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Machine Learning for the Monitoring and Optimal Control of Smart Factories

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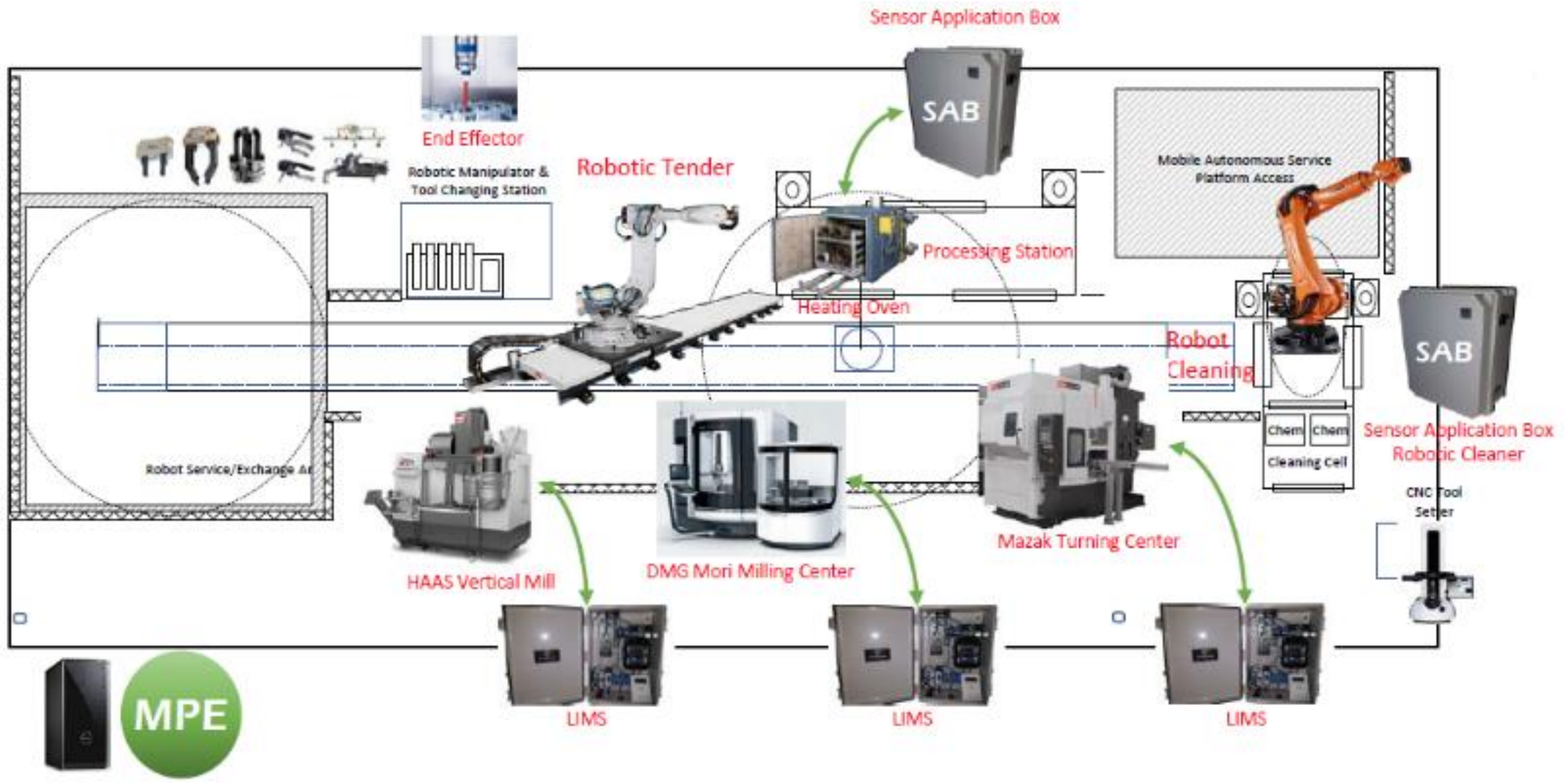
IIoT

