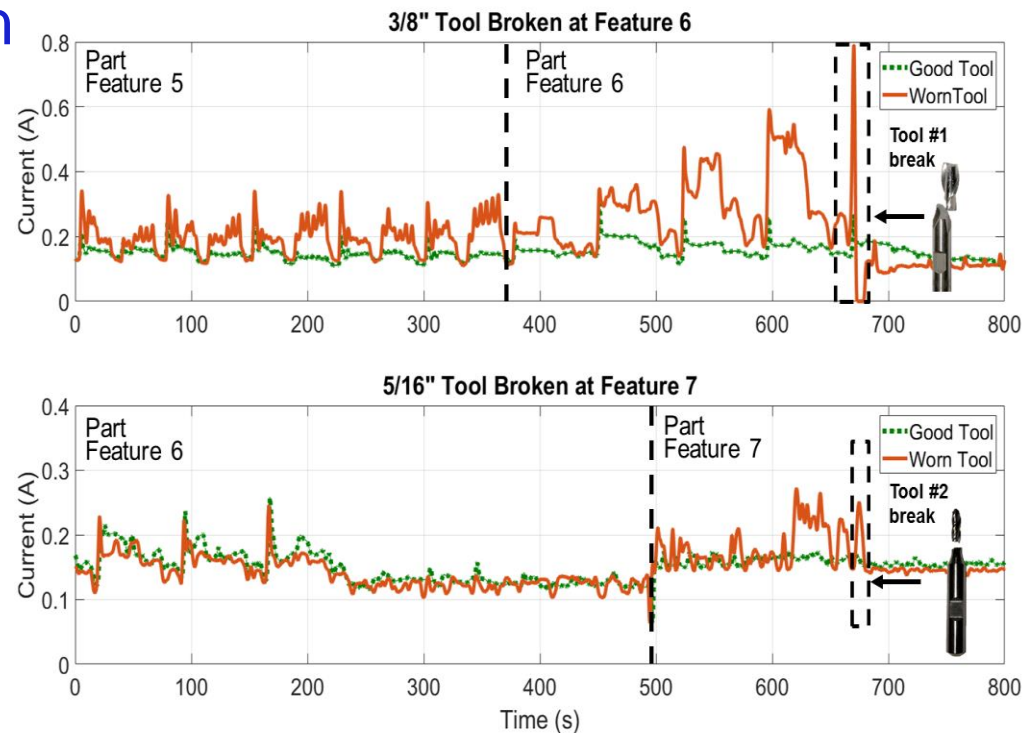
DEFINE CONTEXT-SPECIFIC CLASSIFICATION MODELS

Case Study: CNC Machine

Develop context-specific diagnosis rules:

- Extract context information
- Identify fault patterns
- Define classification rules

Diagnose tool breakage
under different operational
context



CONTEXT KNOWLEDGE CAN SIMPLIFY DIAGNOSIS



Case Study: Electro-Pneumatic Systems

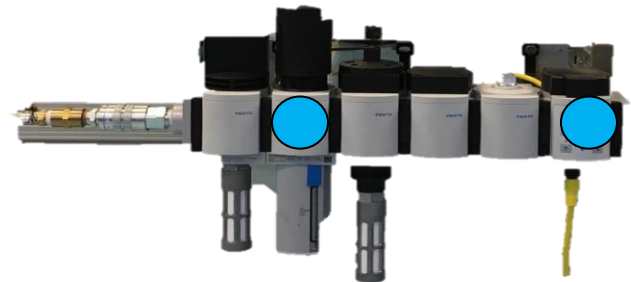
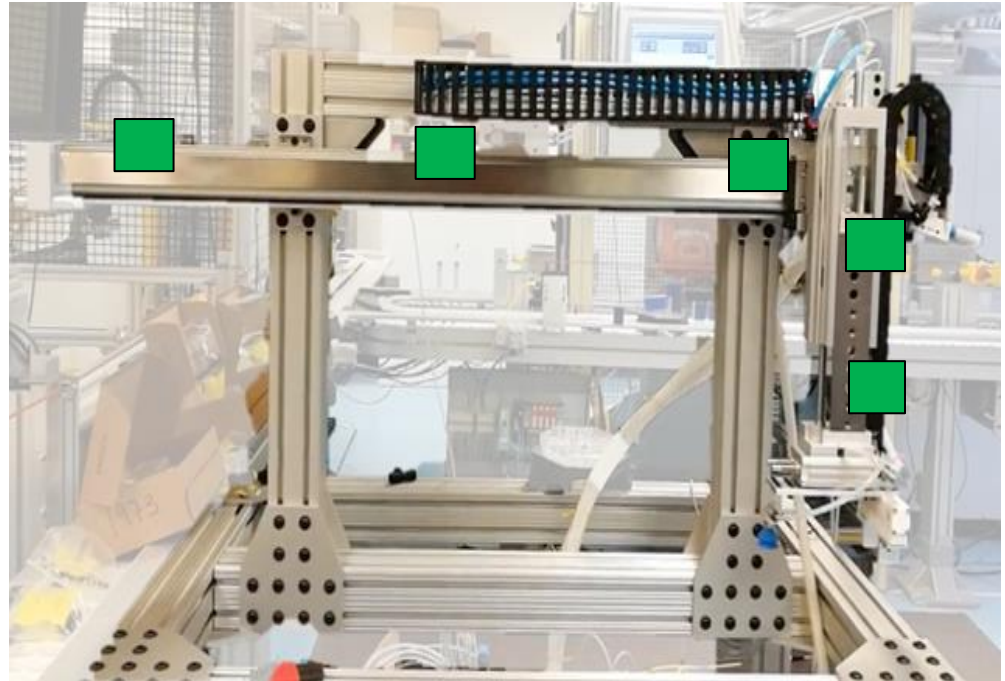
Common automation applications:

Examples:

- Welding fixtures
- Gantry systems
- Assembly stations

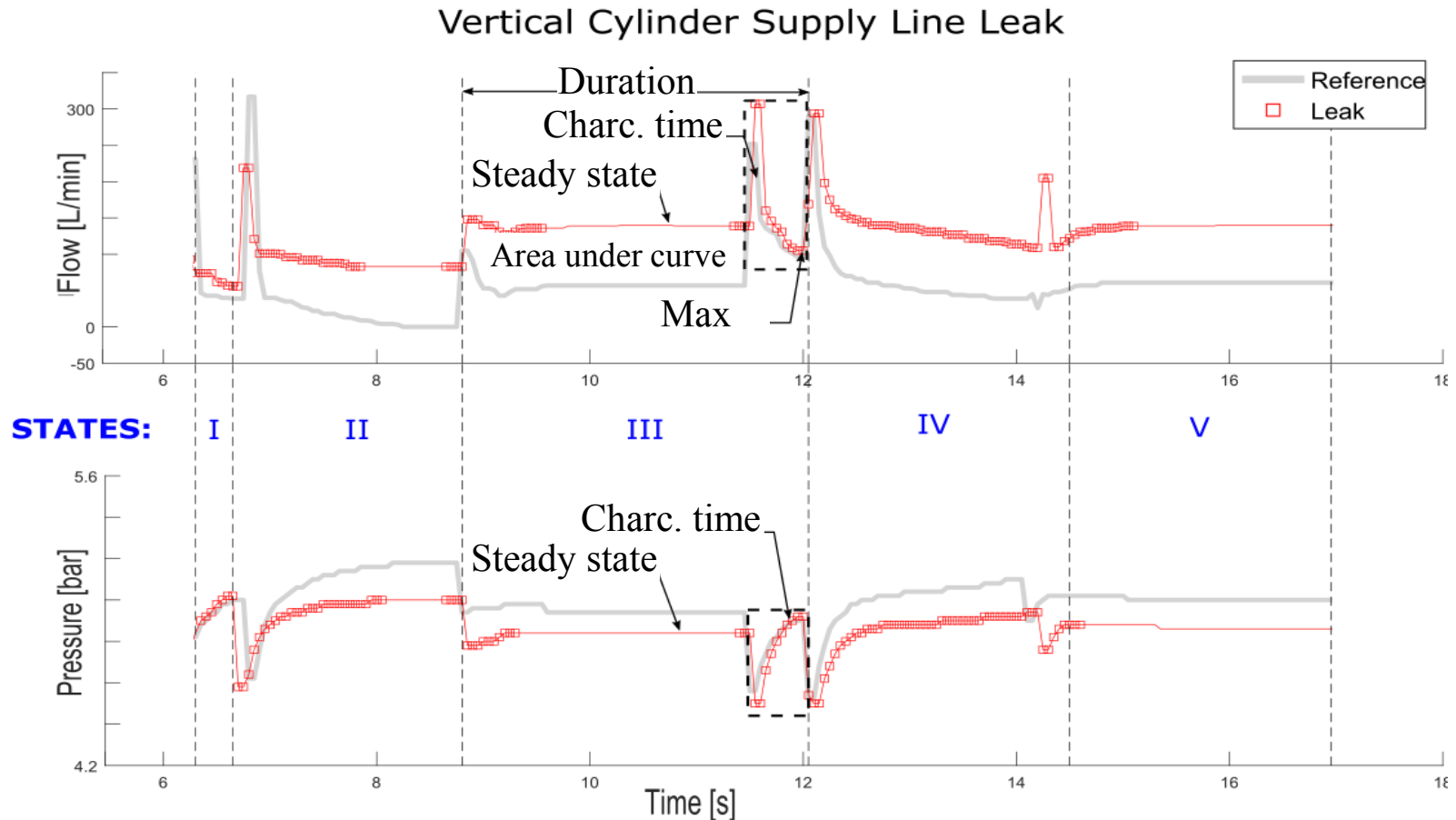
Approach:

- ✓ Monitor data from:
 - Position sensors 
 - Pressure and flowmeters 
- ✓ Study discrete states



Case Study: Electro-Pneumatic Systems

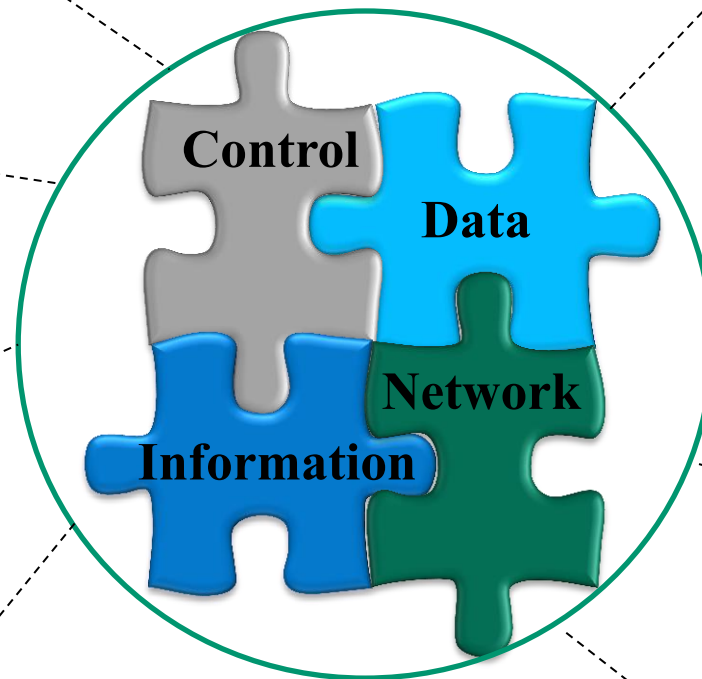
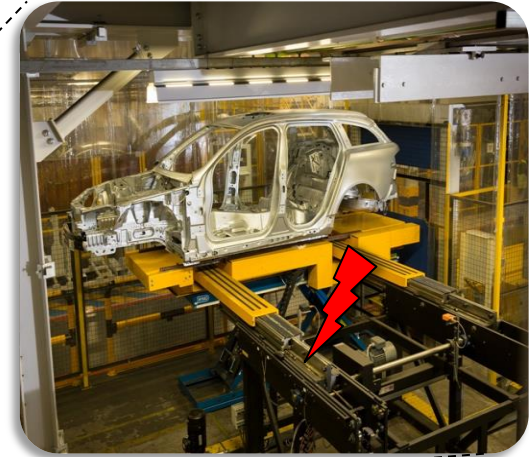
Merge sensor data and controller model to detect leaks in multiple location and sizes



Cyber-Physical Manufacturing Systems

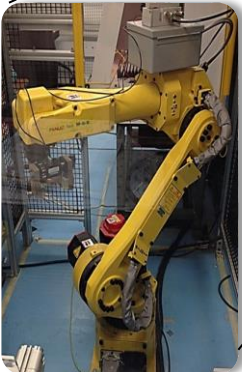


- Worn components
- Backlash

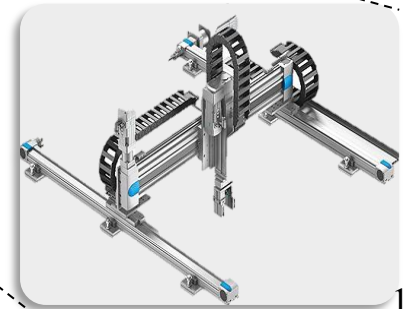


- Worn/Broken tool
- Damaged fixture
- Wrong part

- Leaks



- Joint problems
- Wrong trajectory



Conclusion

- Merging sensor data with context information help to **understand the machine operational context**
- **Feature extraction of a non-stationary signal** can be improved by adding information of the cyber domain
- Modeling requires merging **expert knowledge and machine data** into process analysis algorithms

Thanks