Beyond Condition Assessment

SMS for Strategic, Tactical, and Operational Intelligence

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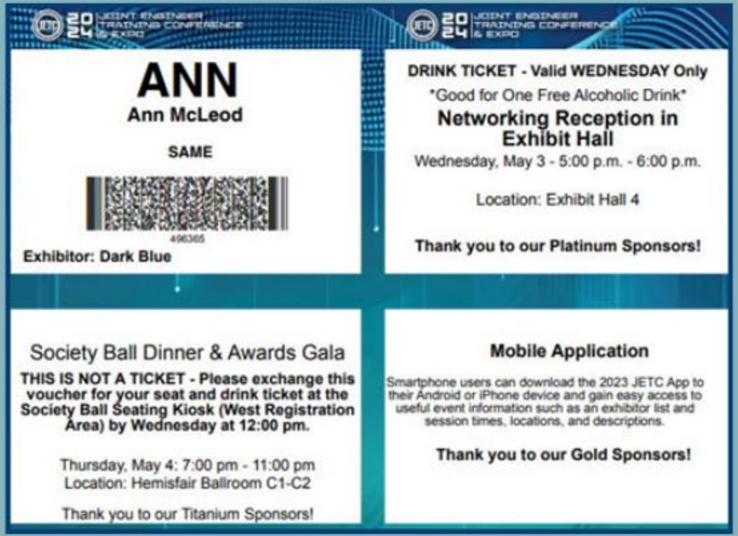

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Live Content Slide

Poll: How familiar are you with the Sustainment Management Systems (SMS)?

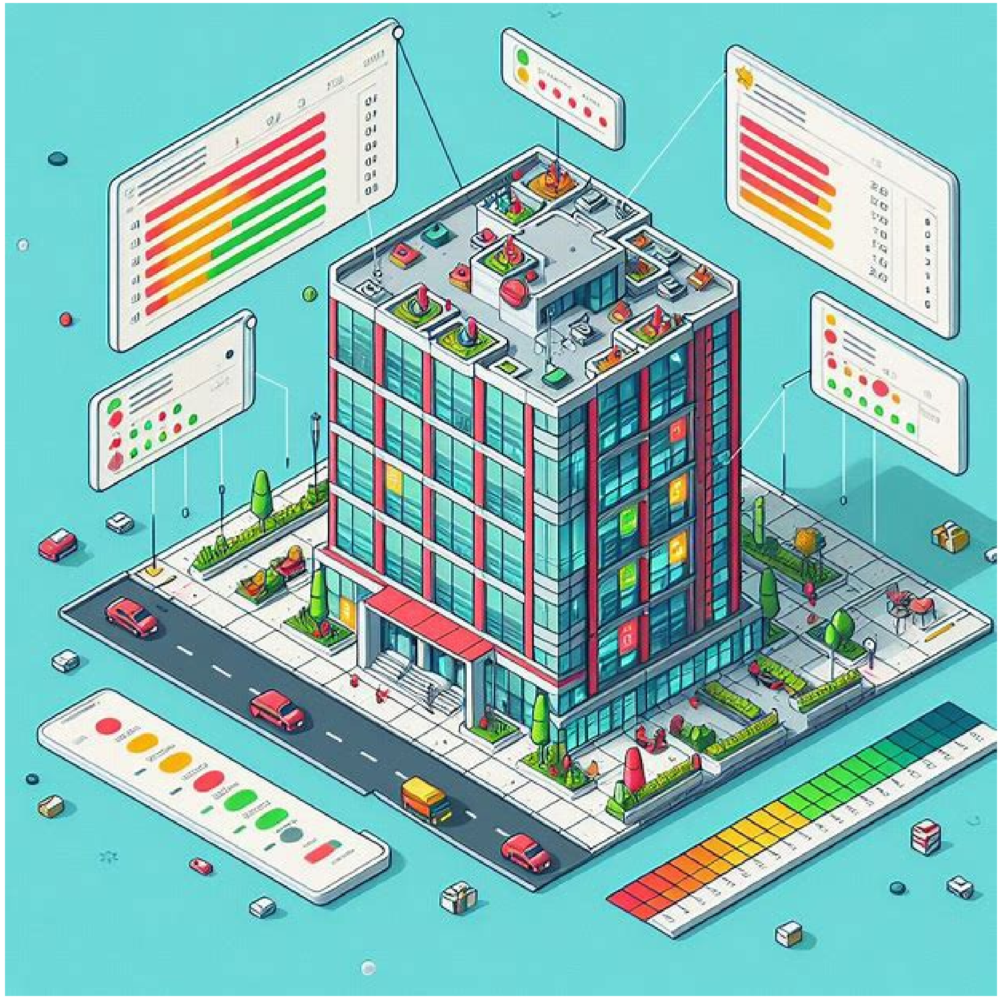
Strategic:

Mission Dependency Index Prediction Modeling

SMS (BUILDER) Data

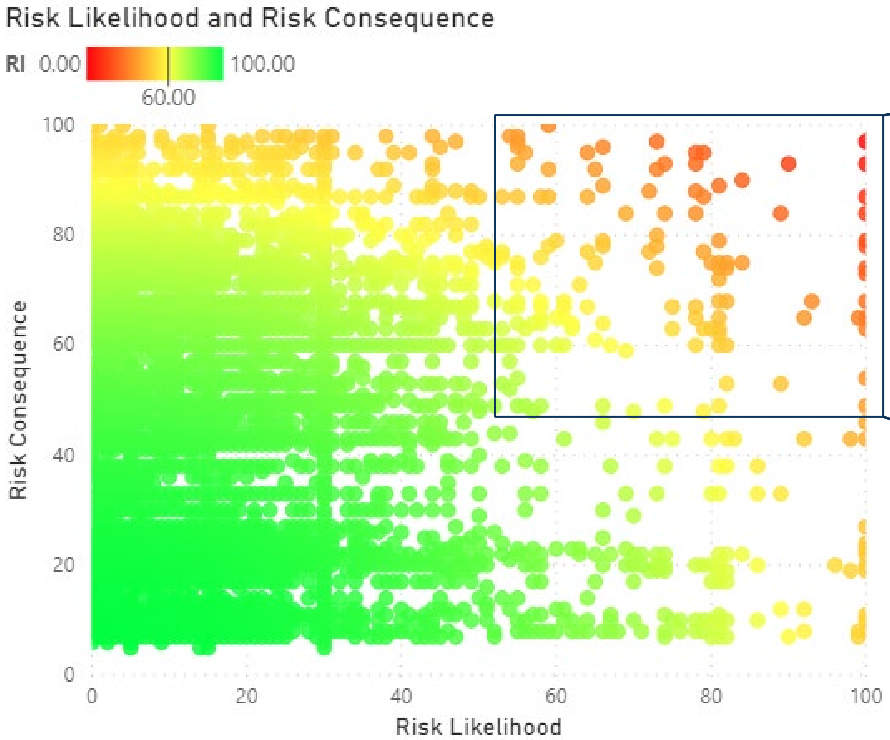
- The SMS database contains extensive information about various buildings across US Army:
  - Detailed Component Inventory
  - Inspection / Condition Assessment
  - Rolled up Facility Condition

"Risk Likelihood"

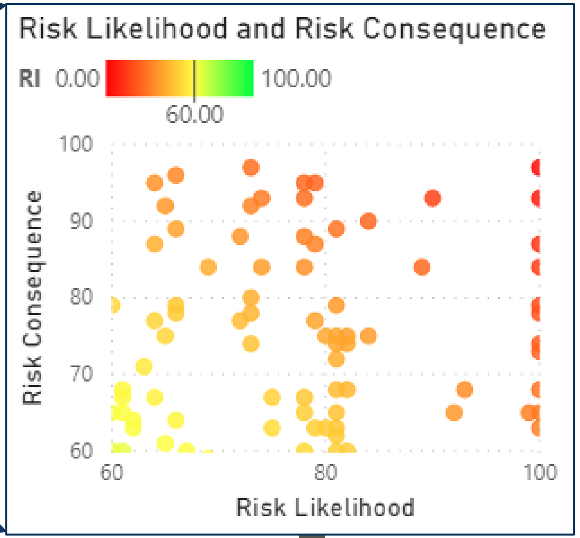


Pairing SMS with Risk Consequence

Risk Consequence
Mission Dependency Index (MDI)