Industrial Need

- IIoT framework provides access to data, and infrastructure for processing and communication
- <u>Motivation</u>:
  how to use newly available data/resources effectively to create optimal and robust processes



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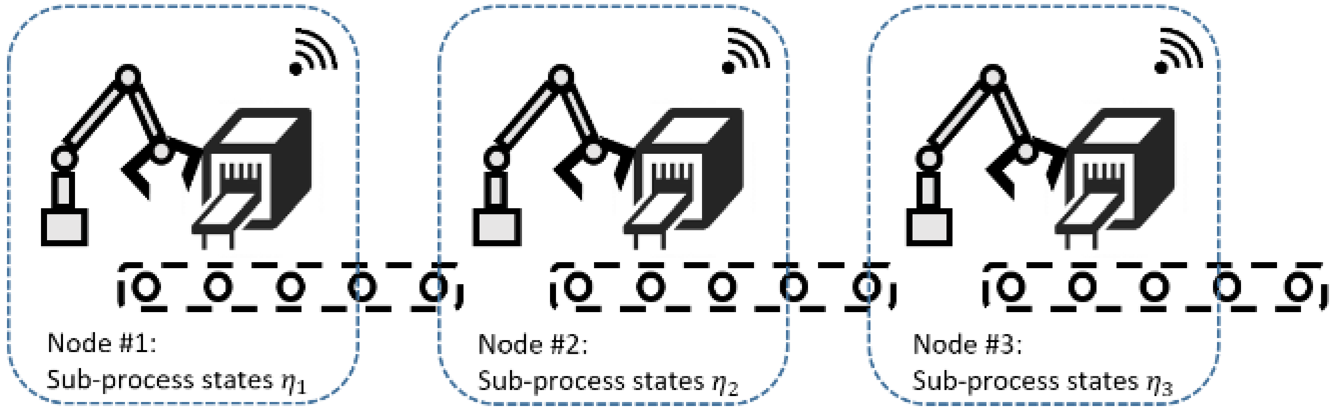
Project Objective

- Create an intelligent manufacturing system of distributed modules
  - Distributed modules enabled to monitor the entire process state without a central hub
  - Module enable to make local manufacturing decisions to optimize efficiently and
    resilience of global process
  - Reduce single point of failure, communication reqs.



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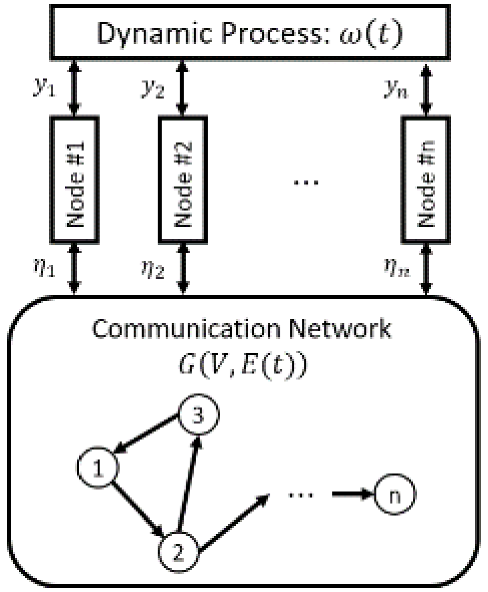
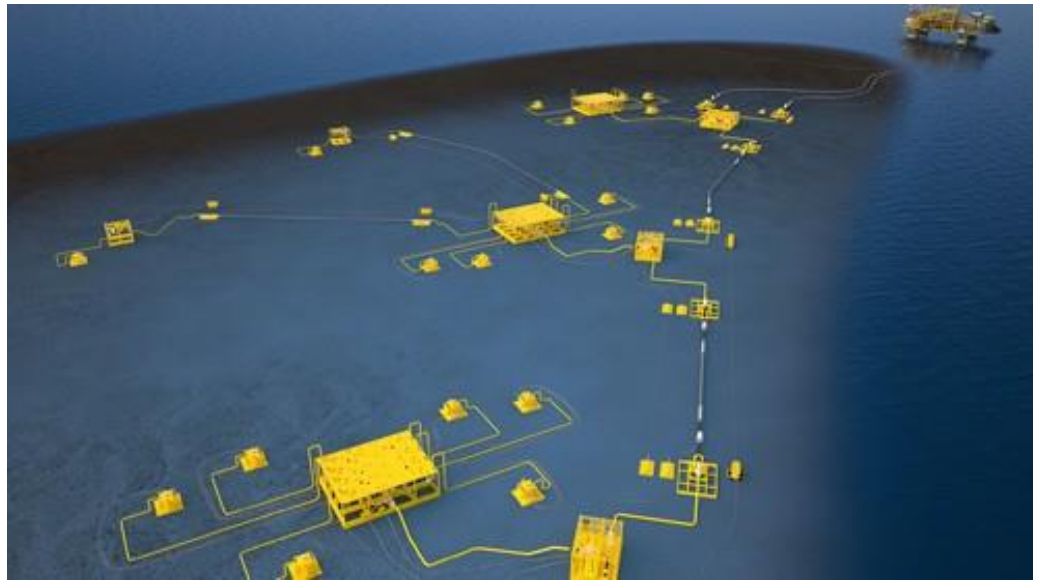
Approach

