Cyber-physical Manufacturing Systems: Improving Productivity with Advanced Monitoring and Control

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Outline

Introduction & Motivation

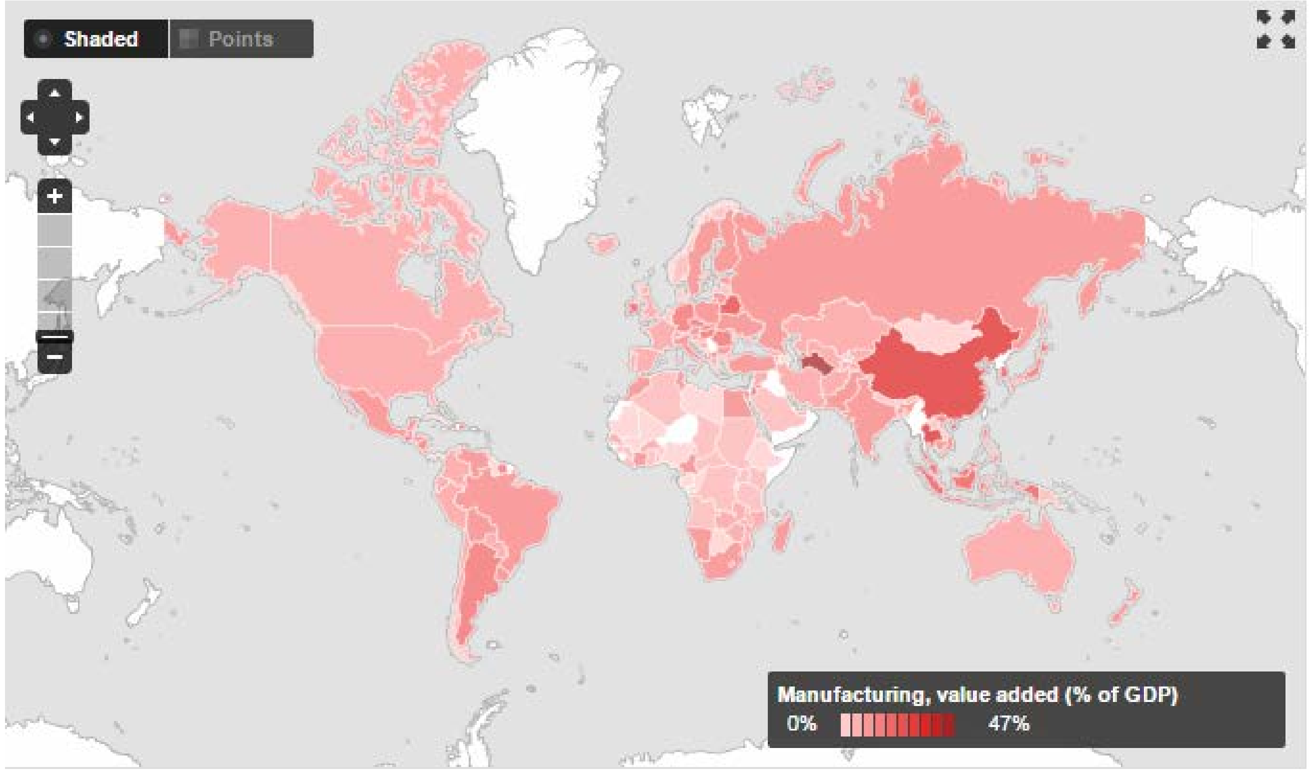
Collecting and integrating diverse data

Condition monitoring and adaptation

Conclusion and future work

Importance of Manufacturing

“The manufacturing industry represents 12% of the United States’ GDP, making it a major engine of our economy that provides millions of well-paying job opportunities”



Also: 32% of energy consumed in the US

75% of US private sector R&D

Problem

Common Overall Equipment Effectiveness (OEE) under 50%

- Blockages and Starvations
- Incorrect Process Parameters

→ **Performance**

- Equipment Failure
- Unplanned Changes

→ **Availability**

- Inconsistent Materials
- Poor Process Setup

→ **Quality**

Performance, Availability, Quality → OEE ↓

Manufacturing productivity shows downtrend or little improvement

Manufacturing opportunity

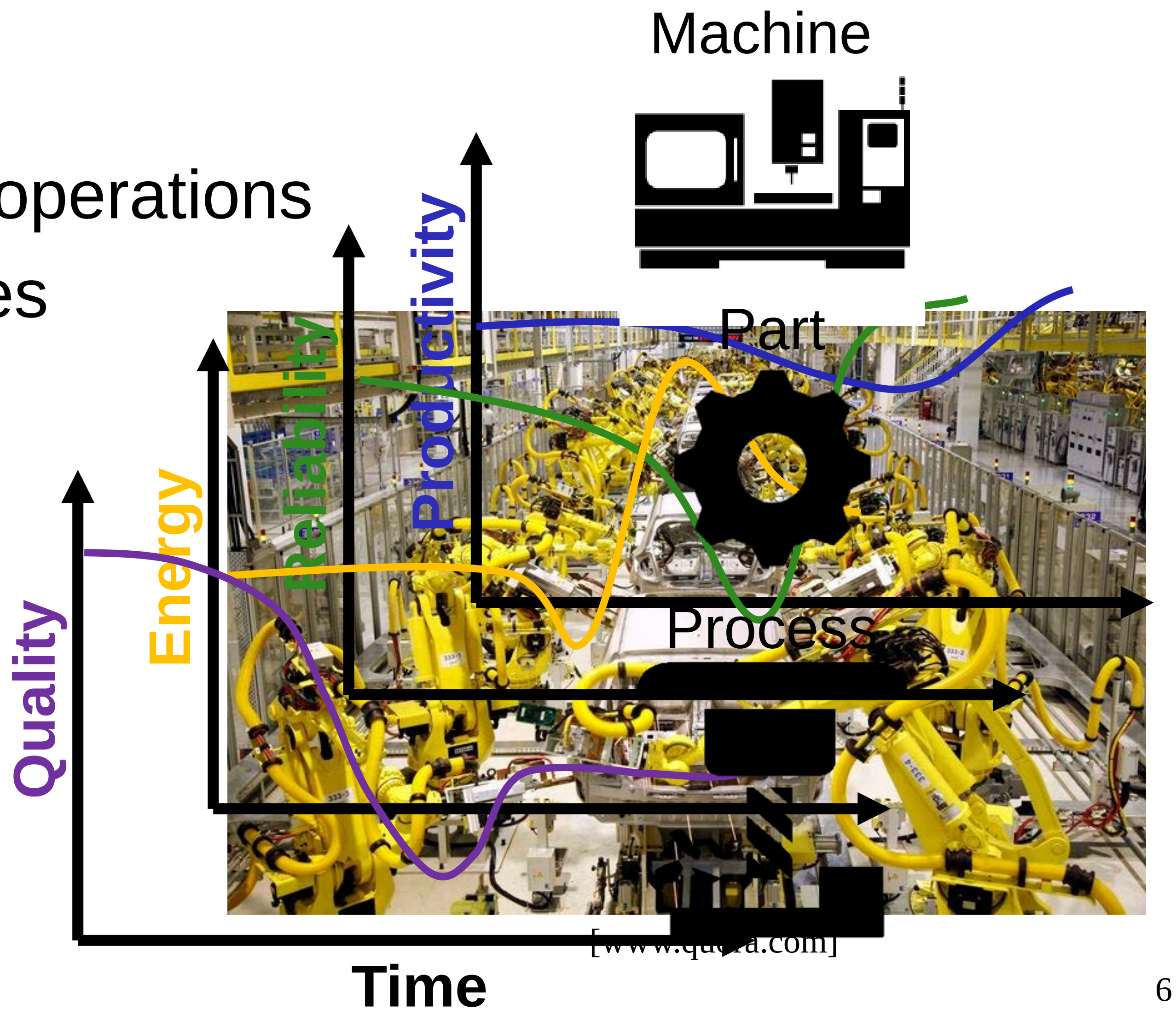
Worldwide studies indicate that the average Overall Equipment Effectiveness (OEE) rate in manufacturing plants is 60%

World Class OEE is considered to be 85% or better. Clearly, there is *room for improvement* in most manufacturing plants!

→ Opportunity for control technologies

Challenges

- **Some major challenges:**
  - – Supervise complex plant floor operations
  - – Various sources of disturbances
  - – Multi-Domain Control Problem
    - Production management
    - Maintenance policies
    - Sustainable Operations
    - Quality Assurance



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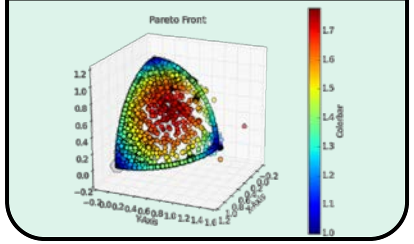
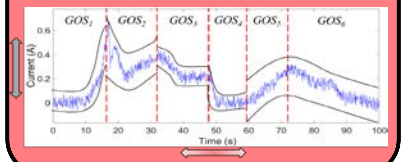
Control Framework for Manufacturing Systems

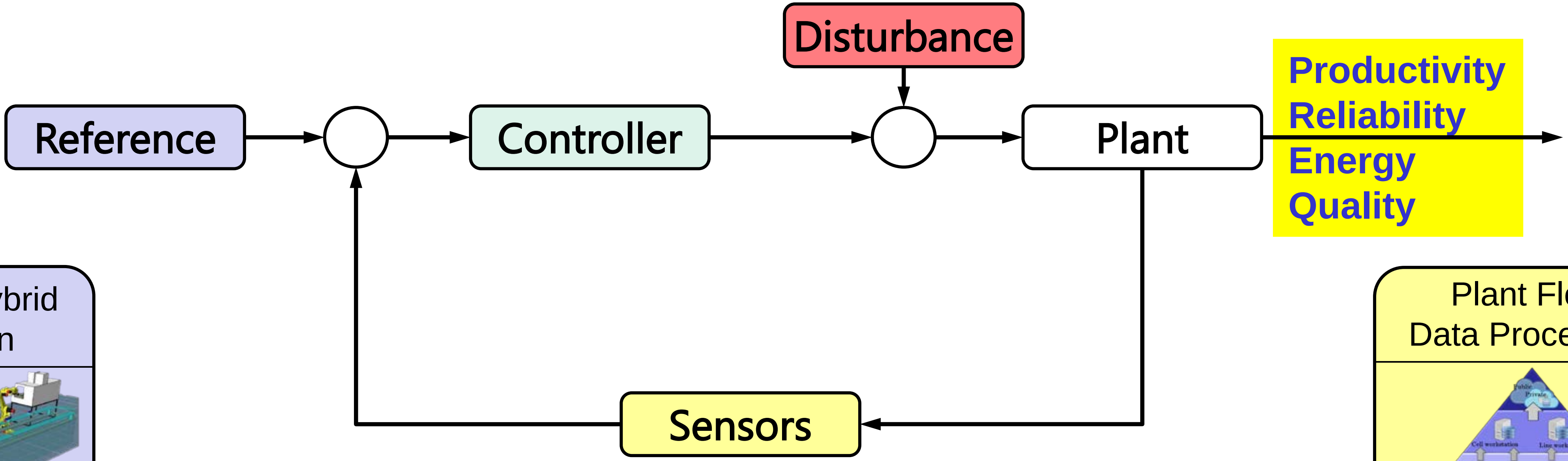
Multi-Objective Decision Making



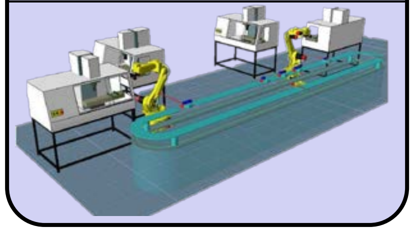
Modeling and Analysis Framework to Support Monitoring, Assessment, and Control of Manufacturing Systems

