

Risk-Informed Operations and Maintenance Decision Making Using Deep Reinforcement Learning

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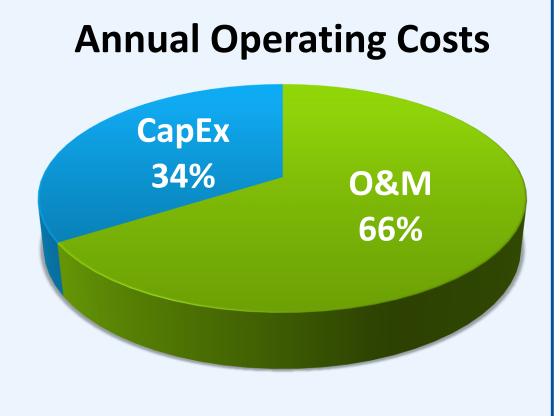
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Background/Motivation

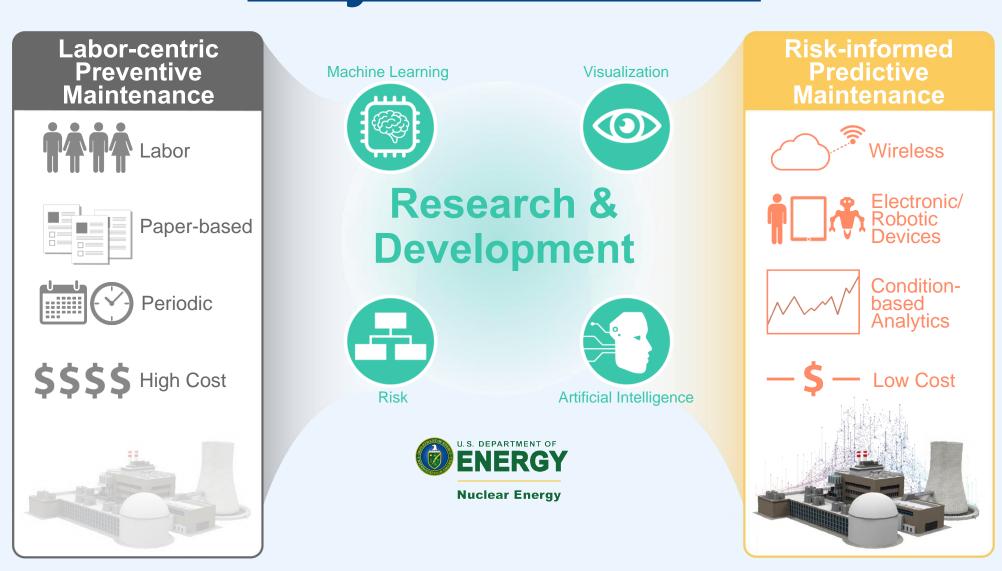
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A challenge for operating nuclear plants is the significant cost of operations and maintenance, at times consuming up to 66% of yearly operating budgets. This research provides a framework for the integration of condition monitoring and artificial intelligence (AI) algorithms to improve risk-informed decision-making and reduce overall costs.



- Operations and maintenance consumes 66% of annual operating costs
- Plant maintenance is not risk-informed and is often periodic and labor-intensive

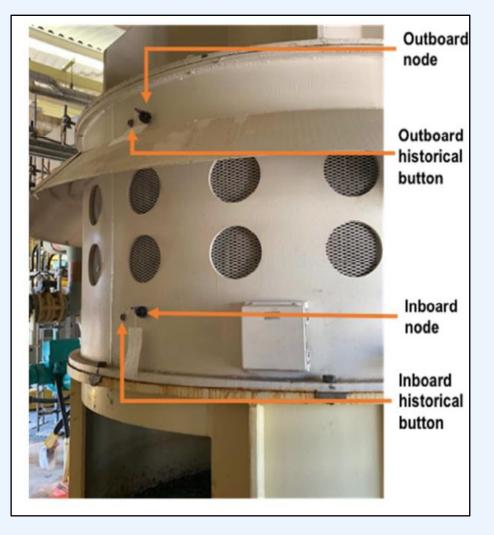
Project Overview

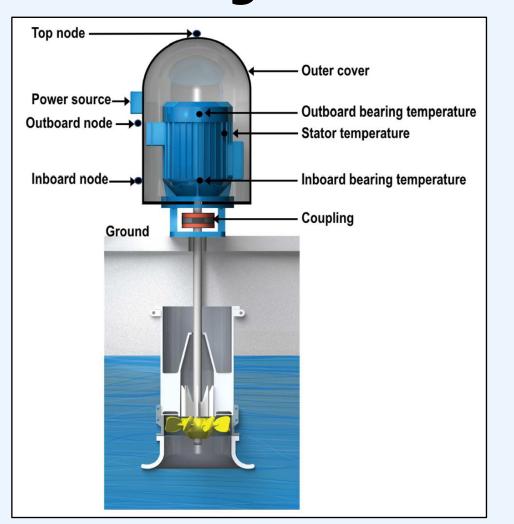


Shifting to a risk-informed predictive maintenance strategy will reduce financial risk and overall operations and maintenance cost