- Investigate frameworks for distributed monitoring, control and optimization
  - Distributed monitoring by nodes with limited sensing and comm. resources
  - Machine learning to account for uncertainties in monitoring, and evaluate trust on neighboring nodes'
  - Distributed learning and optimal control to optimize global process by sensing and decisions at the node level





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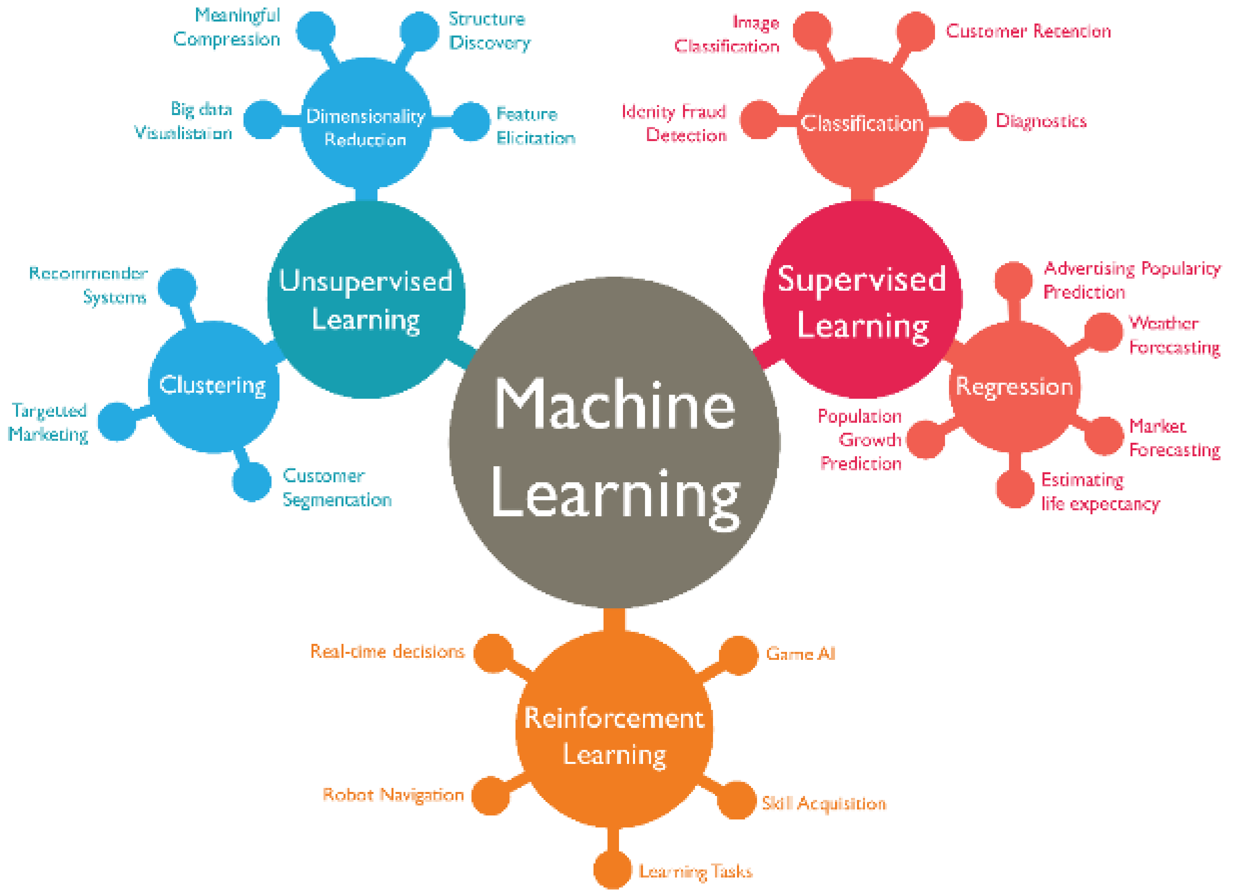
Approach