Context-Sensitive Anomaly Detection

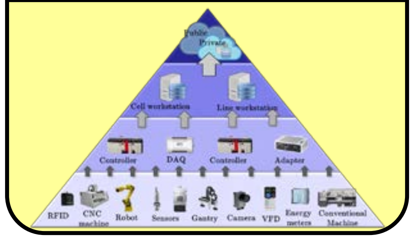




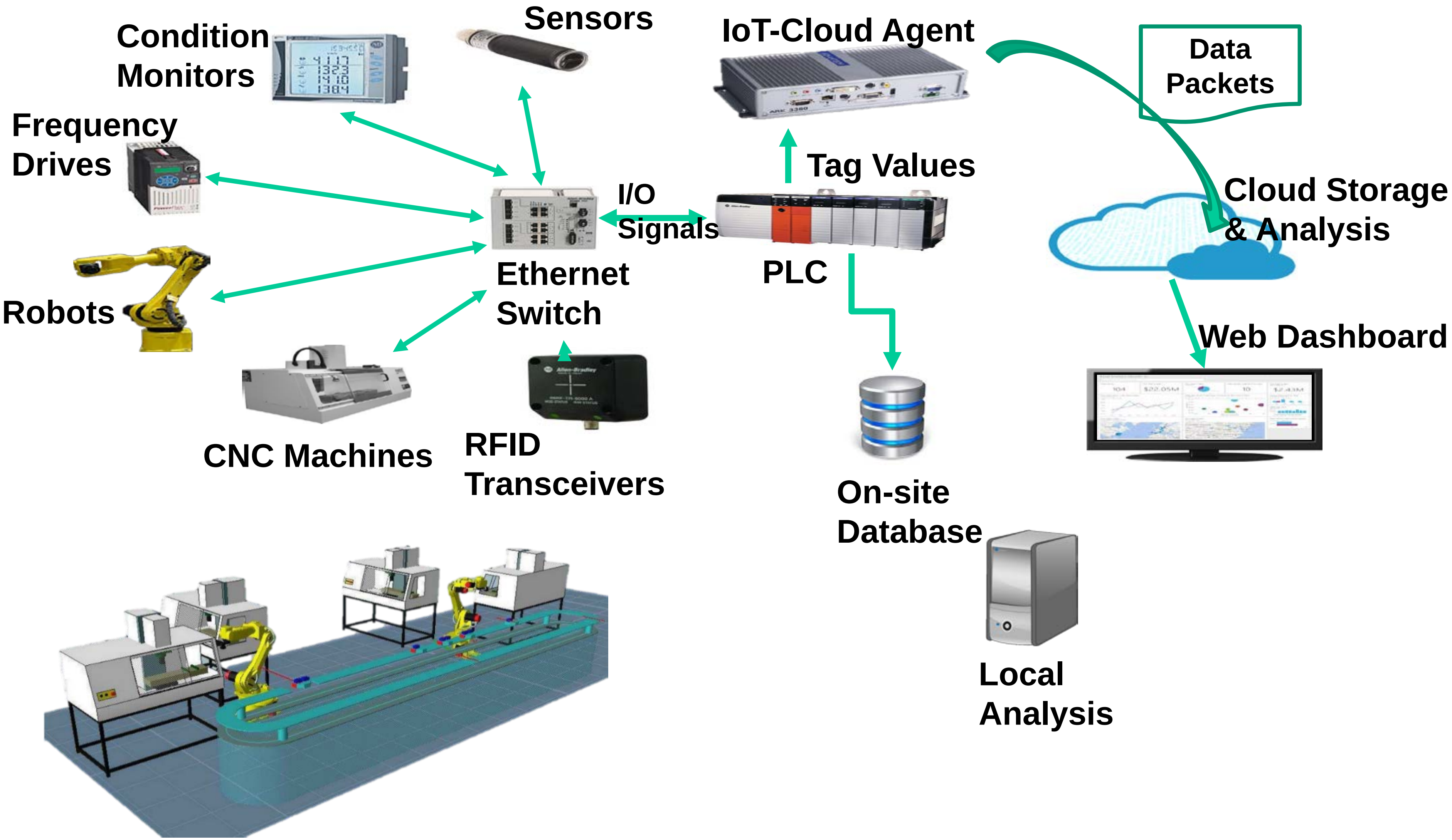
Real-time hybrid Simulation



Plant Floor Data Processing

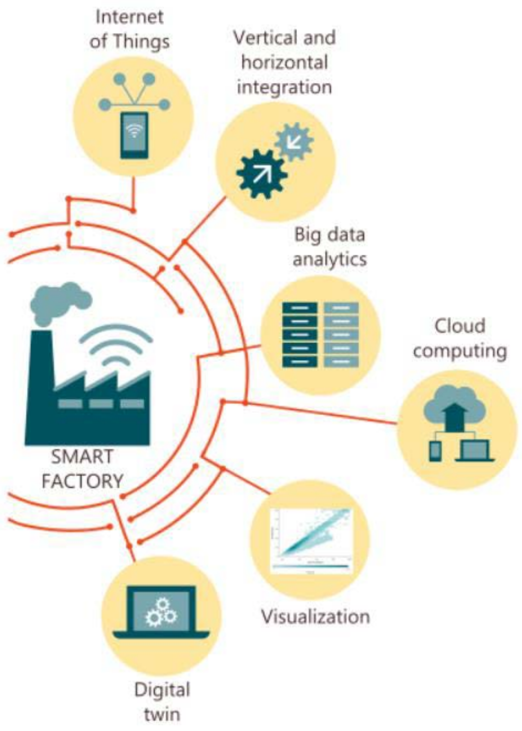


Data Collection & Analysis



Big Data in Manufacturing: Opportunities

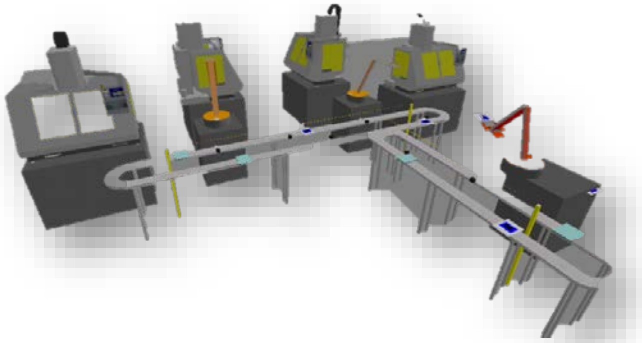
- **Improve quality:** Combine part, production, and warranty data
- **Reduce downtime:** Monitor machine health using data and AI models
- **Increase energy efficiency:** Monitor energy consumption and develop energy saving policies



PRODUCTIVITY IMPROVEMENT AND COST SAVINGS

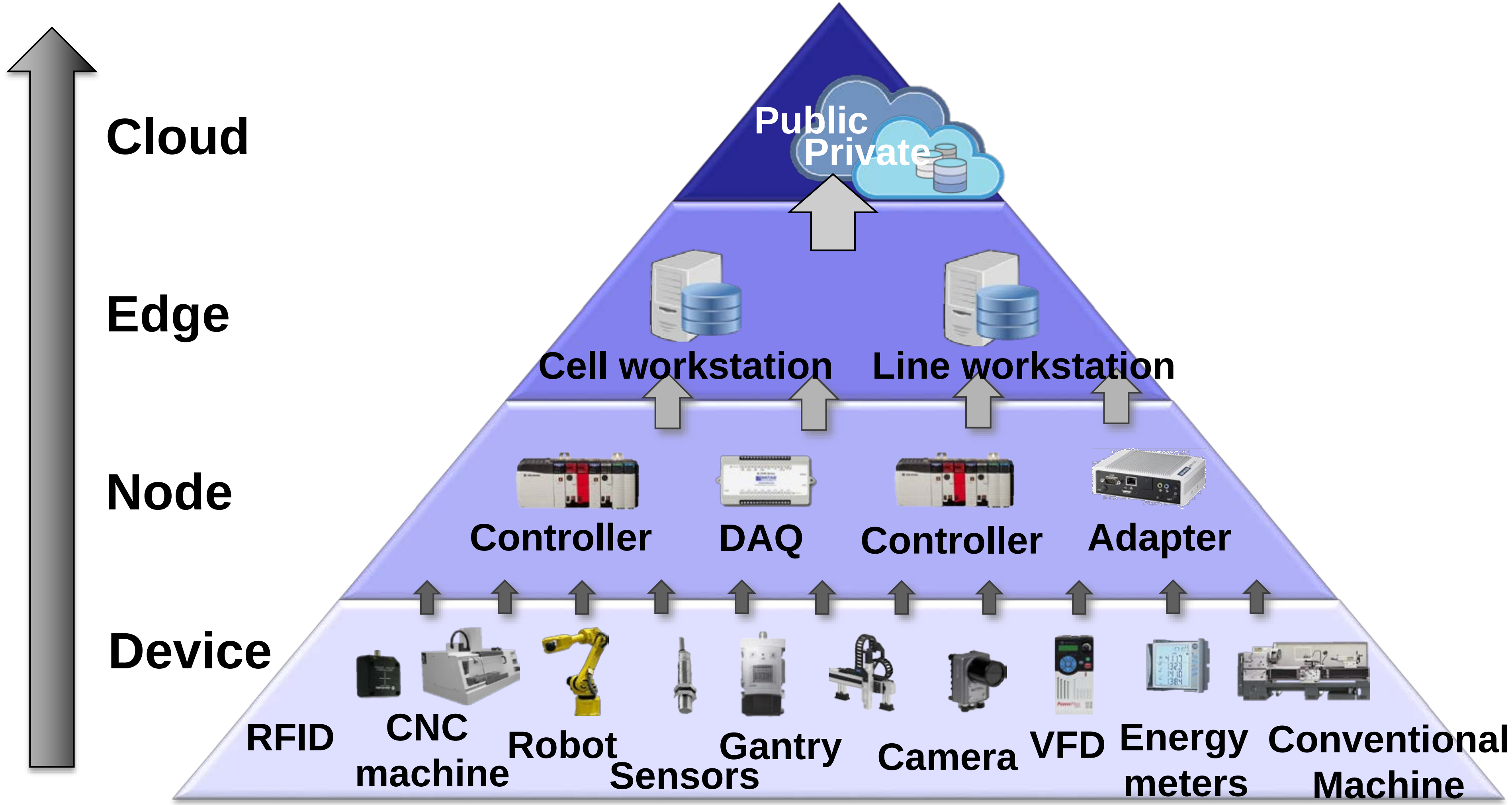
Big Data in Manufacturing: Challenges

- **Heterogeneity:** Different sources, languages, protocols, and types
- **Scalability:** Cost of extracting, storing, and processing Big Data
- **Privacy and Ownership**: Security and governance concerns



BIG DATA, BIG OPPORTUNITIES, BIG CHALLENGES

Background: Data Processing Architecture



Objective

Improve data processing to support more efficient cloud and edge computing

Solution:

- ✓ **Transform** the data on edge devices to a common language
- ✓ **Reduce** data prior to transmission
- ✓ Define **rules and conditions** for data storage and transmission

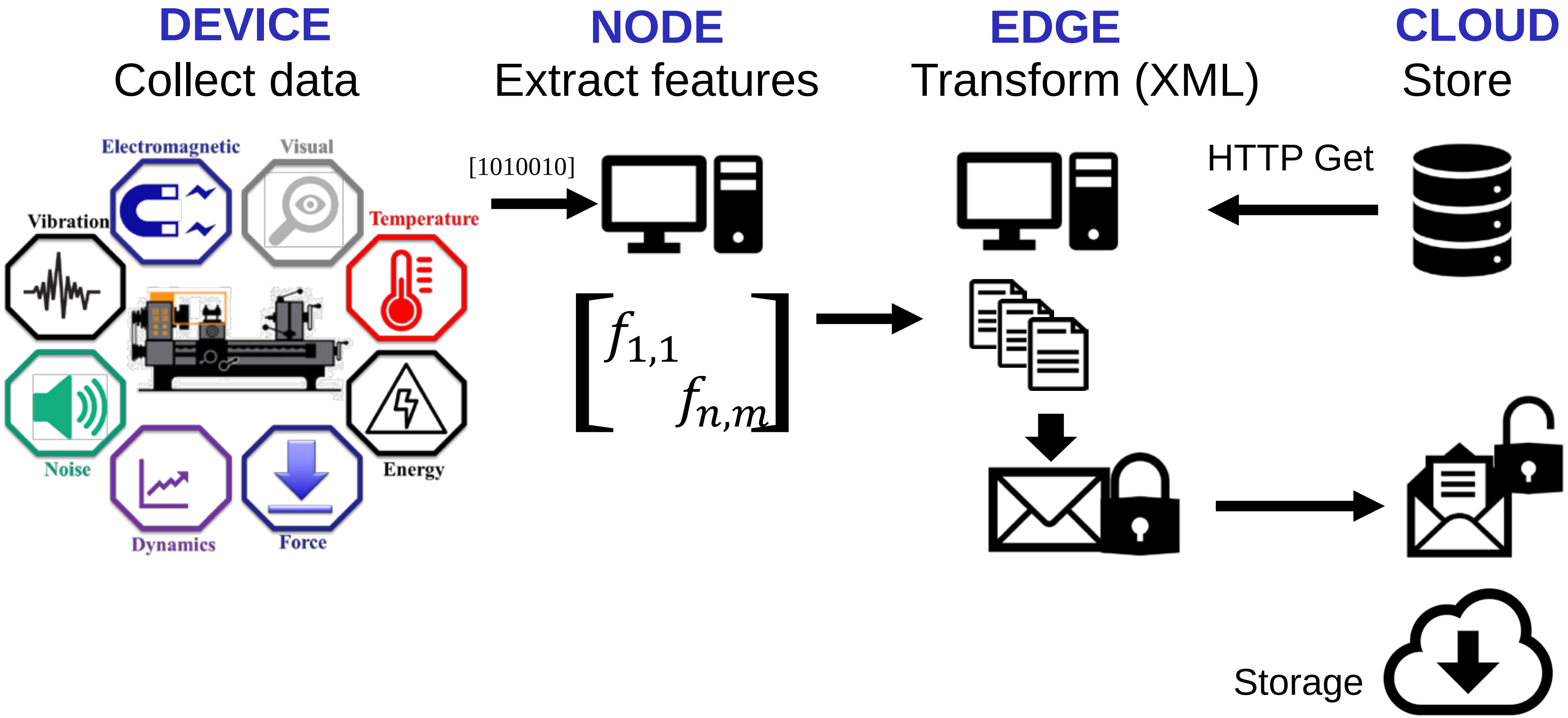
Data reduction

- **Geometry-based:** Key dimensions from images
- **Signal-based:** Key characteristics in the time or frequency domain
- **Condition-based:** Additional information about events