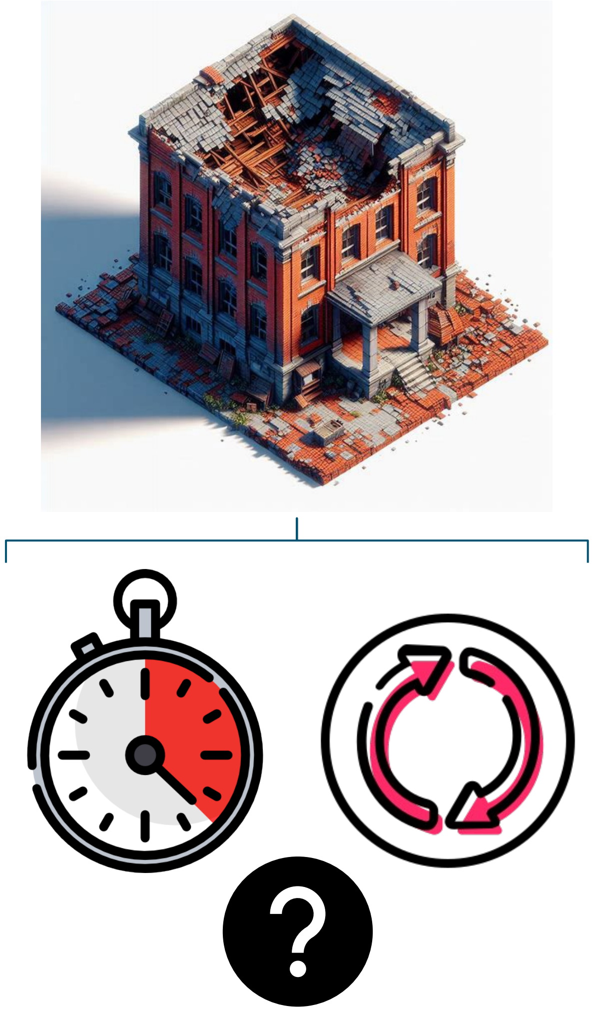
Risk Likelihood
SMS (BUILDER) Data



- 1-N prioritization
- More useful prioritization schemes for Sustainment work generation

What is Mission Dependency Index (MDI)?

- A measure from 0 to 100 of criticality of buildings to overall mission
- Built on two other values:
  - Interruptability: How fast would the mission be impacted if the asset's operations were interrupted?
  - Replicability: How difficult would it be to relocate the asset's mission capacities?



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MISSION DEPENDENCY INDEX

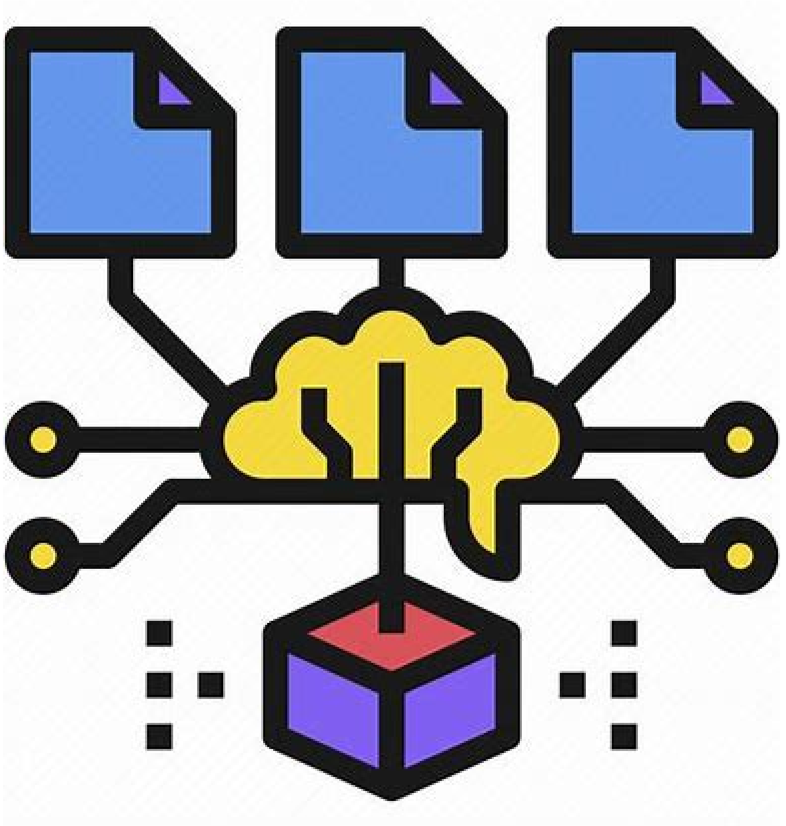
MDI		Question 1 INTERRUPTABILITY How fast would the mission be impacted if the asset's operations were interrupted?			
		IMMEDIATE < 15 minutes	BRIEF < 24 hours	SHORT < 7days	PROLONGED > 7 days
Question 2 REPLICABILITY How difficult would it be to relocate the asset's mission capabilities?	IMPOSSIBLE	100	88	76	64
	EXTREMELY DIFFICULT	92	80	68	56
	DIFFICULT	84	72	60	48
	POSSIBLE	76	64	52	40

How can we harness this information?

- It can be difficult to capture the behavior of multi-feature data without some sort of trend modeling
- Even some of the more complex models might not grasp enough information to make reasonable estimates on new data
- Need for something stronger

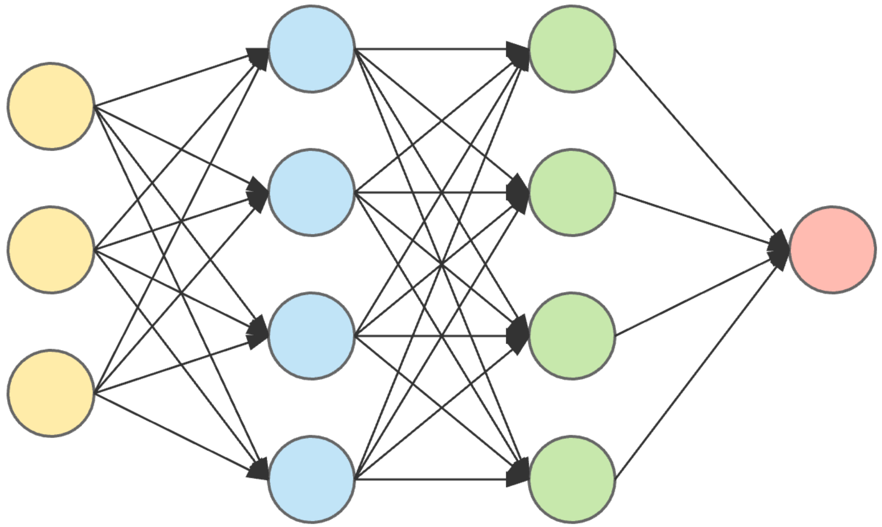
Machine Learning

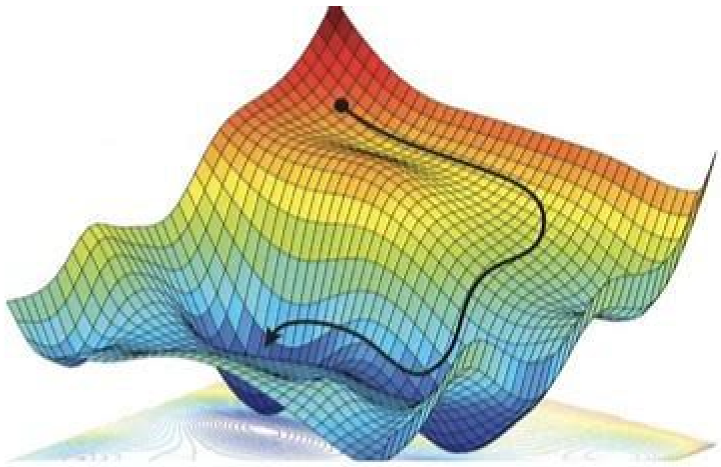
- An extremely powerful tool in the realm of data science and mathematics
- These models are far deeper than standard data models
- Complexity of models can be decided based on individual problems



Neural Networks

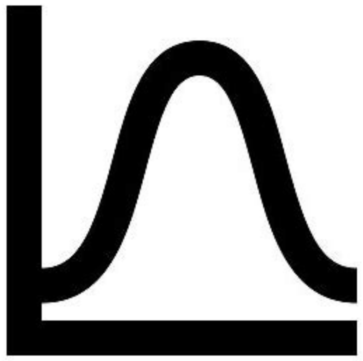
- A specific machine learning model that works for almost any problem type
- Based on the structure of the human brain
- Uses linear algebra and calculus to actually learn how to best understand data and make predictions on new data