Machine Learning for Distributed Manufacturing

- Distributed are difficult to control and maintain
- Effective management by human operators is difficult and expensive
  - Big data sets available
- ML: Computer systems learn from data



Source: WordStream.com

Methodology

Reinforcement Learning

- **ML**: Predict future behavior
- **RL**: Select best action for long-term profit
- Decide when to:
  - Inspect a component
  - Replace a component
  - ...
- RL excels in complex, large stochastic environments like manufacturing

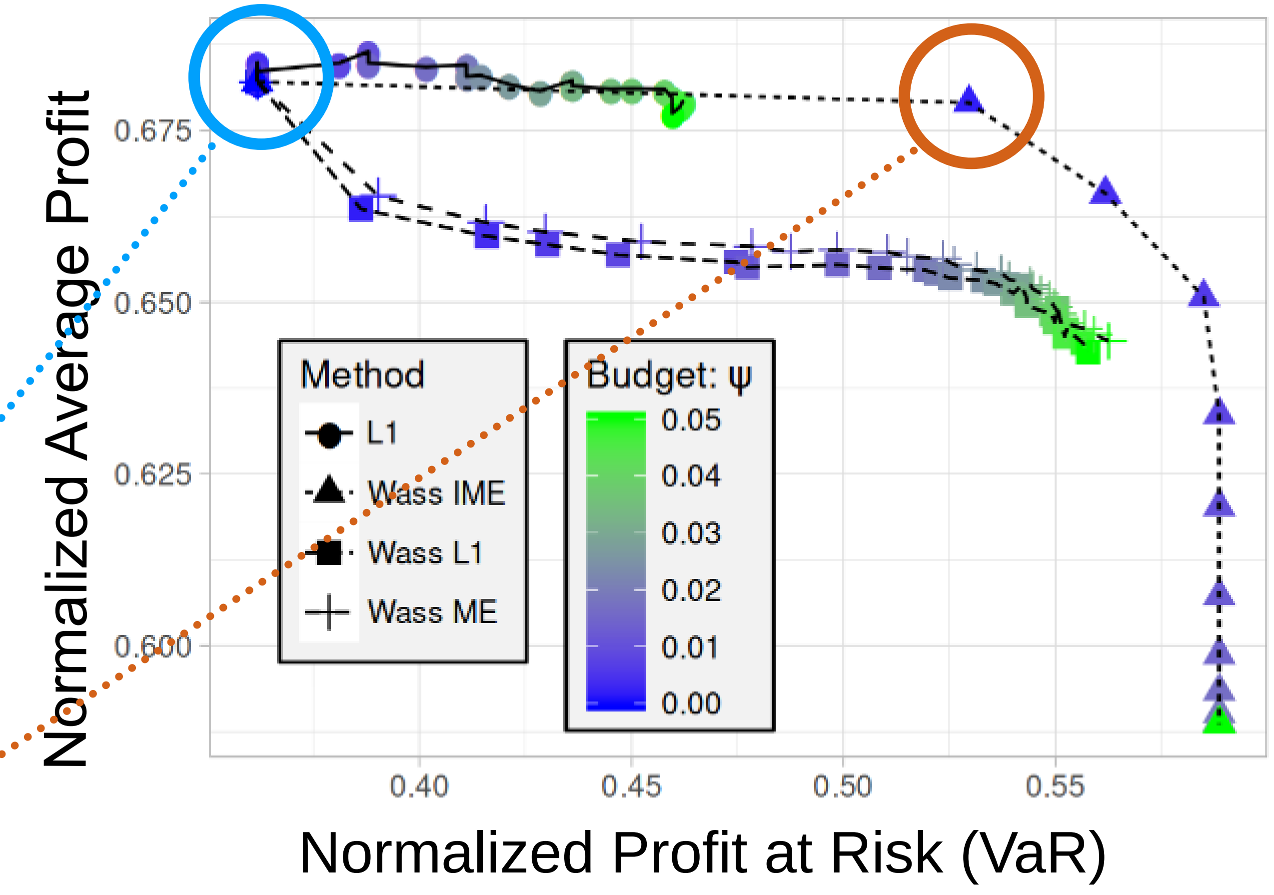
Google DeepMind: RL Beats Humans in Go

Methodology and Results

Risk-averse Reinforcement Learning

- Average solution quality is important, but
- Data is often biased, noisy, limited, …
- Mitigating risk is important in manufacturing (large losses)
- RL methods that reduce risk and preserve solution quality
- *Example*: Risk-RL vs standard RL
    - 97% average performance
    - 155% worst-case performance