REDUCE DIMENSIONALITY BY EXTRACTING FEATURES

Data Transmission

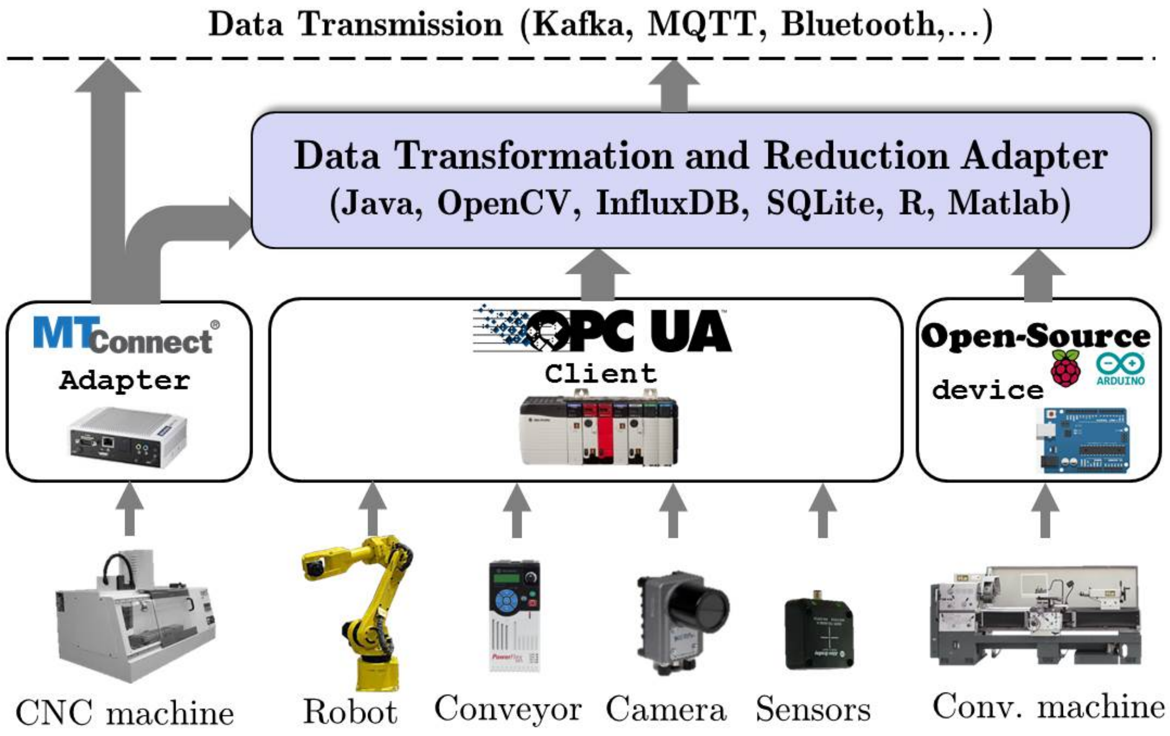
Use common communication protocols



DEFINE CONDITIONS TO DATA TRANSMISSION

Integration of Adapters

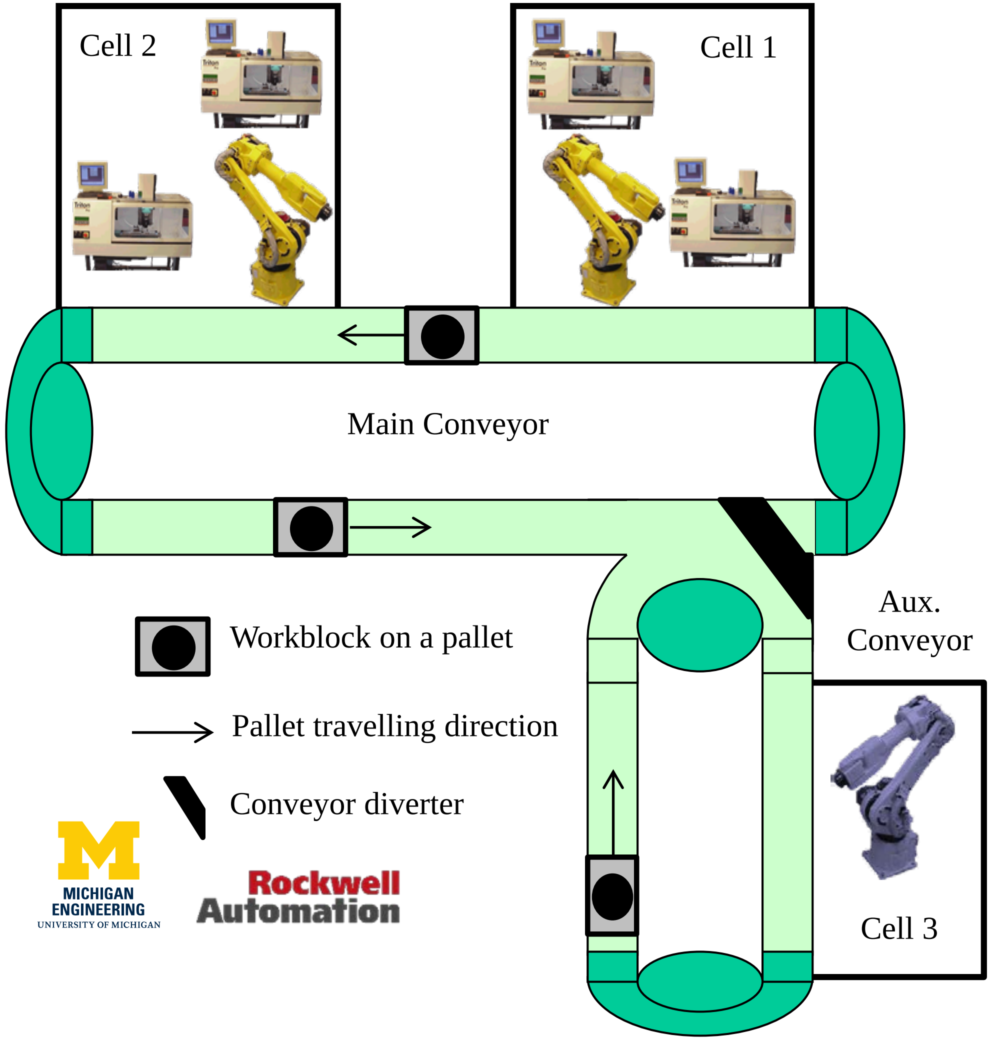
Heterogeneous data sources and protocols



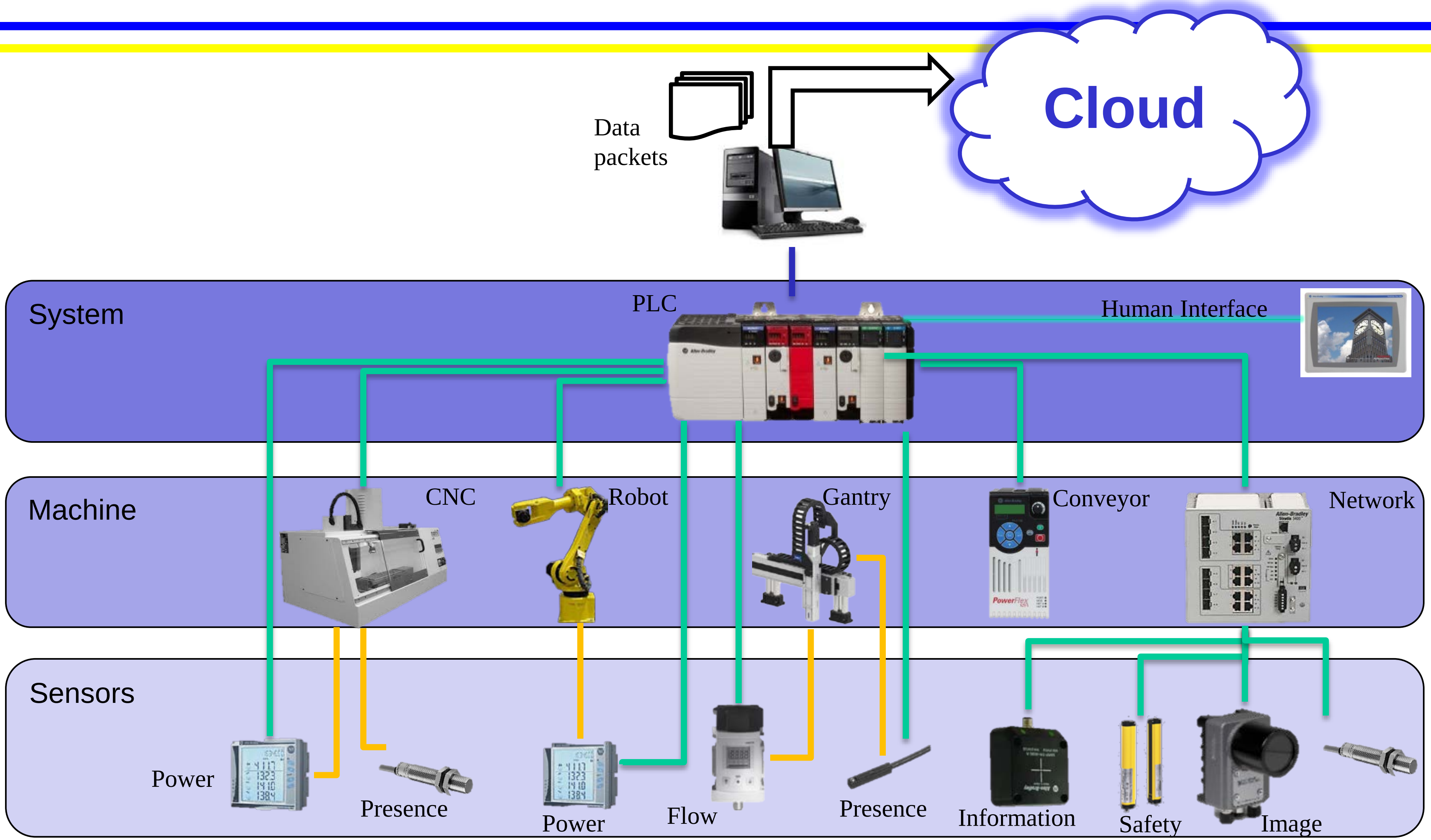
COMPATIBLE WITH DIFFERENT DEVICES AND NODES

Case Study: Description

- Serial-parallel manufacturing line for subtractive and additive manufacturing
- Used for research and education
- Supported by U-M and Rockwell Automation.