Research Approach

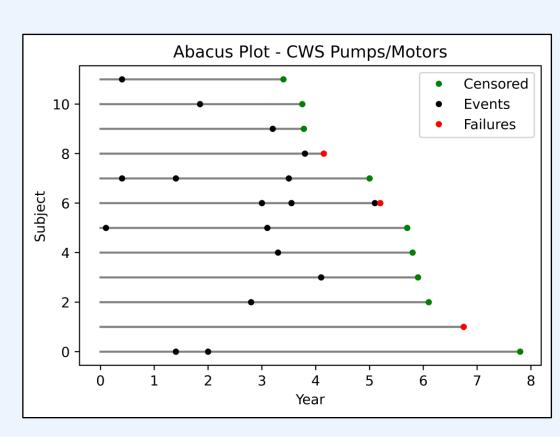
Condition Monitoring

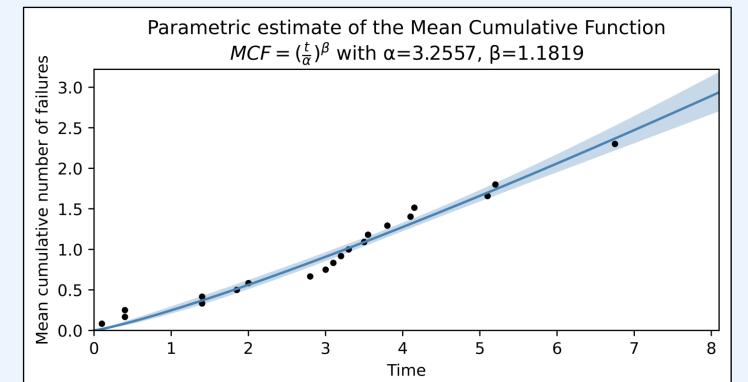




Acceleration sensors were placed on the circulating water system pumps and motors to collect vibration data for condition monitoring.

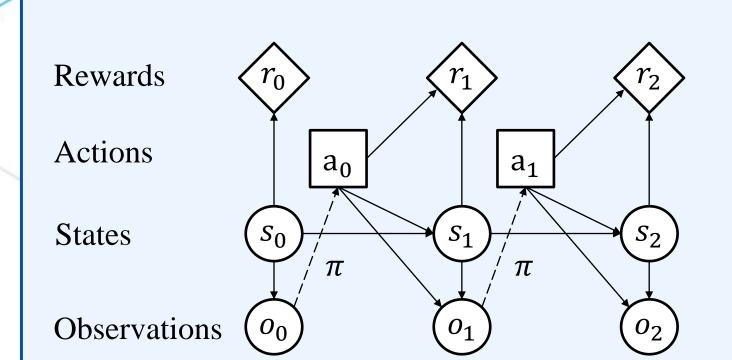
Data-Driven Reliability Modeling





Using recurrent event analysis, we can fit a mean cumulative intensity curve to the data to find the expected number of events, given the age of the pump and effectiveness of maintenance.

Partially Observable Markov Decision Process



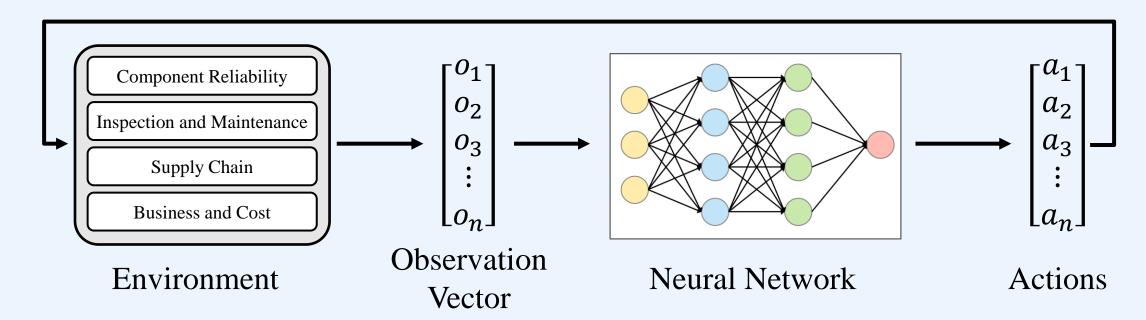
 $\pi^* = \operatorname*{argmax} V^{\pi}(O)$ π The optimal policy, π^* , maximizes the long-term

reward, given the current

observation.

Once the reliability model is created, we can integrate decisions, cost, and sensor observations into a Markov decision process where we can simulate decision making and test maintenance policies.

Deep Reinforcement Learning



Using deep reinforcement learning, we can solve for the optimal policy approximation using neural networks. Once solved, this allows for real-time decision making that balances the cost of maintenance, downtime, and financial risk.

Expected Lifecycle Cost by Maintenance Strategy 5000 4500 4000 500 2500 1500 DRL Agent 3 4 5 6 7 Maintenance Interval (Outages)

Preliminary Results

- Once the neural network was trained to approximate the optimal maintenance policy, it was compared to time-based maintenance strategies using Monte Carlo simulations.
- The deep reinforcement learning (DRL) agent was able to reduce expected costs by 50%.

Impact/Benefits

- Improves O&M decision-making and for short and long-term assetmanagement using condition monitoring estimates.
- Integrating condition monitoring and decision-making will allow for reduced O&M spending, improving plant economic viability.

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