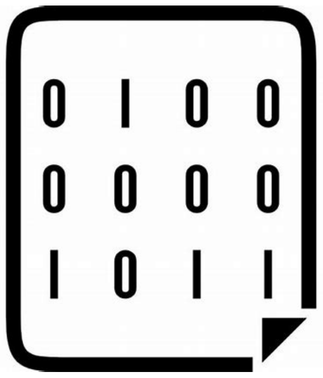


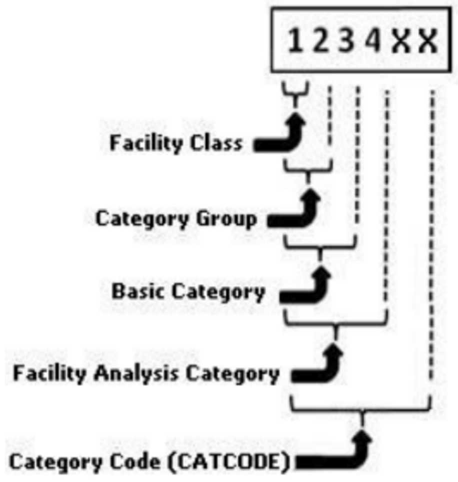


Data Treatment

- This particular data set is from a pilot set of two Army Installations
- Three primary input data types in utilized:
  - Numeric
    - Building Value, Size, Age, …
  - Labels/Classification
    - Structure Type, Authority/Accountability, …
  - Word Data
    - Unit Name, CODE info, …
  - Feature Selection



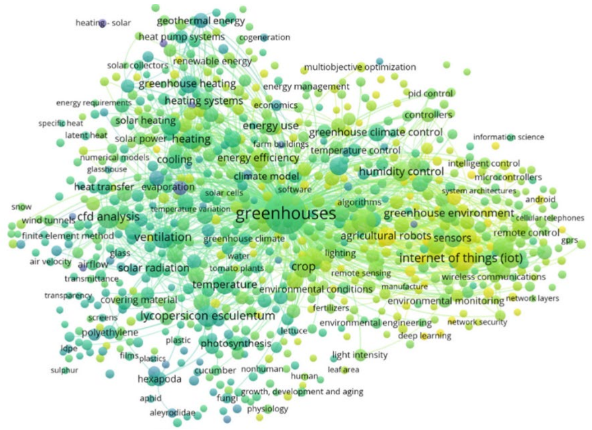




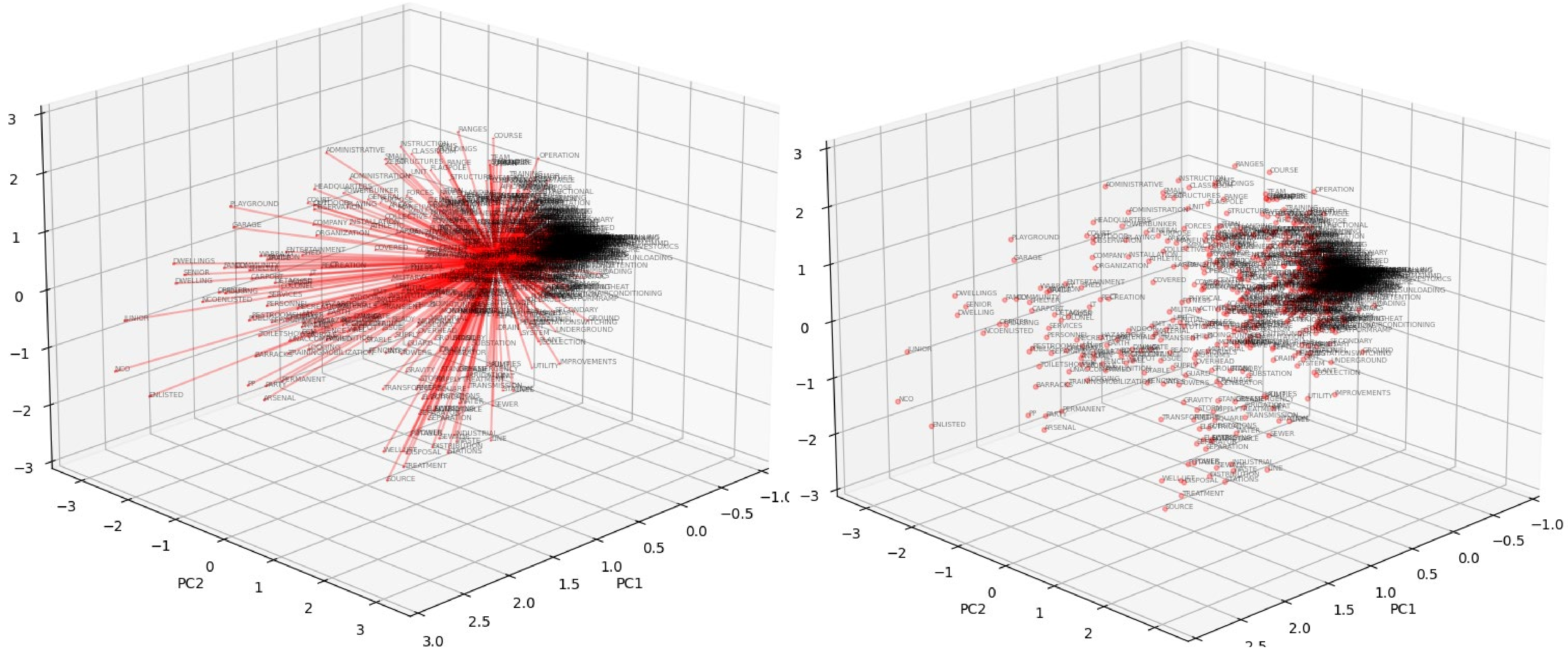
Data Treatment

- Word Embedding
  - Unit names and CATCODE labels form large word data frames
  - These are not easy for models to read directly
  - Utilize neural networks to create vector representations of words within a “context space”

CODE	TITLE
1	Operation and Training
2	Maintenance and Production
3	Research, Development, Test, and Evaluation
4	Supply
5	Hospital and Medical
6	Administrative
7	Housing and Community
8	Utility and Ground Improvements
9	Land



Data Treatment



Data Treatment

Data Treatment

- Two output values:
  - Interruptability
  - Replicability
- These are scaled by severity combined to output an MDI value
- This turns our problem of predicting MDI into a classification task

	0	1	2	3
Interruptability	Prolonged	Short	Brief	Immediate
Replicability	Possible	Difficult	Extreme Difficult	Impossible

MISSION DEPENDENCY INDEX

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The Models

- Interruptability and Replicability have distinct meanings and have different degrees of impact on MDI
- Using two separate models allows for important information from the input data to be learned in unique ways that best suit the values individually