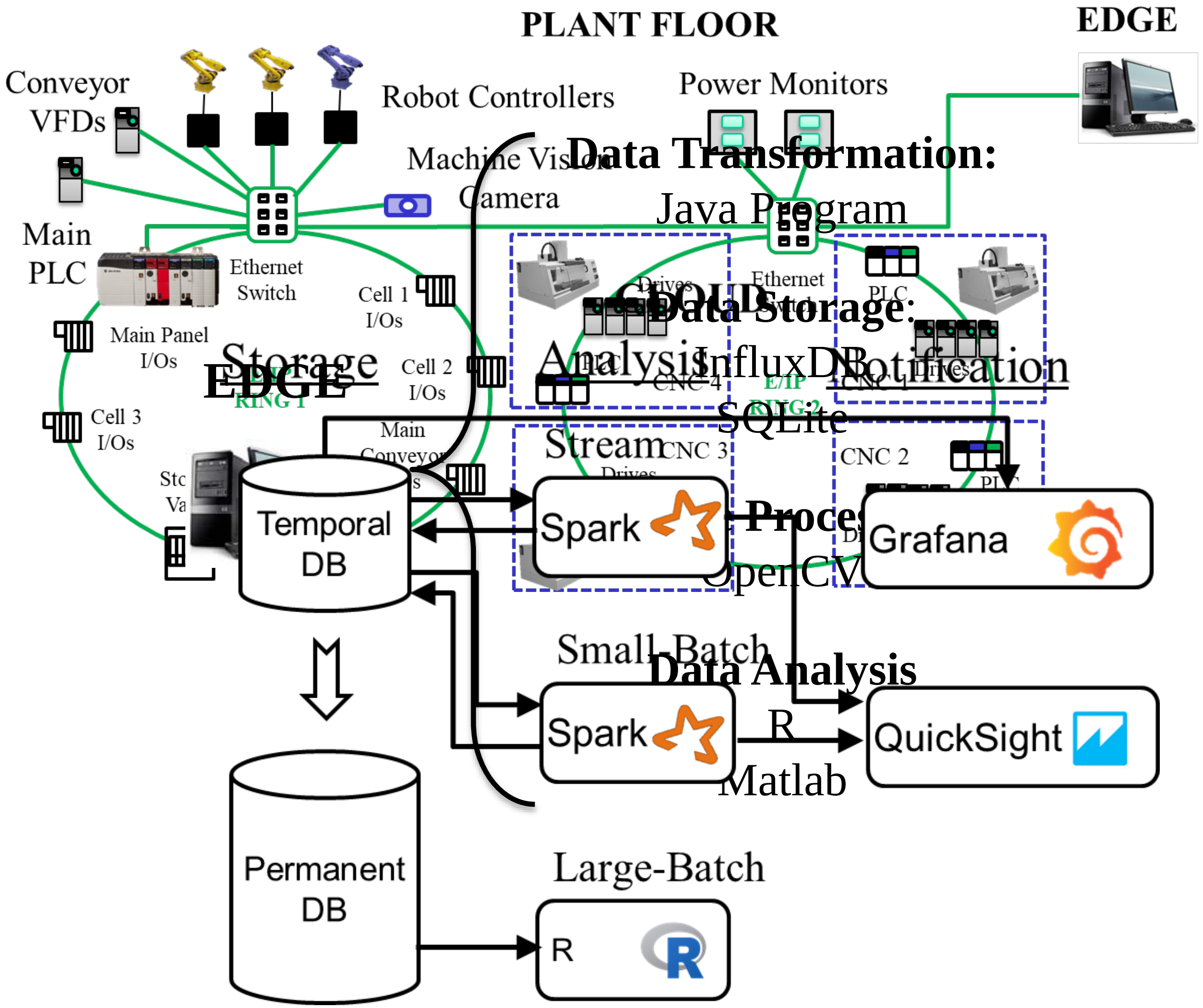


Case Study: Data extraction



Case Study: Architecture

1. Plant floor data extraction
2. Data transformation and reduction
3. Cloud architecture

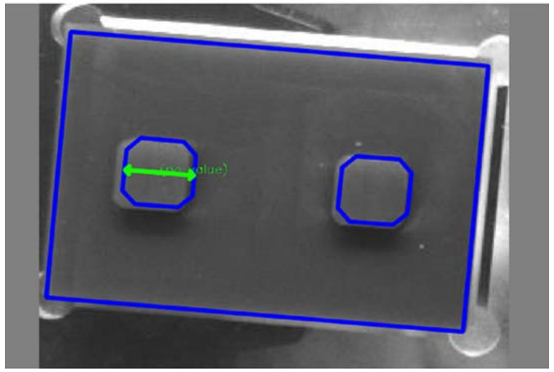


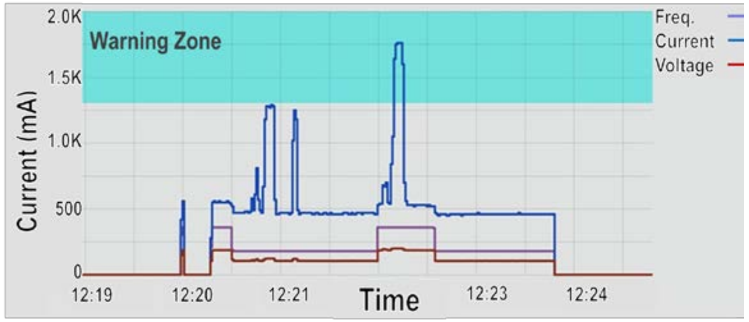
Case Study: Results

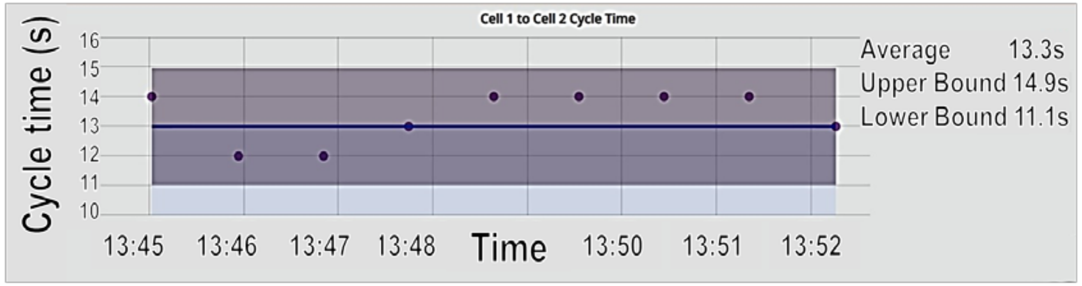
- **Geometry-based:** Extract, send and store part features

- **Signal-based:** Monitor motor conveyor motor overload

- **Condition-based:** Identify event occurrence







Challenges

Feature extraction:

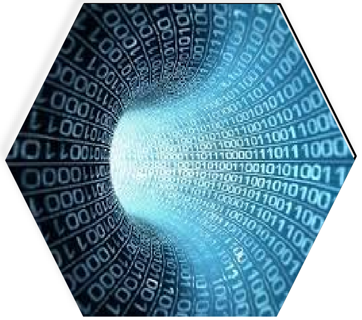
Identify what features to keep from different signals

Scalability:

Expert knowledge is required to define data transmission rules

Data collection

Latency constraints (50 – 1000ms)



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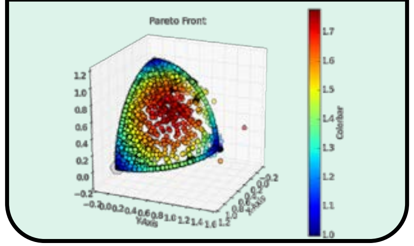

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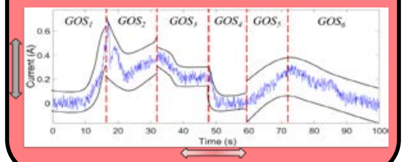

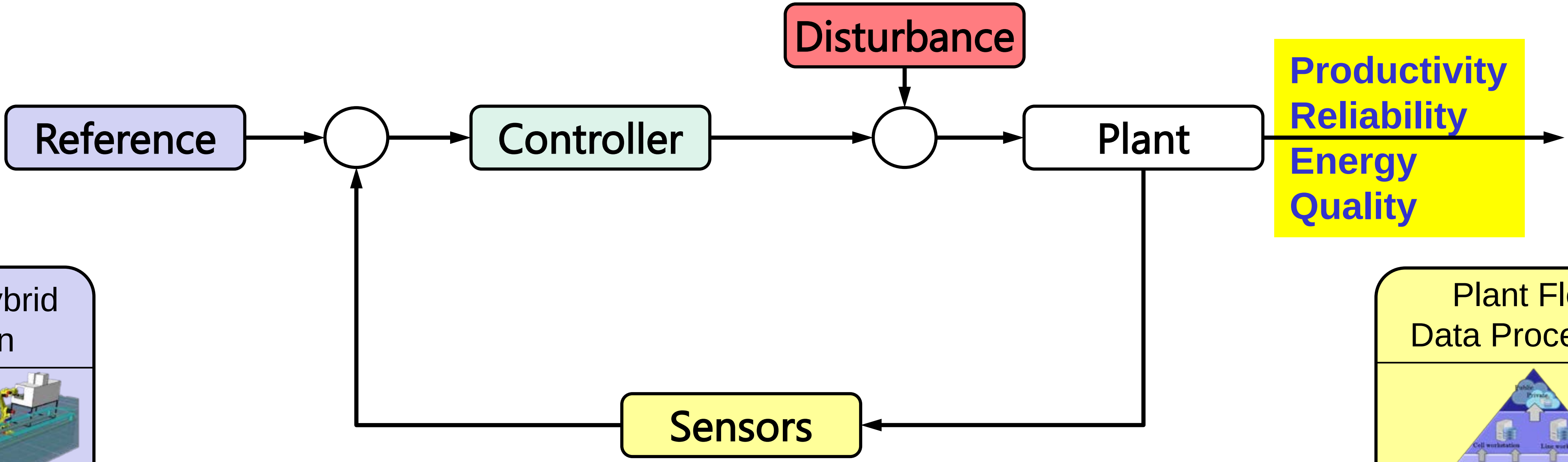

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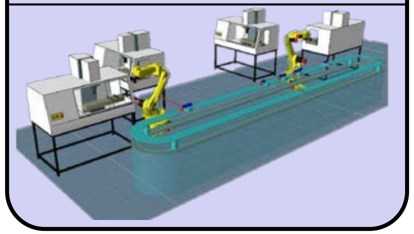

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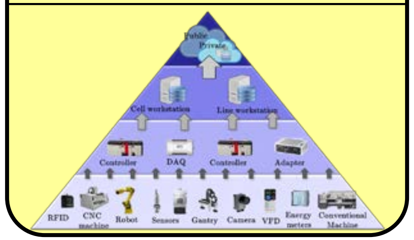
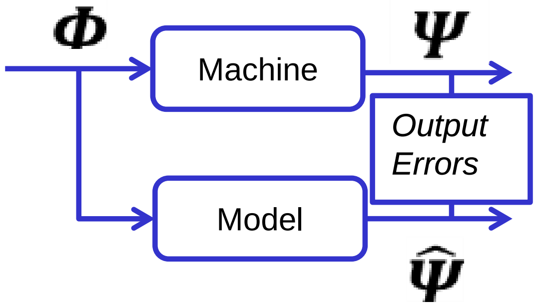
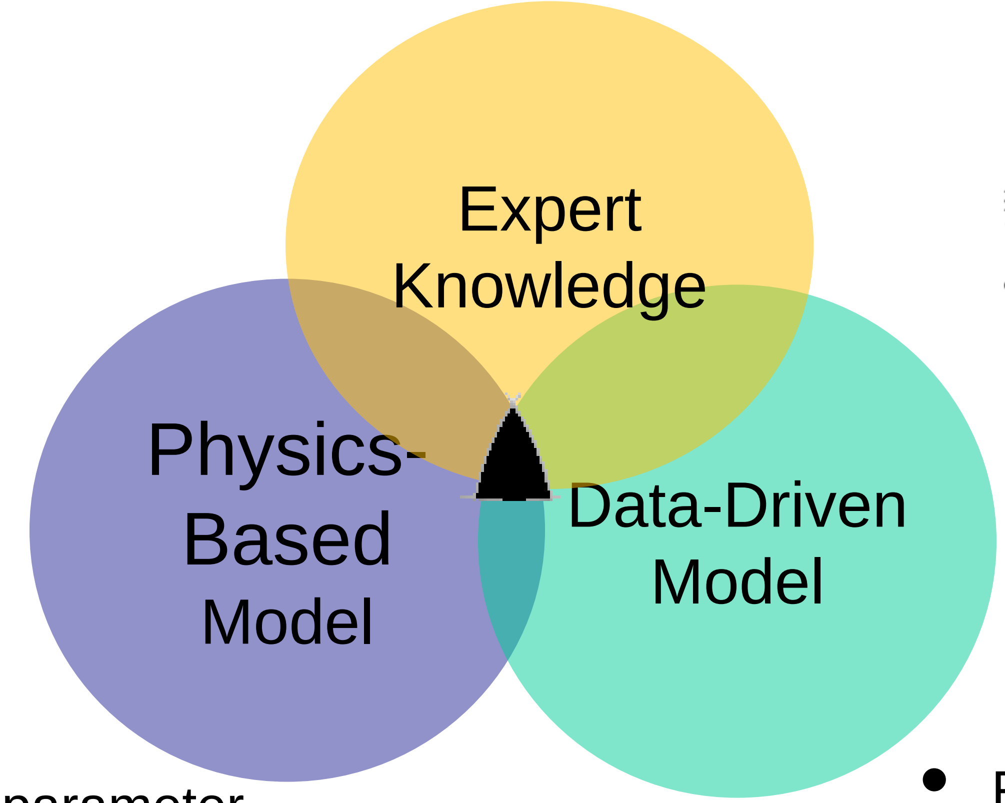
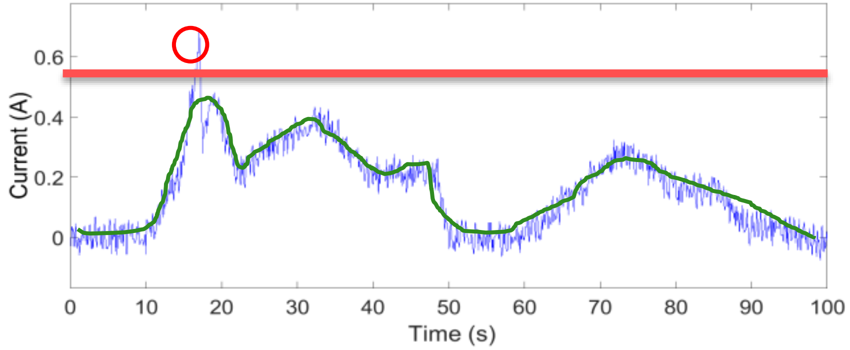