Spatial resource allocation problem



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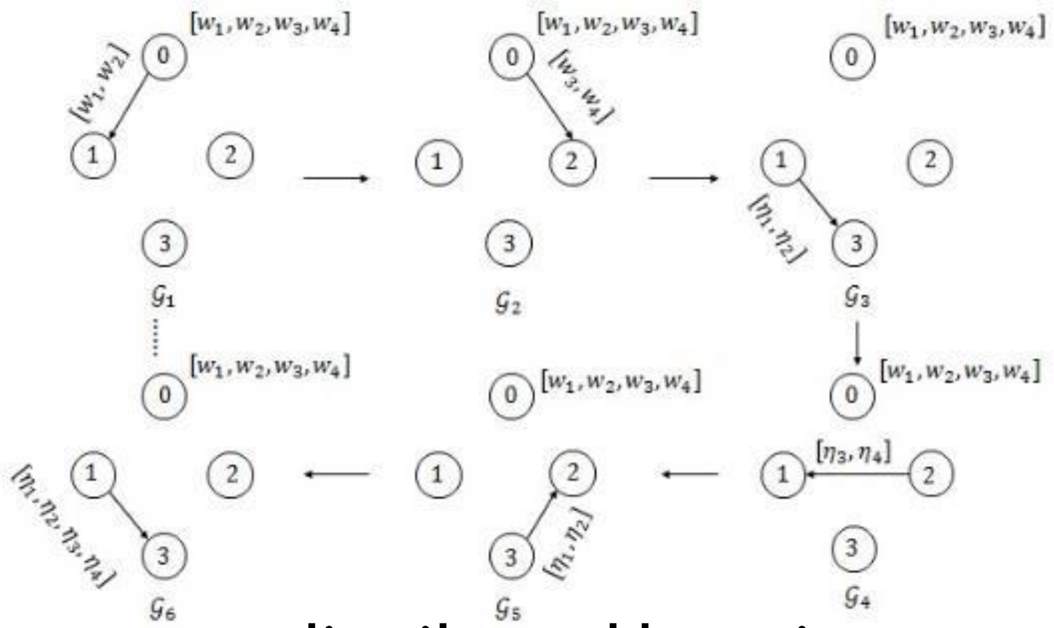
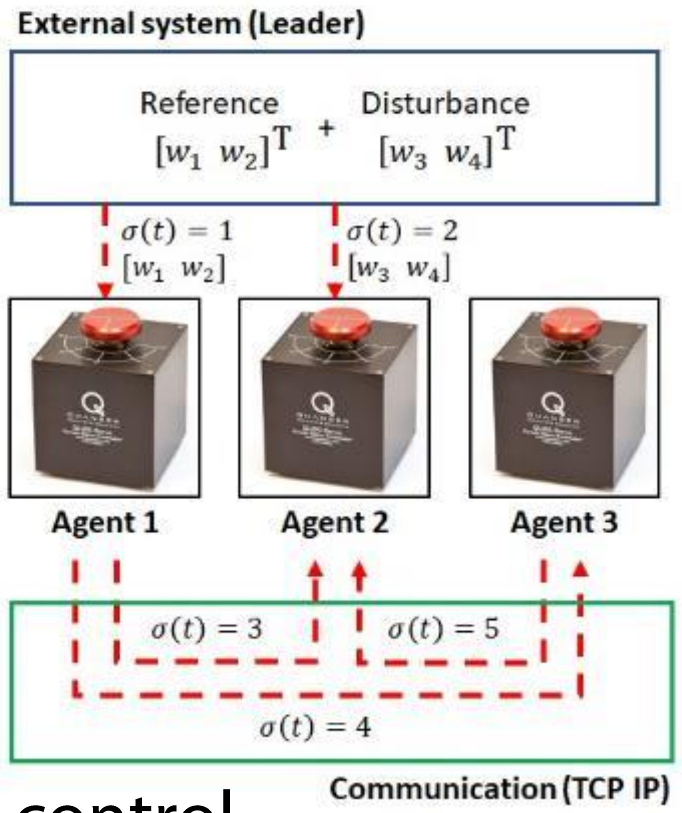
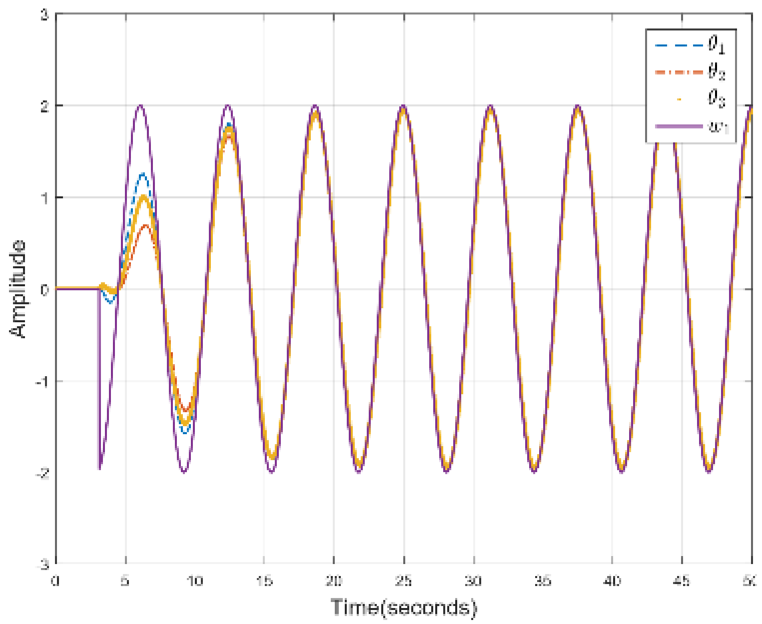
Results

Results: distributed real time monitoring and real-time synchronization under comm. constraints







Incorporate distributed learning

- Resilient monitoring, estimation and control
- Robust fault detection and predictive maintenance

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