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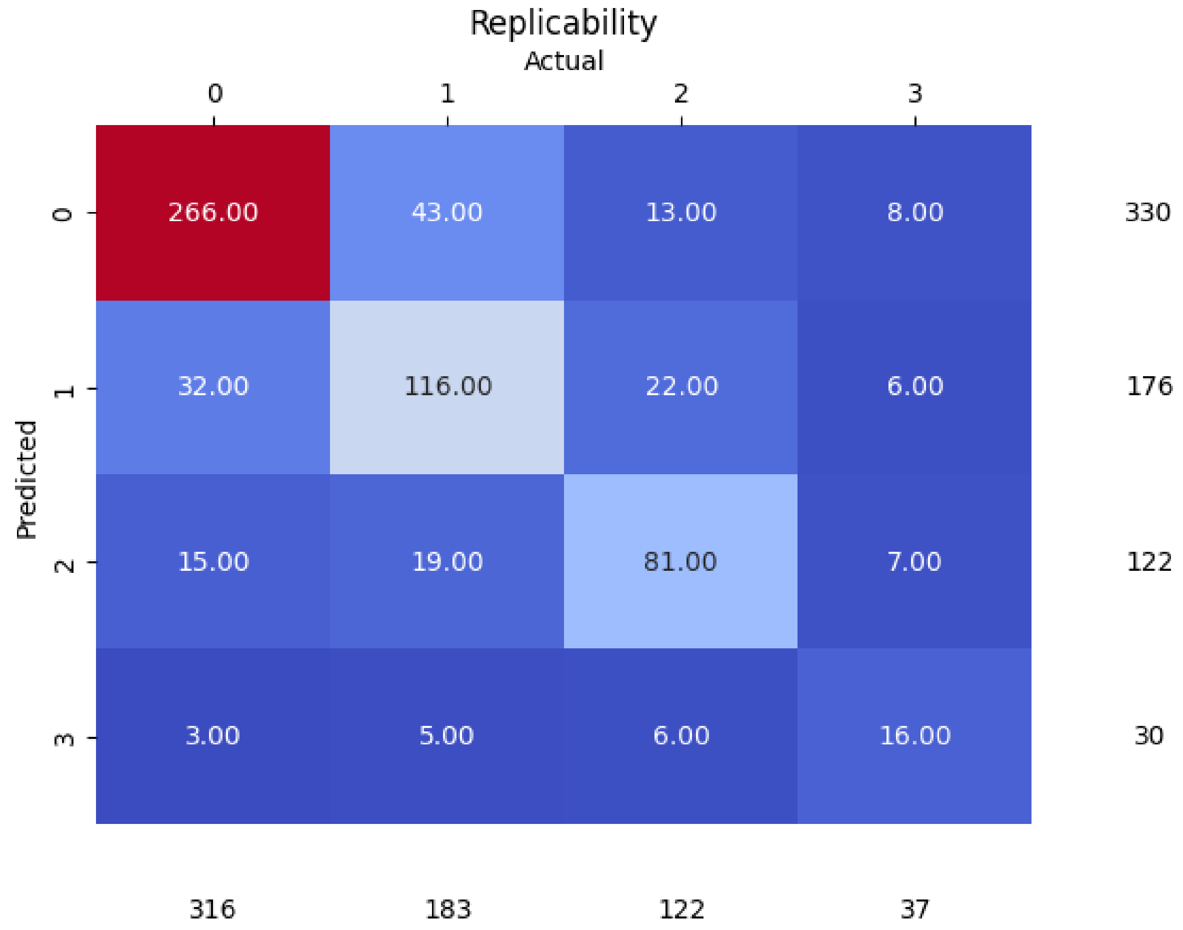
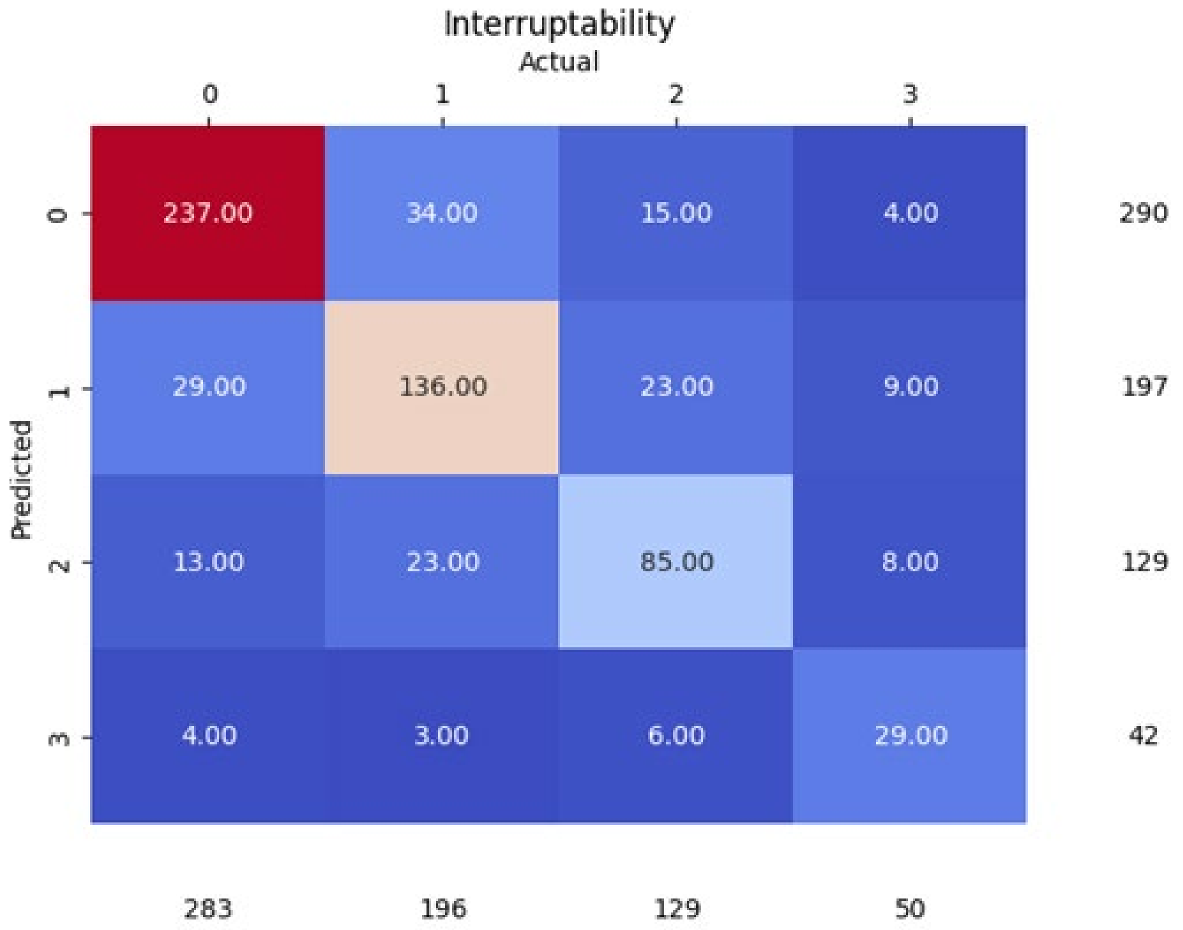
Replicability Model

- Hidden Layer Sizes:
  - 64,256,256,256,32, 8
- Activation function:
  - Rectified Linear Unit
- L2 Regularization Strength:
  - 0.0001
- Solver:
  - Adam
- **Accuracy**: 72.8%

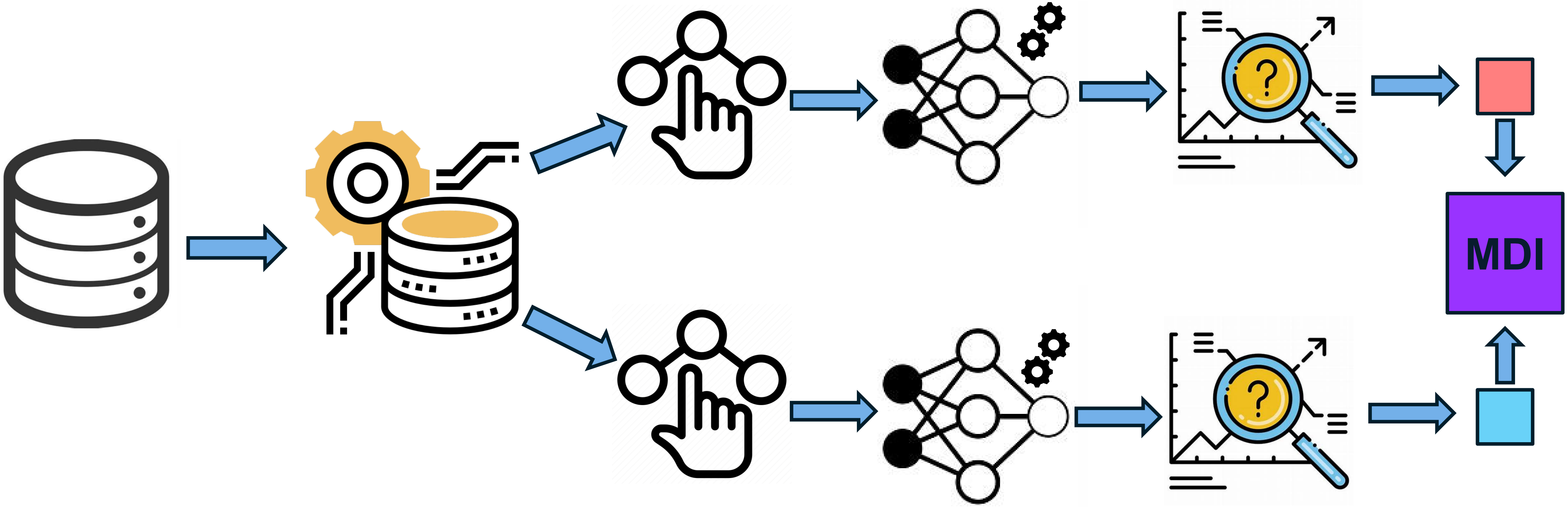


Interruptability Model

- Hidden Layer Sizes:
  - 64,256,256,256,32,16
- Activation function:
  - Rectified Linear Unit
- L2 Regularization Strength:
  - 0.0001
- Solver:
  - Adam
- **Accuracy**: 74.0%



Summary



Performance

- **MDI RMSE**: 13.20
- **MDI MAE**: 6.72
- Neural networks and other machine learning models have massive potential in uncovering new information from existing data

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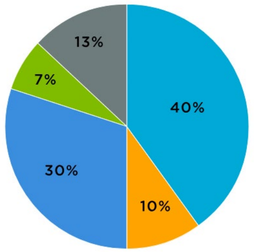
Tactical:

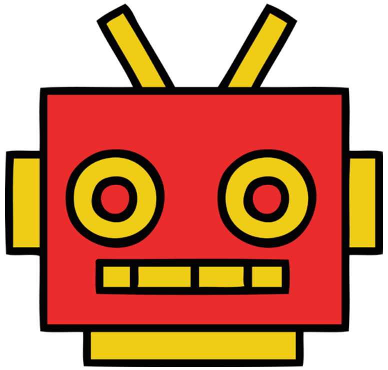
Optimizing Maintenance Policies with Reinforcement Learning