Condition Monitoring: Background

Detection







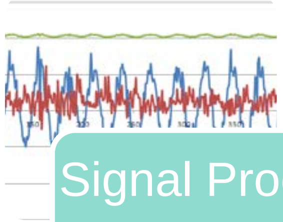
- Model development and parameter estimation
- Bank of Observers to detect faults
- Noise reduction using Kalman Filters

- Fault detection based on vibration or temperature
- Learn discrete states and transitions
- Energy signature analysis

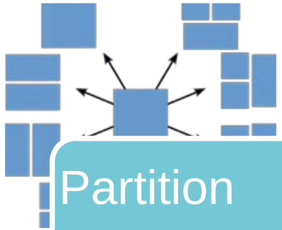
Condition Monitoring

Diagnosis

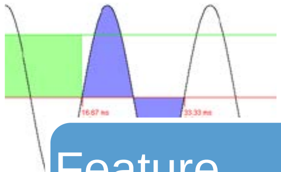
Sensor
- Accel
- Current



Signal Proc.
- Analog
- Digital

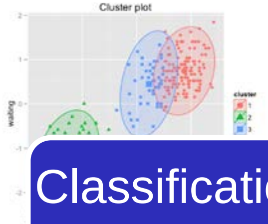


Partition
- Window



Feature Generation
- RMS
- Peak …

Feature Extraction
- PCA
- Ranking



Classification
- DoE
- Machine Learning

Instruction
Change detection
Process
…

Supervised:
- SVM
- KNN
- D.Tree

Unsupervised
- SOM

Condition Monitoring: Gaps

- **Gap**

o Combine different models for various machine-part interactions

o Diagnosis based on operational context of non-stationary signals

o Consider risks or severity in part and process

- **Research Questions:**

o How to detect anomalies in machines operating under different states?

o How to identify machine-part interactions?

o How to develop a context-sensitive multi-model framework?

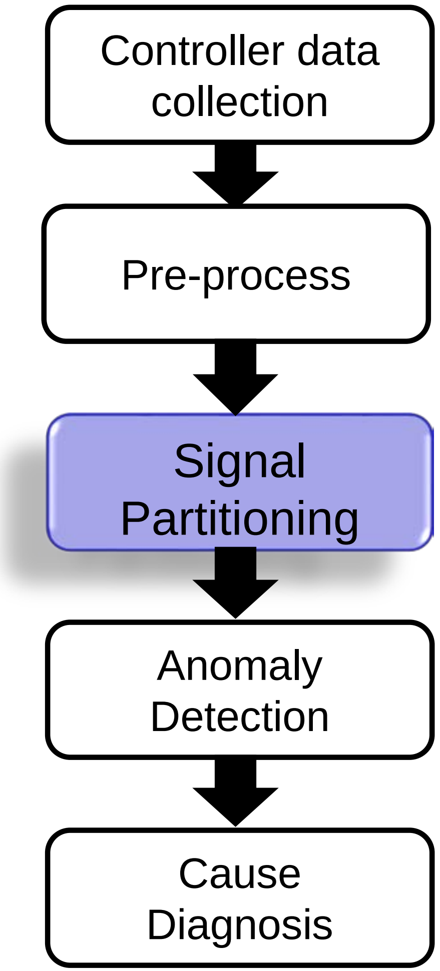
Condition Monitoring: Solution

Leverage controller data and expert knowledge:

- **Explicit operation descriptors:**
  - **Part** (e.g.: type, material, supplier)
  - **Tool** (e.g.: dimensions, features, material)
  - **Process step** (e.g.: G-code, task, states)

- **Implicit operation descriptors:**
  - **Machine dynamics** (e.g.: velocity, acceleration)
  - **Machine-part interactions** (e.g.: side milling, drilling, welding)

Condition Monitoring: Solution



- Sensor data: Encoder $(q, \dot{q})$ and energy (I, V)
- Context information: State, Process step, tool,…

Signal Filtering and data fusion

Identify operational context
- Machine-part interactions
- Transient states

Context-sensitive adaptive threshold limits

Context-specific classification models

Modeling Framework: Global Operational States

Functional States Idle, set-up, repair, processing, …	**Dynamic States** **(machine dynamics)** Accel, decel, constant velocity, …
Interactive States **(interact w/part)** Roughing, finishing, face milling, …	**Process Descriptors** **(part & process)** Part type, tool type, material, …

Use Expert knowledge, Event detection, and Dynamic Time Warping to separate states

Condition Monitoring: Solution

Identify Operational Context

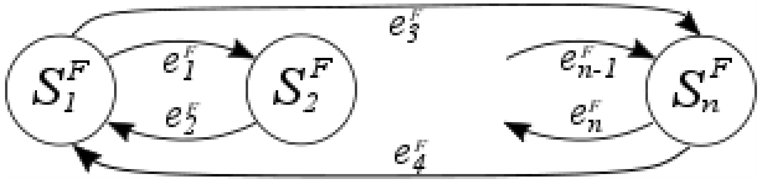
$$GOS(k) = (\boxed{S^F(k), S^D(k), S^I(k)}, \boxed{p(k), t(k), s(k)})$$

Implicit Descriptors:
States: Functional
Dynamic
Interactive

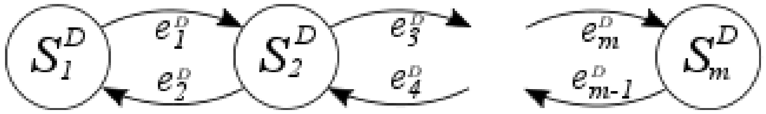
Explicit Descriptors:
Part
Tool
Process Step

Define Discrete States

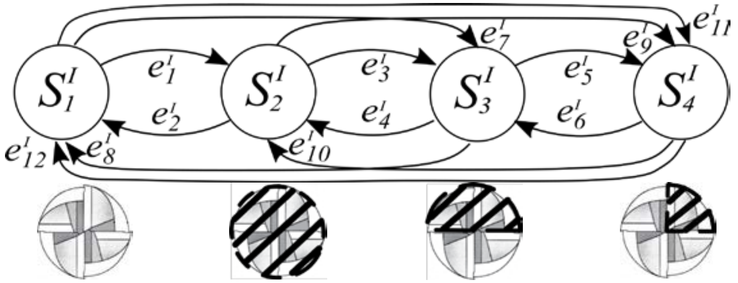
Functional states (S^F):
Reduced model of logic controller.
e.g.: setup, repair, Idle, processing



Dynamic states (S^D):
Discrete set describing continuous machine dynamics
e.g.: Accel, Constant velocity, Decel,



Interactive states (S^I):
Describes consecutive operations to the part *e.g.: drilling, roughing, finishing, side milling*



Condition Monitoring: Solution

Identification of Interactive Events:

Algorithm 1 Event Search Algorithm

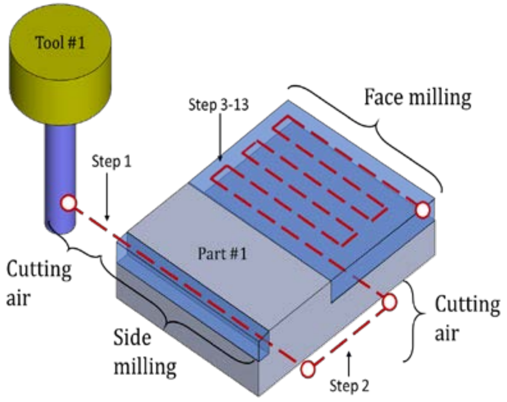
Input: $e^I = [Y_{ref}(1)...Y_{ref}(n)]^T$, $G = [Y(1)...Y(m)]^T$
Output: Event Start, Event end

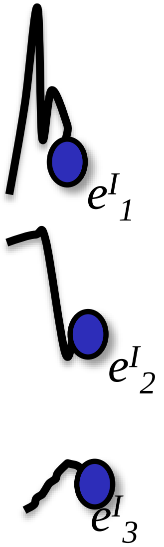
```
    Initialization :
Best-so-far ← ∞
    LOOP
for i = 1 to m − 1 do
    for j = 2 to m do
        if DTW(e^I, G_{i,j}) < Best-so-far then
            Event Start = i
            Event end = j
            Best-so-far = DTW(e^I, G_{i,j})
        end if
    end for
end for
return Event Start, Event end
```

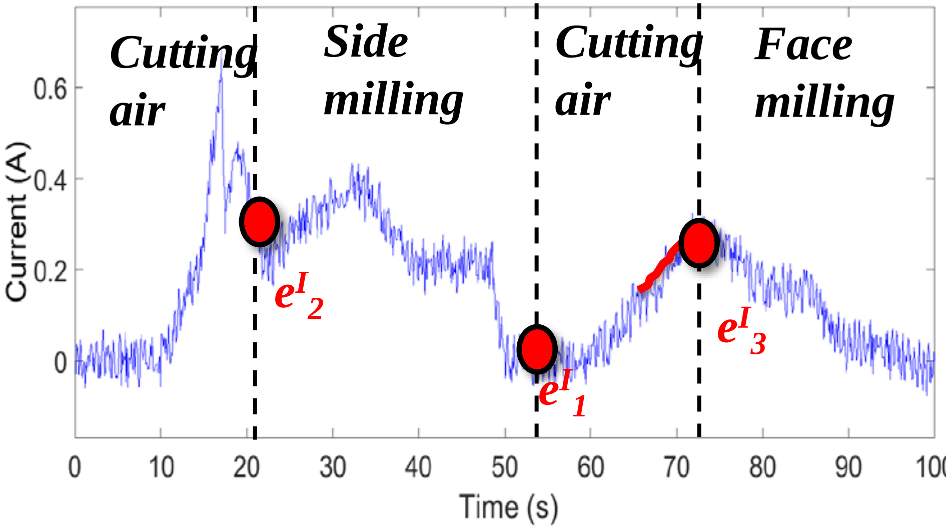
$$G = [Y(1) \ldots Y(m)]^T$$

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

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





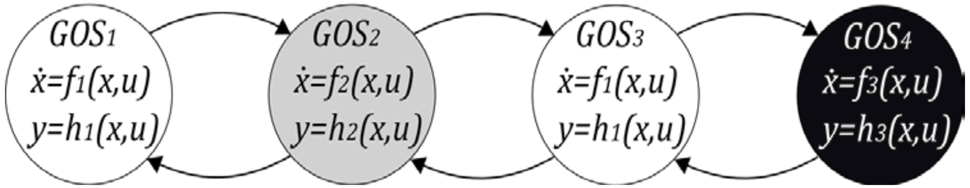


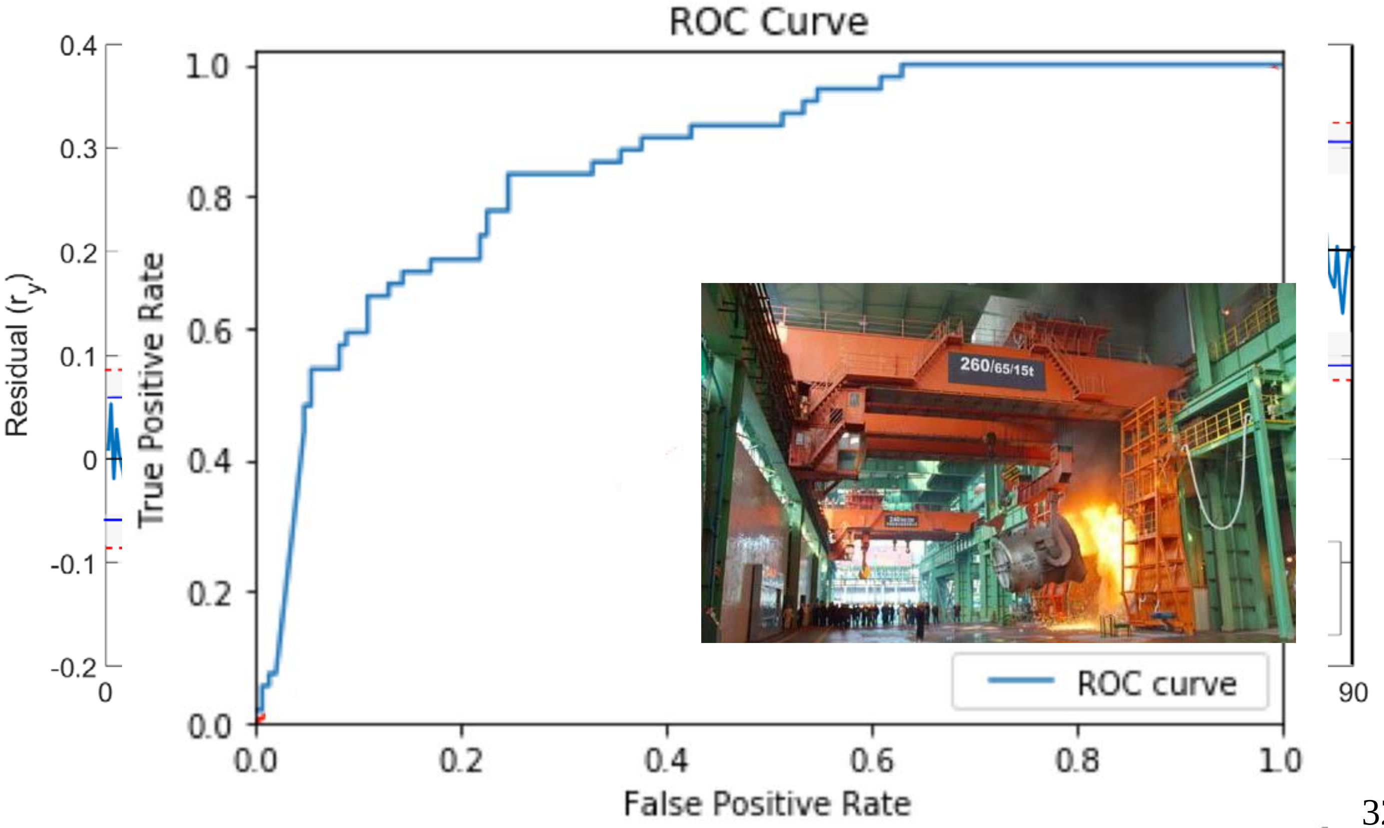
Condition Monitoring: Solution

Multi-model Specification:

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

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:

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

$\boldsymbol{\mu}: mean, \boldsymbol{\sigma}: Std, \boldsymbol{Z}: Score$

$\boldsymbol{\psi_R}: Risk\ Coefficient$

Condition Monitoring: Solution

- **Context-Specific Classification:**
  1. Partition signal by Context

     $[GOS_1 \ldots GOS_3 \ldots GOS_1 \ldots GOS_n]$

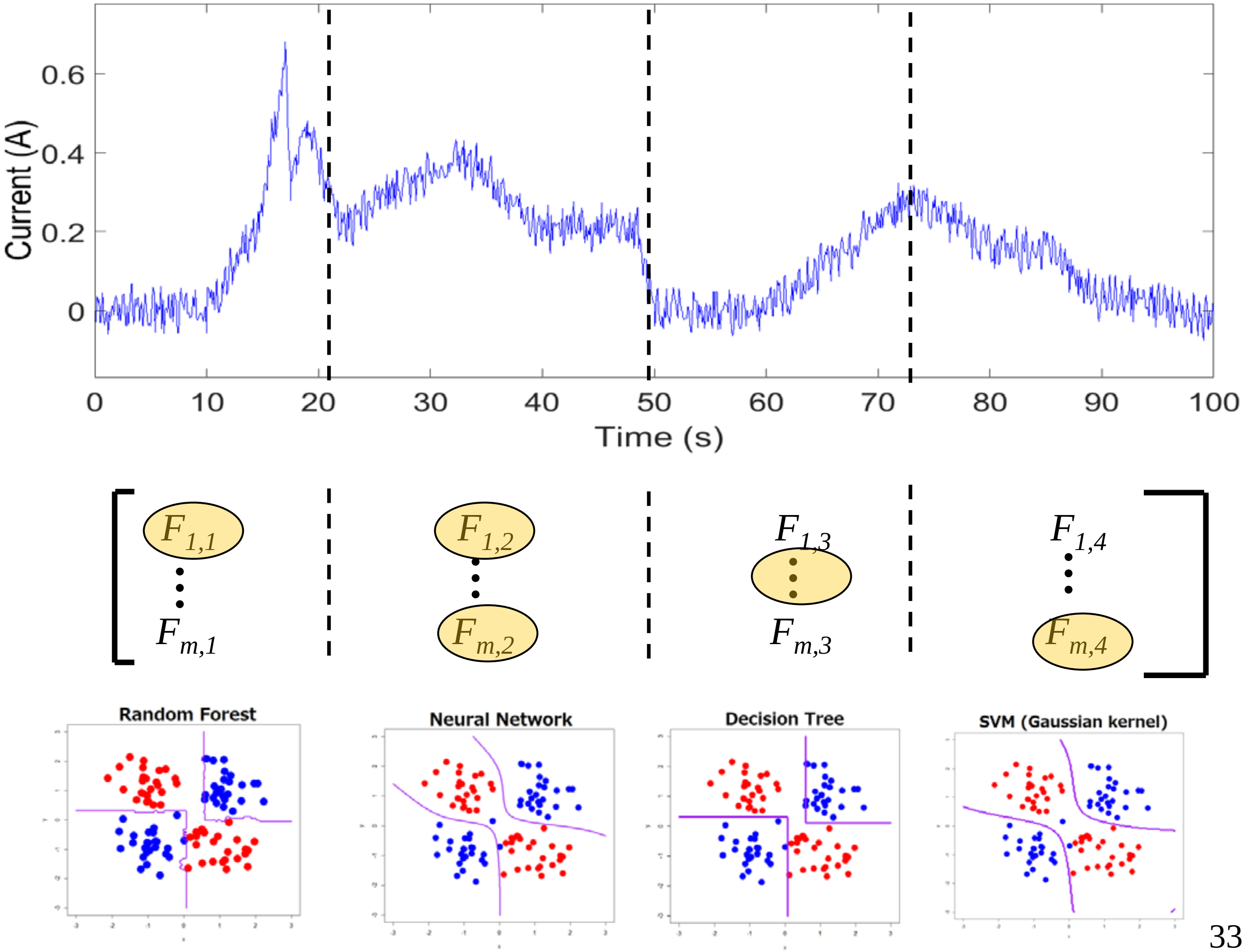
  2. Generate Features

     Time domain: $\{\mathrm{F1: RMS, F2: Max, \ldots}\}$

     Frequency domain: $\{\mathrm{F3: Peak\ Freq.,}$ $\mathrm{F4: Amplitude, \ldots}\}$

  3. Extract Features

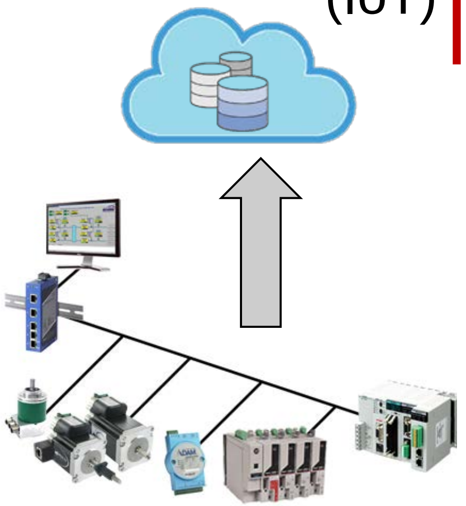
  4. Classify

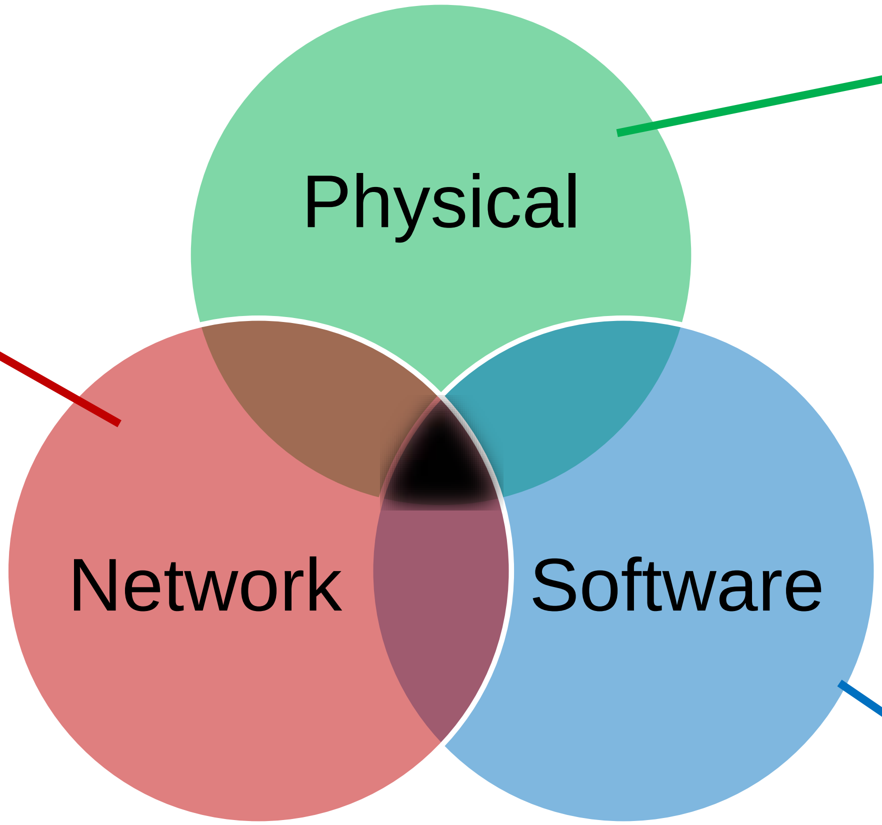


Condition Monitoring: Case Study

Cyber-Physical Manufacturing Systems

DeviceNet
Ethernet/IP
Internet of Things
(IoT)





Sensors data
Dynamic models
Part information

G21

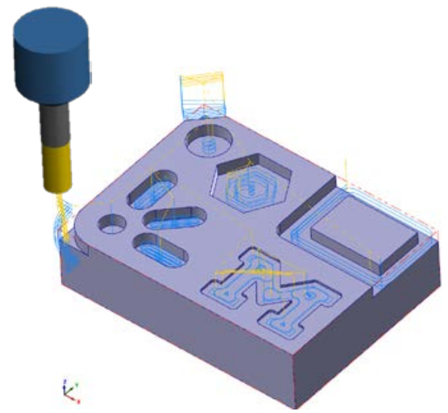
G90
G00 X143.135 Y107.226 S3500
M03
Z60.237
G03 X-.627 Y.627 Z0 I-.627 J0. K0
....