Previous SMS Research

- Previously, Reinforcement Learning (Proximal Policy Optimization) was used to train an agent to make Maintenance Decisions for a single Building
- The Maintenance Actions were high scope

Building Component Data Analytics

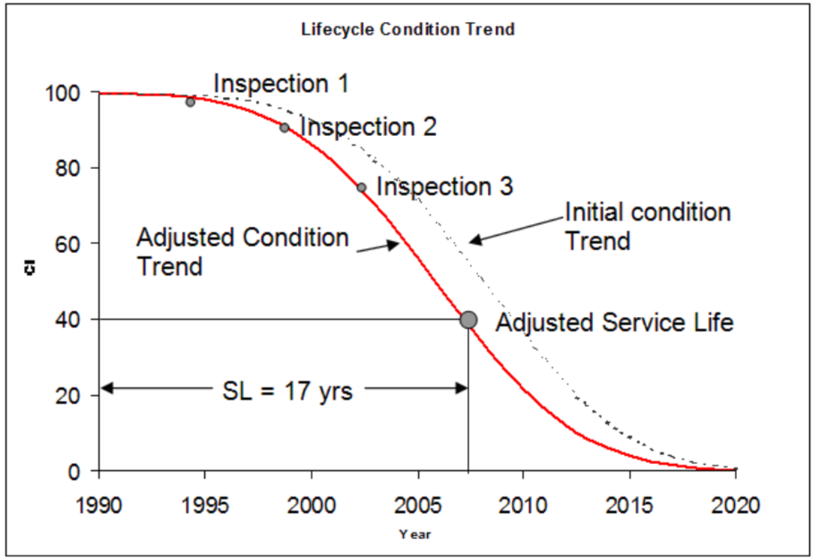




Building Maintenance Decision

Challenges:

- Previous Method had very general building maintenance actions:
  - Do Nothing
  - Replace
  - Full Maintenance
  - Reduced Maintenance
  - Minimum Maintenance

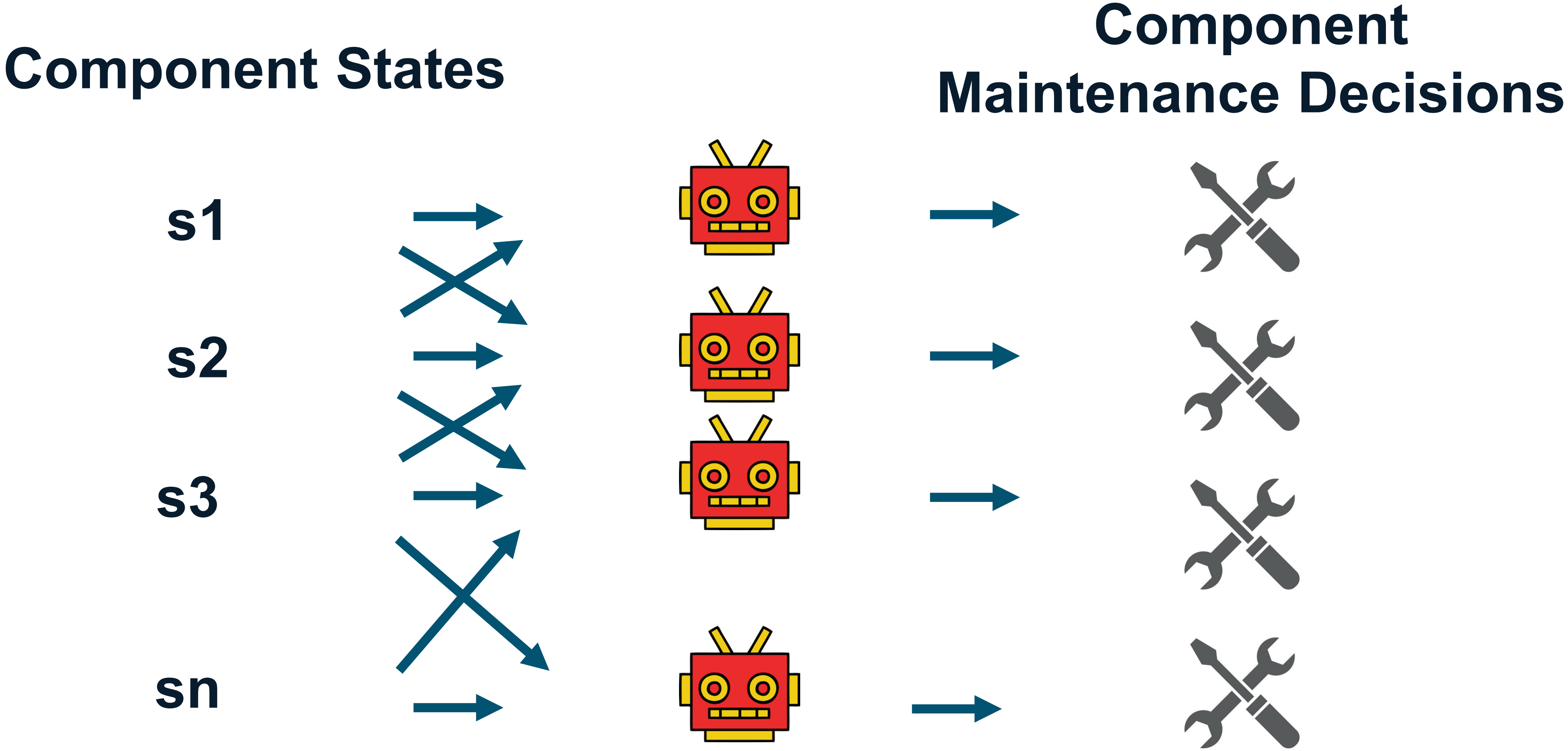


- Markov Environment was Deterministic
- Infinite Markov States

Goals:

- Create a discrete Markov environment
- Optimize a component-specific policy
- Better reflect mission/inter-dependencies of components in environment
- Scalable Environment with Multiple Buildings

Multi Agent Framework:



Previous Research

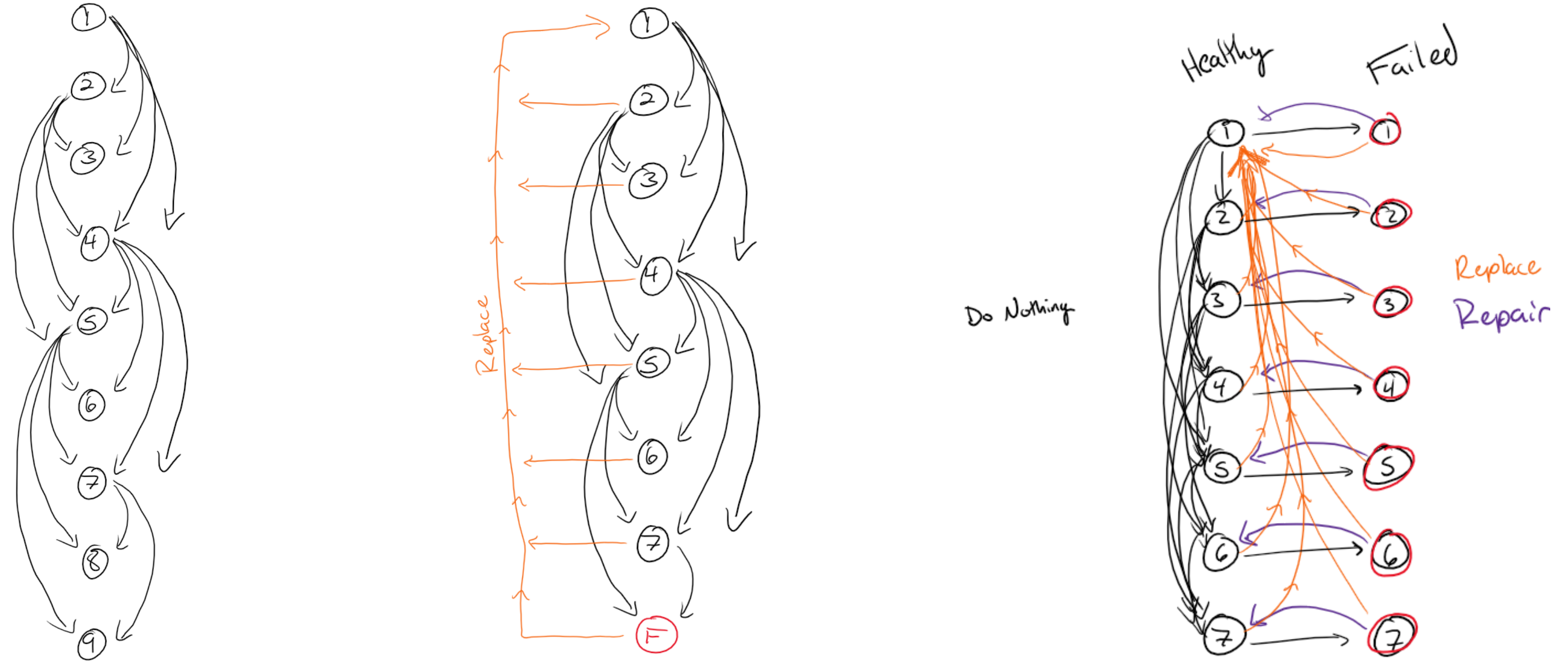
- Previously, SMS researched a creation of Markov Transition Matrices for components
- Each condition is pooled into a discrete state:
  - 1 : 100 - 95 CI
  - 2 : 95 - 85 CI
  - 3 : 85 - 75 CI
  - etc …

```
> transition_matrix
           [,1]      [,2]      [,3]       [,4]       [,5]       [,6]        [,7]        [,8]        [,9]
 [1,] 0.05810147 0.4238953 0.4296236 0.04909984 0.02045827 0.01063830 0.004091653 0.002454992 0.001636661
 [2,] 0.00000000 0.3333333 0.4333333 0.15555556 0.04444444 0.02222222 0.011111111 0.000000000 0.000000000
 [3,] 0.00000000 0.0000000 0.4843750 0.21354167 0.16666667 0.08854167 0.015625000 0.026041667 0.005208333
 [4,] 0.00000000 0.0000000 0.0000000 0.72058824 0.13235294 0.08823529 0.029411765 0.029411765 0.000000000
 [5,] 0.00000000 0.0000000 0.0000000 0.00000000 0.55102041 0.22448980 0.081632653 0.081632653 0.061224490
 [6,] 0.00000000 0.0000000 0.0000000 0.00000000 0.00000000 0.45454545 0.181818182 0.363636364 0.000000000
 [7,] 0.00000000 0.0000000 0.0000000 0.00000000 0.00000000 0.00000000 0.000000000 0.000000000 1.000000000
 [8,] 0.00000000 0.0000000 0.0000000 0.00000000 0.00000000 0.00000000 0.000000000 0.000000000 0.000000000
 [9,] 0.00000000 0.0000000 0.0000000 0.00000000 0.00000000 0.00000000 0.000000000 0.000000000 1.000000000
```