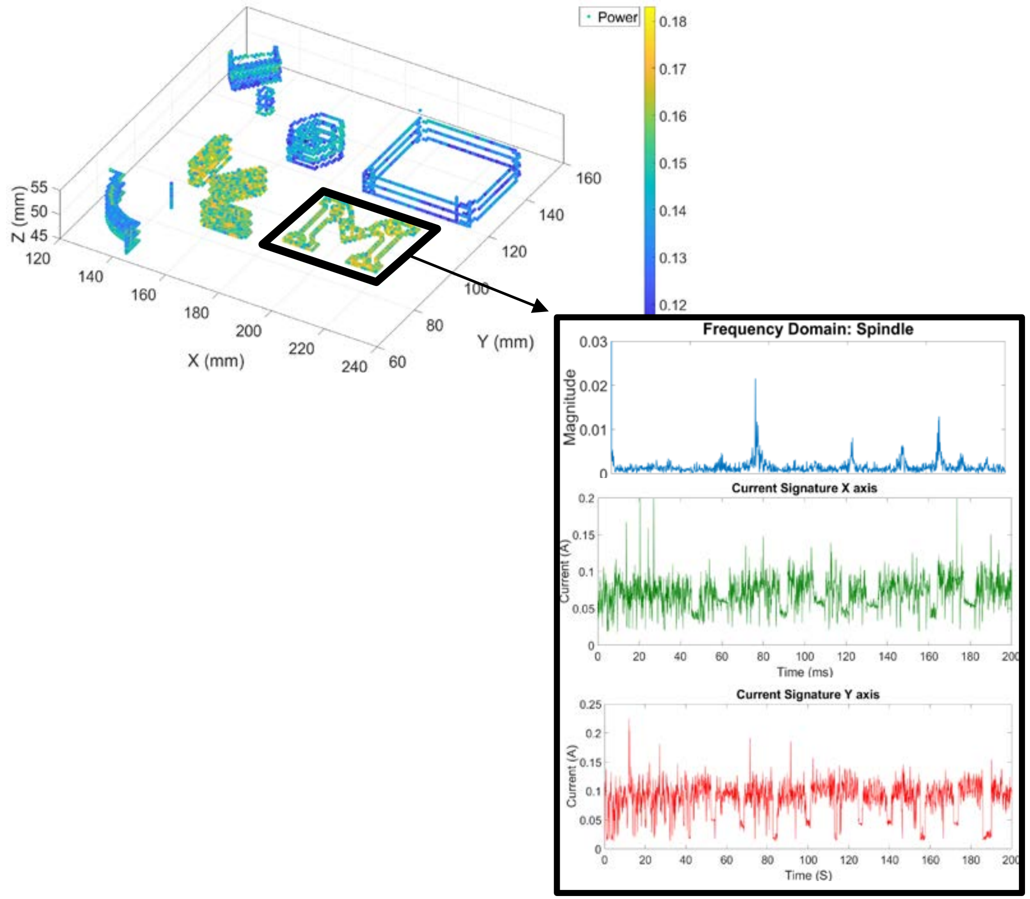
Control logic
Commands
Algorithms

Condition Monitoring: Case Study

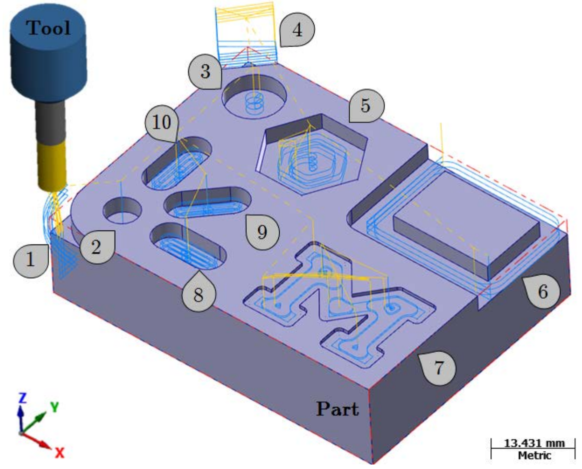
- **Inputs: Sensor data and Context information**

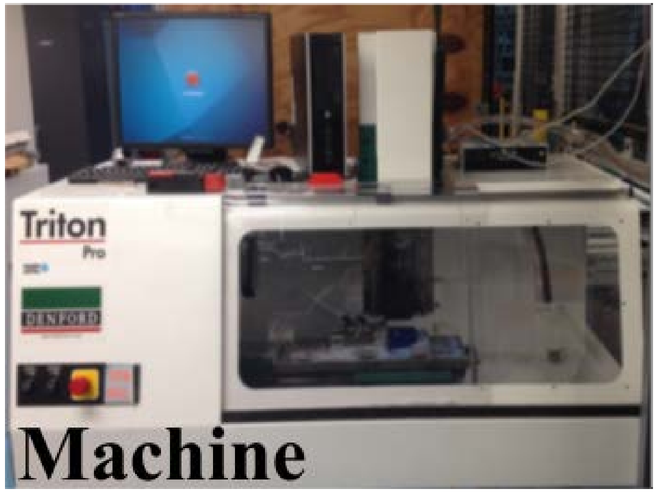
Process step + Artificial vision + Energy signature

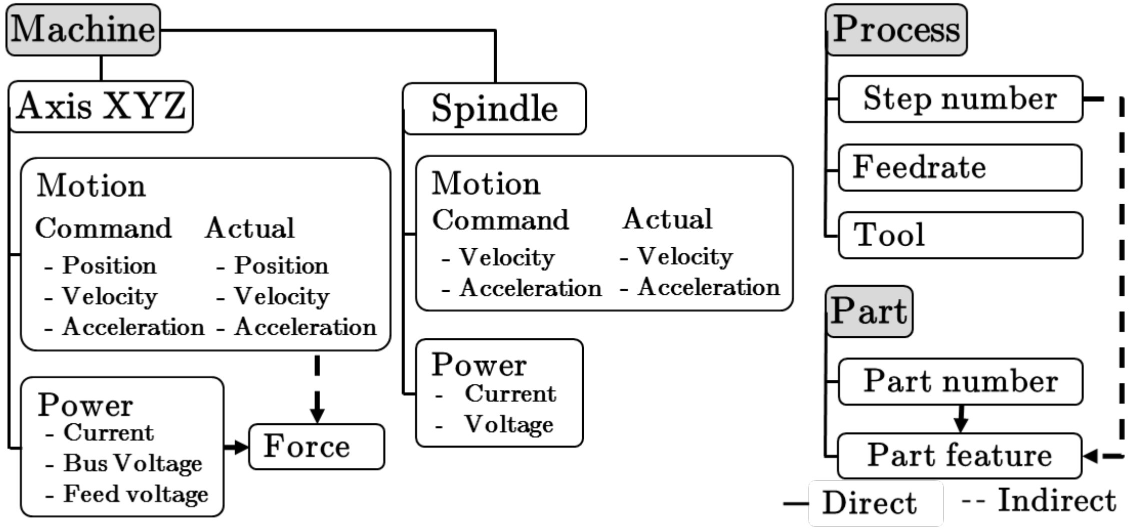




Condition Monitoring: Case Study







Global Operational State (GOS):

Information:
Tool, Part, Step

Functional:
Processing, Idle

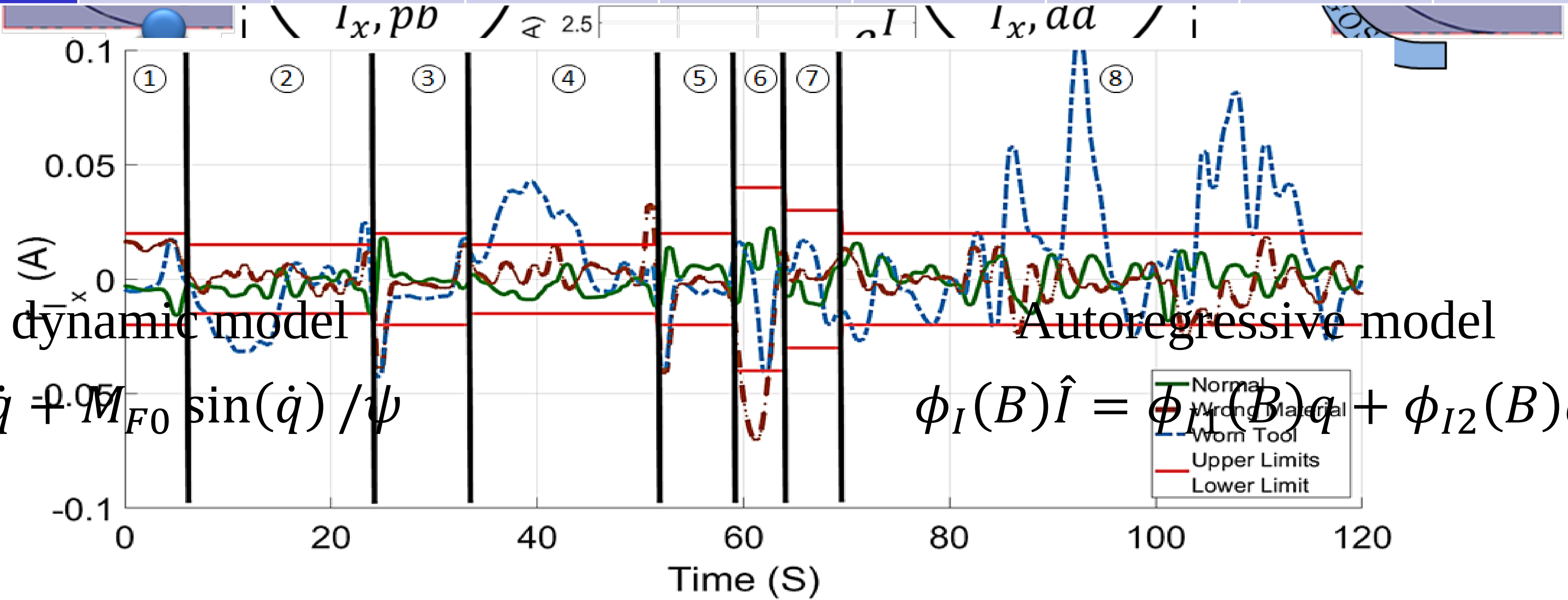
Dynamic:
Accel, Const, …

Interactive:
No Int, Drilling,..

Condition Monitoring: Case Study

- Multi-Model Framework:

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



Single Mass dynamic model

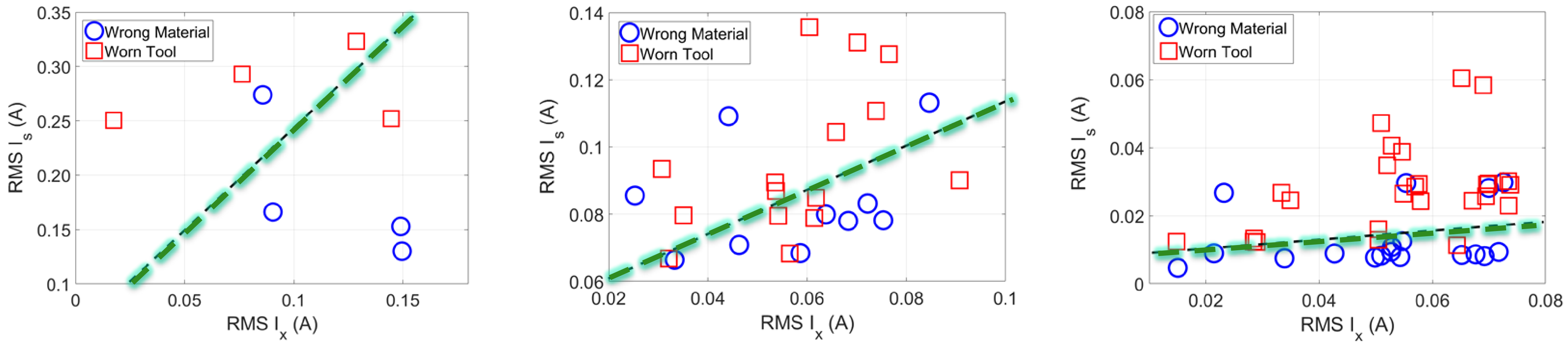
$$\hat{I} = Jq + M_{F1}\dot{q} + M_{F0}\sin(\dot{q})\,/\psi$$

Autoregressive model

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

Condition Monitoring: Case Study

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



Entire signal: 75%

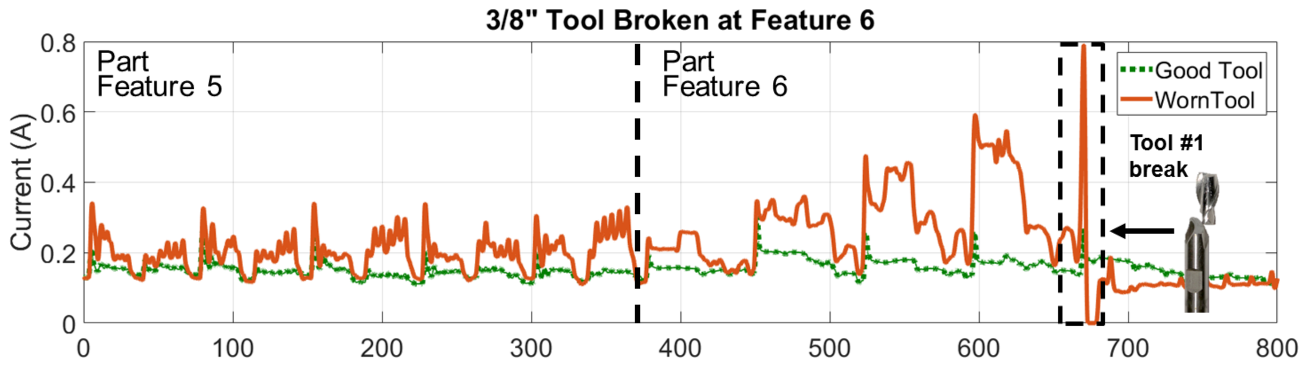
Partition by part feature: 81.2%

Partition by part feature and GOS: 93.6%

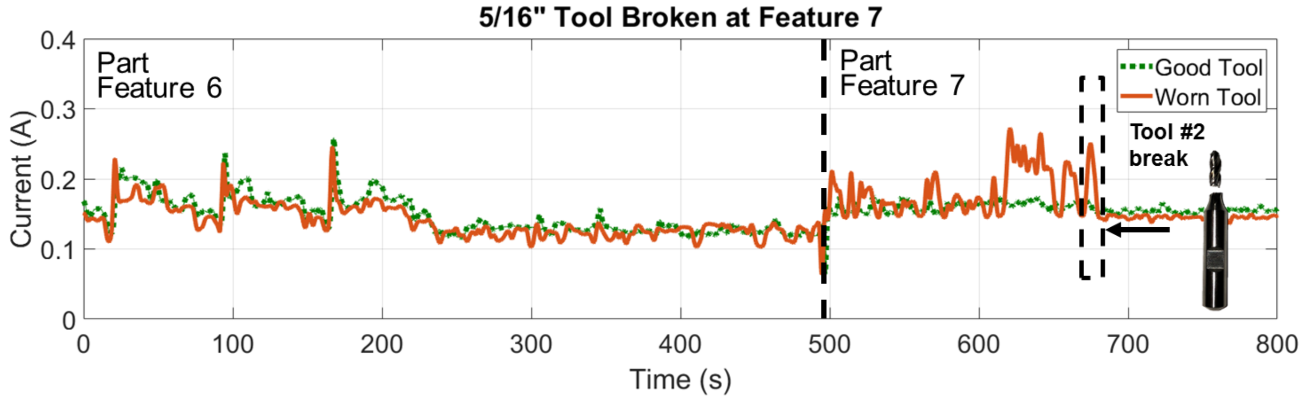
Condition Monitoring: Case Study

Develop context-specific diagnosis rules:

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



Diagnose tool breakage under different operational context

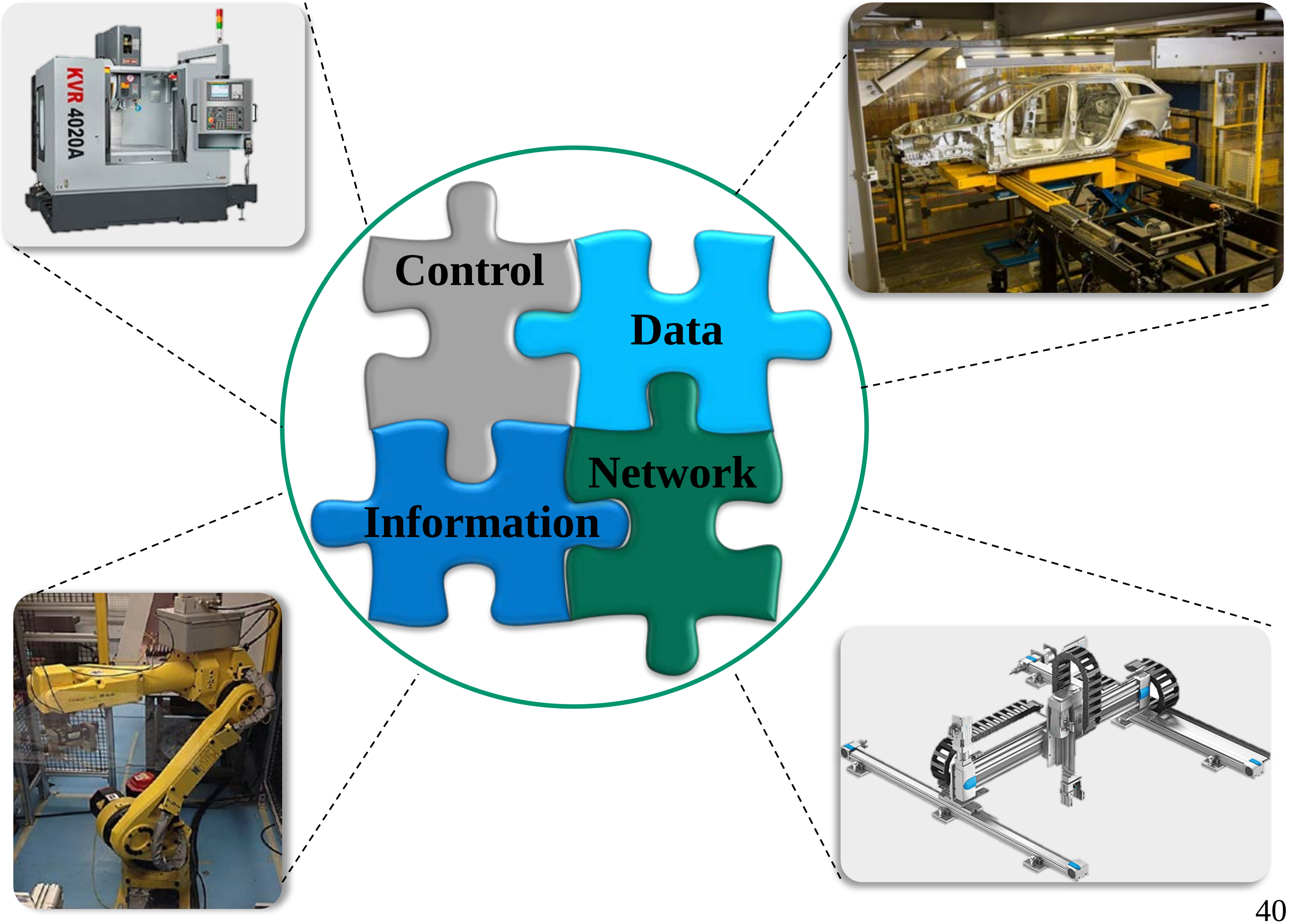


Condition Monitoring: Contribution

Identification of machine-part interaction to enable context-sensitive analysis

Improve anomaly detection and diagnosis using a multi-model framework

Impact: Support condition monitoring for more effective maintenance actions



Outline

Introduction & Motivation

Collecting and integrating diverse data

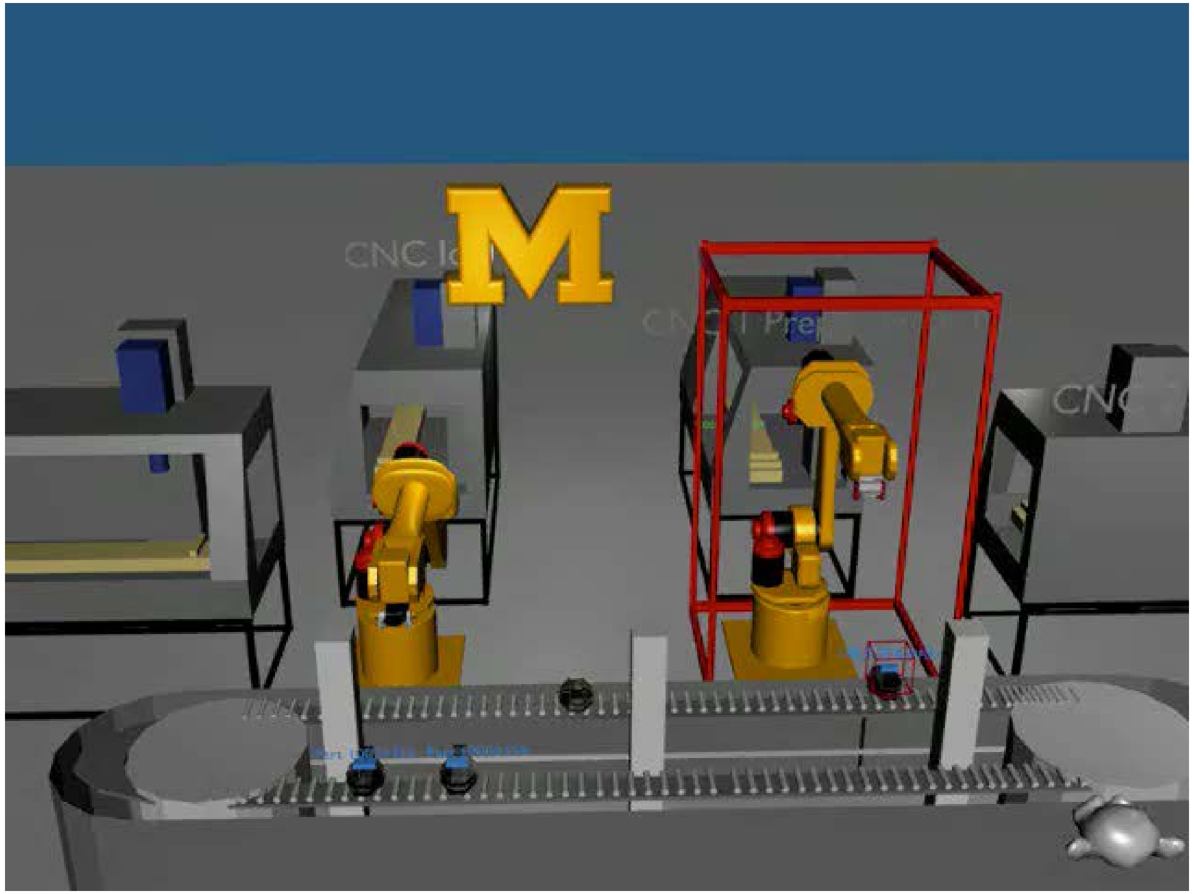
Condition monitoring and adaptation

Conclusion and future work

Monitoring system real-time data

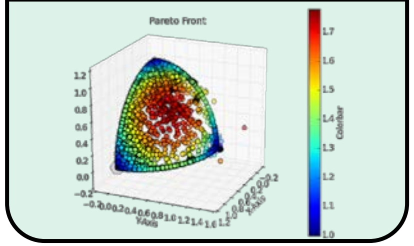
Virtual world reflects real time "ground truth" of the plant floor

Improved information visualization leads to better understanding of system operation, rapid fault diagnosis and reduced downtime



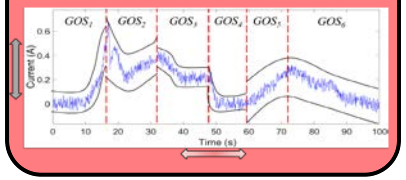
Using data to improve manufacturing operations

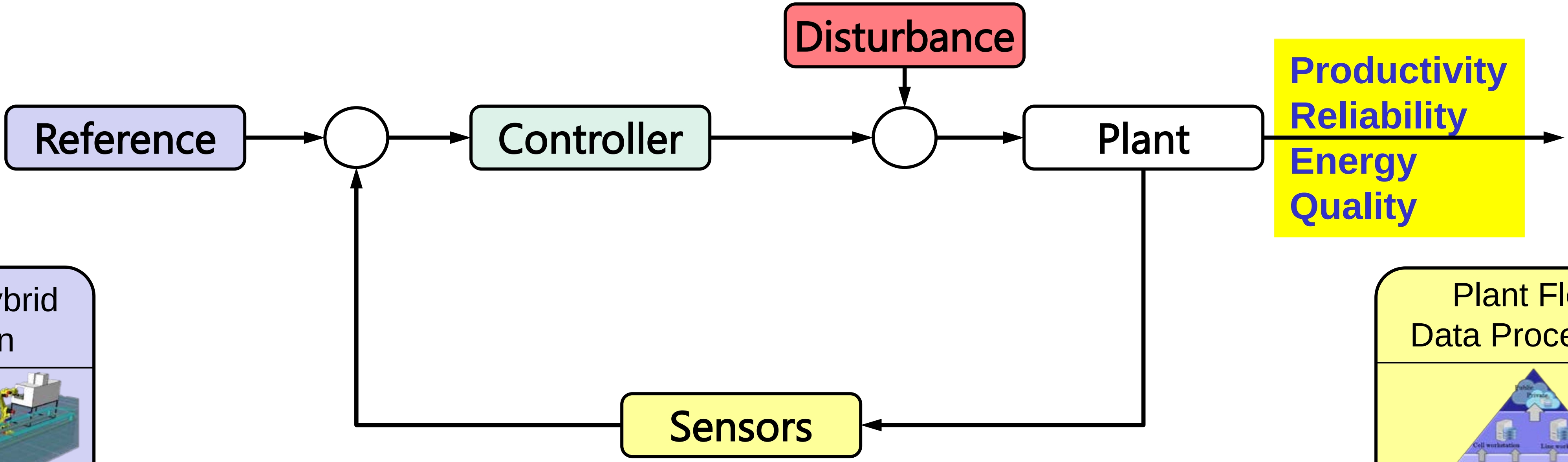
Multi-Objective Decision Making



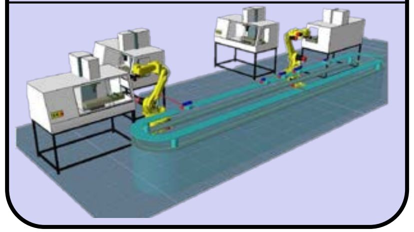
- **Better knowledge → better decisions**
  - **Maintenance**
  - **Scheduling**
  - **Reconfiguration**

Context-Sensitive Anomaly Detection





Real-time hybrid Simulation



Plant Floor Data Processing