- Transition Matrix gives the probability of observing a component in state *n* given its in state *m*

Component States

- We consider 8-9 to be Failed States
- More failed states are added to embed state memory



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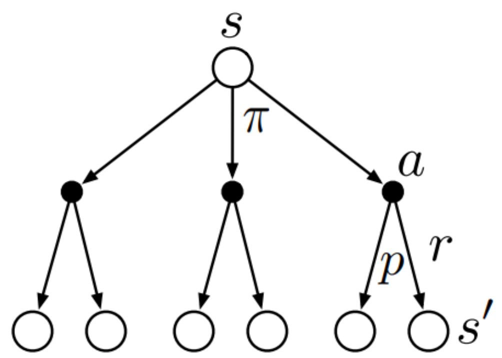
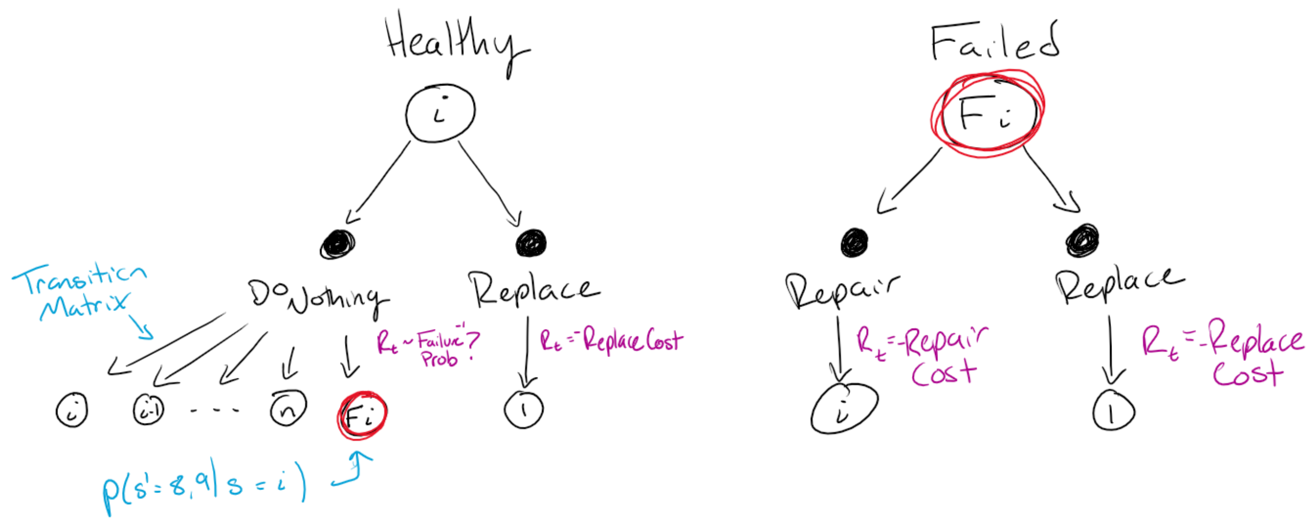
Component Actions

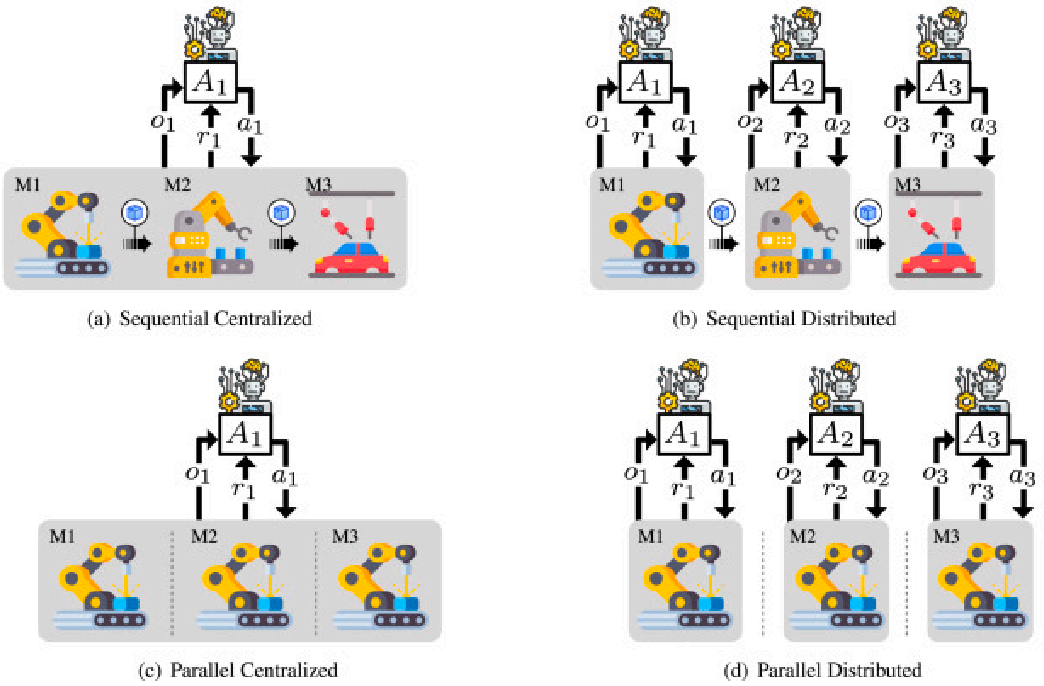
- Actions When Healthy
  - Do Nothing
  - Replace
  - *Maintain
- Actions When Failed
  - Repair
  - Replace





Previous External Research:

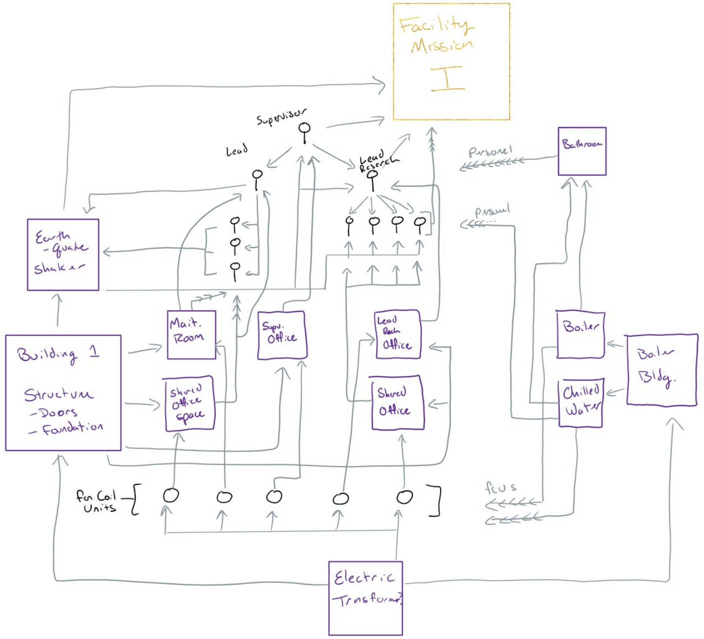
- There is plenty of research for using Multi Agent Reinforcement Learning in Manufacturing Maintenance
- Mission Production Networks apply “Manufacturing” pipelines to components
- “How much do components help each other / the mission”

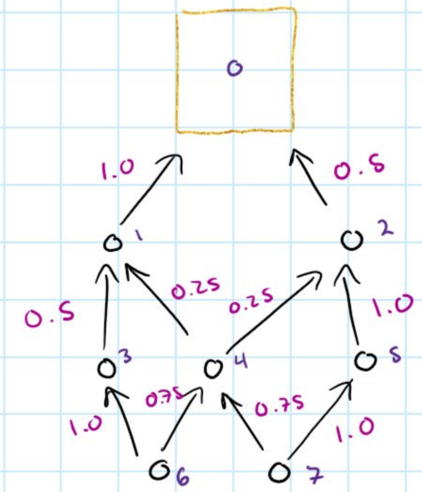


Marcelo Luis Ruiz Rodríguez, Sylvain Kubler
Multi-agent deep reinforcement learning based Predictive Maintenance on parallel machines, Robotics and Computer-Integrated Manufacturing, Volume 78, 2022

Mission Production Network:

- These networks can be Complex, Facility, System or Component level





	0	1	2	3	4	5	6	7
0	0	0	0	0	0	0	0	0
1	1.0	0	0	0	0	0	0	0
2	0.5	0	0	0	0	0	0	0
3	0	0.5	0	0	0	0	0	0
4	0	0.25	0.25	0	0	0	0	0
5	0	0	1.0	0	0	0	0	0
6	0	0	0	1.0	0.75	0	0	0
7	0	0	0	0	0.75	1.0	0	0

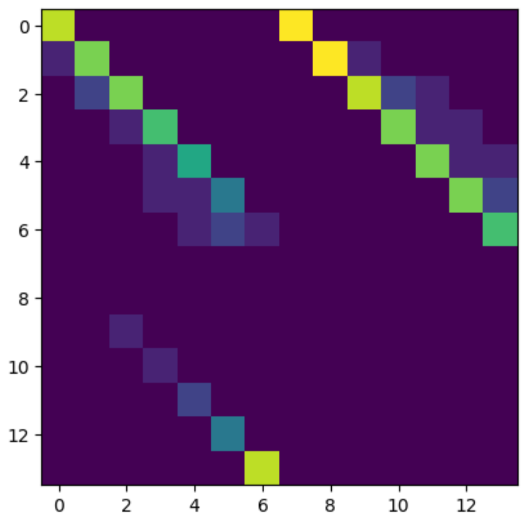
Dynamic Programming:

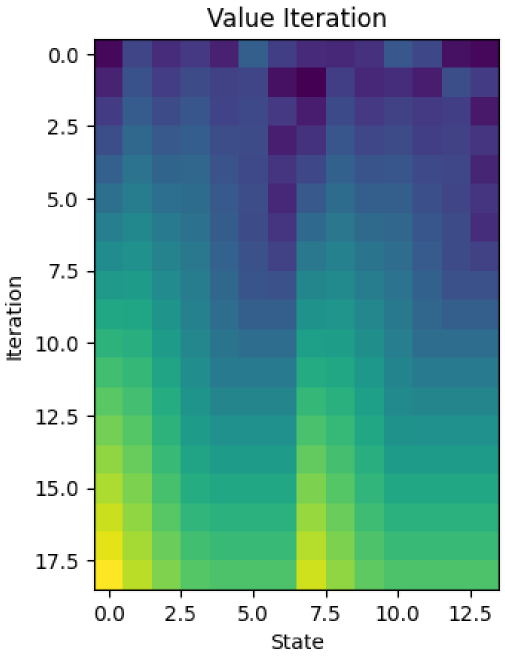
- We can use the Bellman Equation to find an optimal policy for a single component

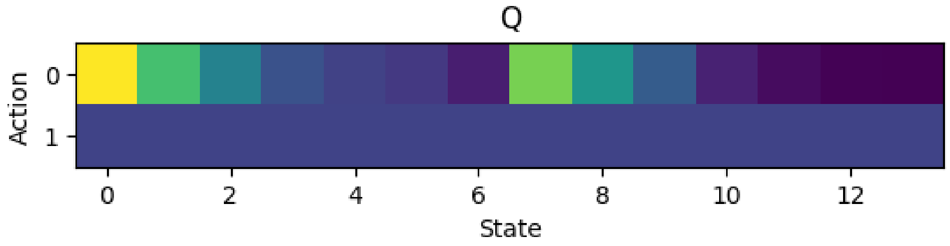
$$\begin{aligned} v_\pi(s) &\doteq \mathbb{E}_\pi[G_t \mid S_t = s] \\ &= \mathbb{E}_\pi[R_{t+1} + \gamma G_{t+1} \mid S_t = s] \\ &= \mathbb{E}_\pi[R_{t+1} + \gamma v_\pi(S_{t+1}) \mid S_t = s] \\ &= \sum_a \pi(a|s) \sum_{s',r} p(s', r \mid s, a)\Big[r + \gamma v_\pi(s')\Big], \end{aligned}$$

Single Component Optimization:

- Using dummy data, we optimized repair/replacement of a single component using dummy data





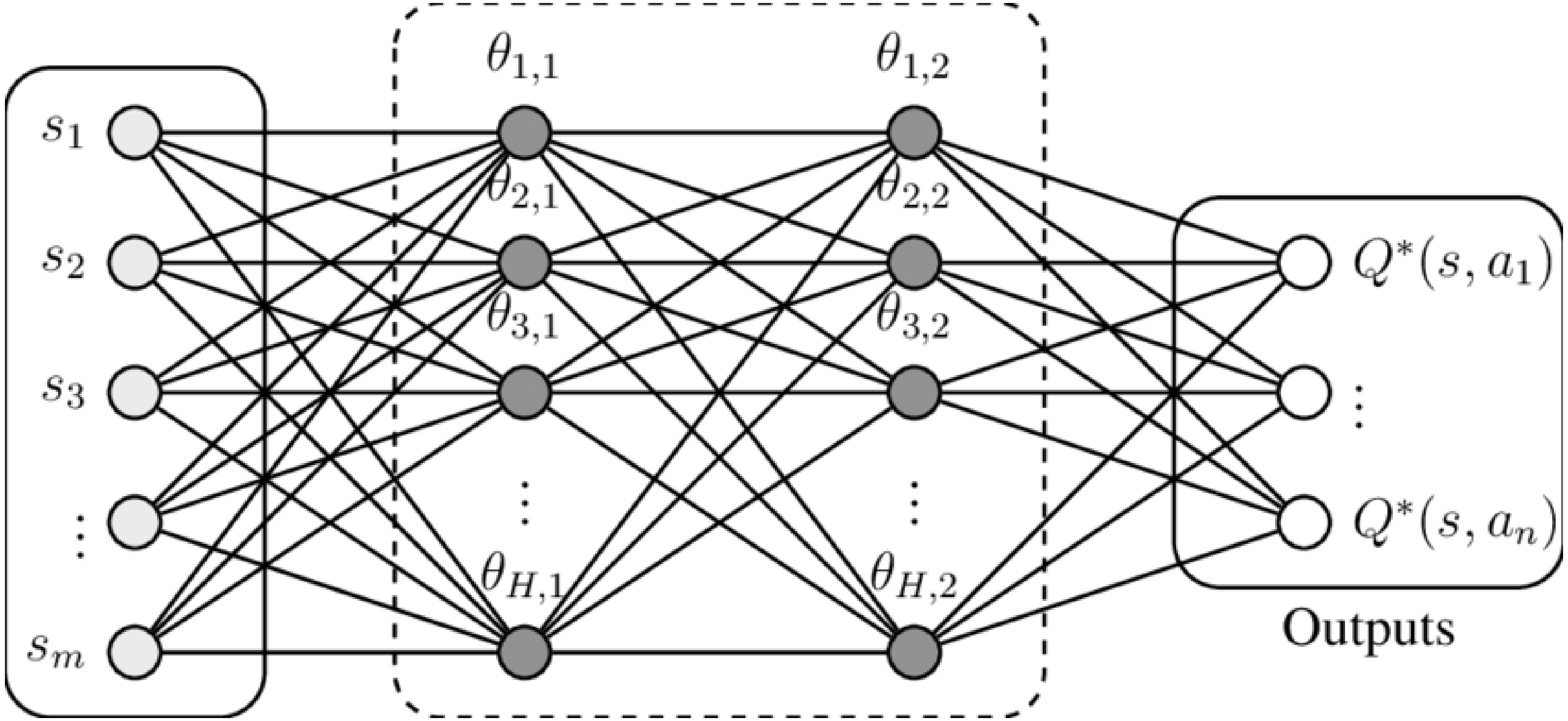


Dimensionality Issue:

- If we expand this to a whole building with *n* components, we will have
  - 14^n states
  - 2^n actions
- We can use Deep Reinforcement Learning to help restructure the states through partial observations
- Two main methods will be examined:
  - Deep Q Learning
  - Actor Critic Methods

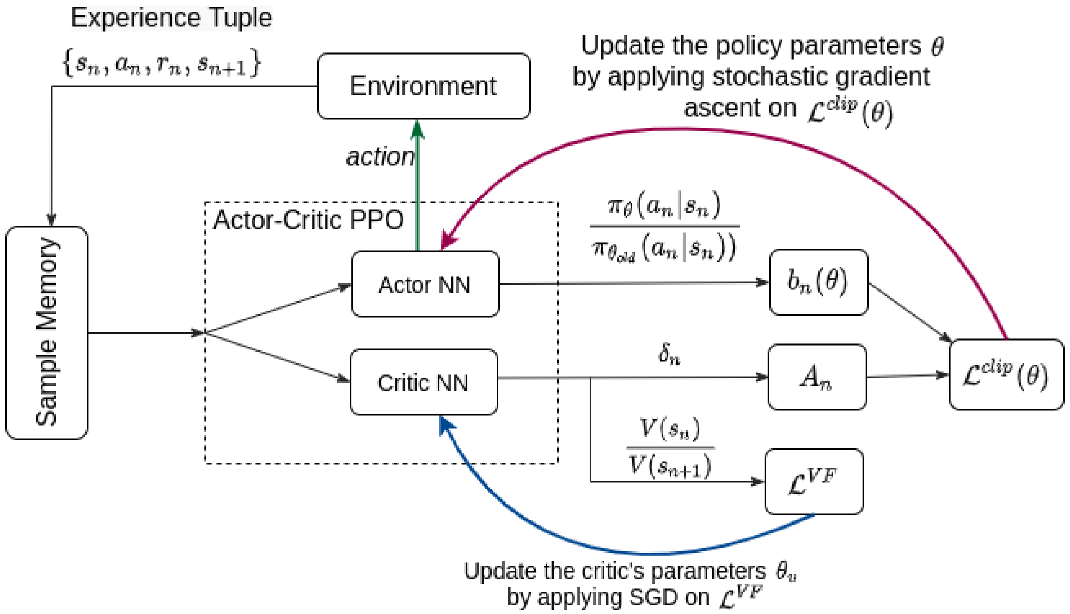
Deep Q Learning:

- Deep Q learning tries to estimate the value of taking an action in a state using Neural Networks



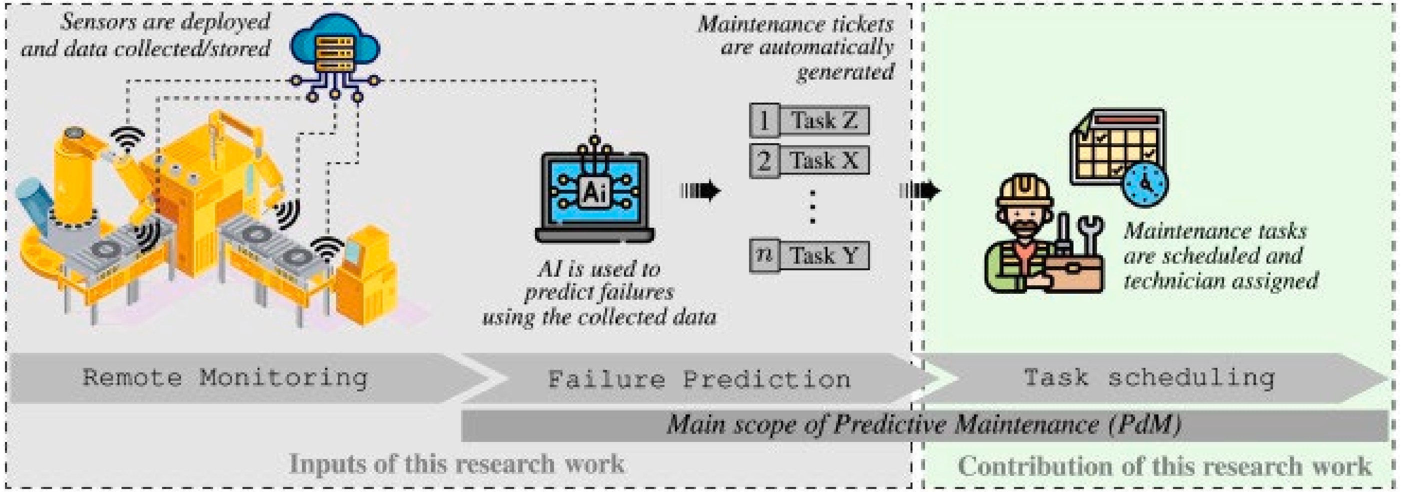
Actor / Critic:

- Actor Critic methods use two neural networks.
- One network estimates the value of a state
- The other determines the policy



Future Research:

- Maintenance Actions
- Repair/Replace Timeouts (a daily timestep)
- Using Sensors and Physics Informed Deep Learning to build more robust digital twins for environments.

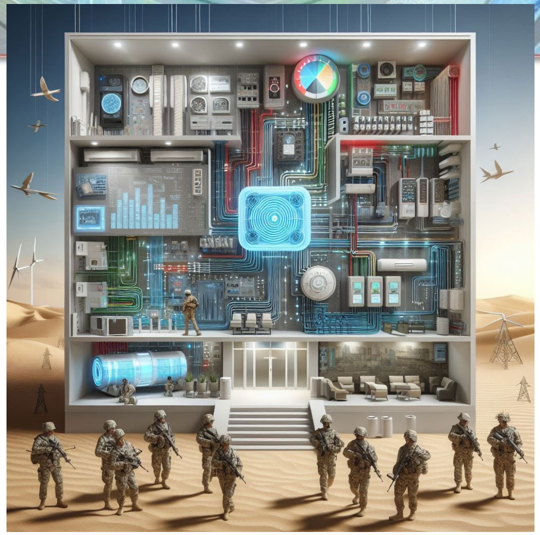


Operational:

Automated Condition Assessment from Operational Performance Data

Project Overview

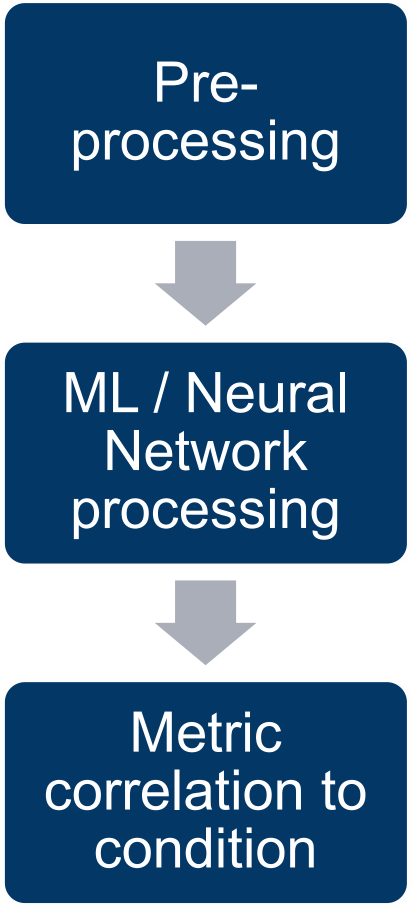
- **Location**
  - Tyndall Air Force Base
  - USACE Construction Engineering Research Laboratory (Champaign, IL)
- **Objective**: Leverage operational technology (OT) performance data to automate condition assessment of HVAC equipment
- **Products**
  - Engineering analytics for automating the creation of SMS condition assessment records and resulting condition rating scores using equipment sensor performance data
  - Demonstration of resulting lifecycle condition forecasts based on automated assessments, work recommendations, and future inspection schedules



Enhanced SMS Process Using Sensors

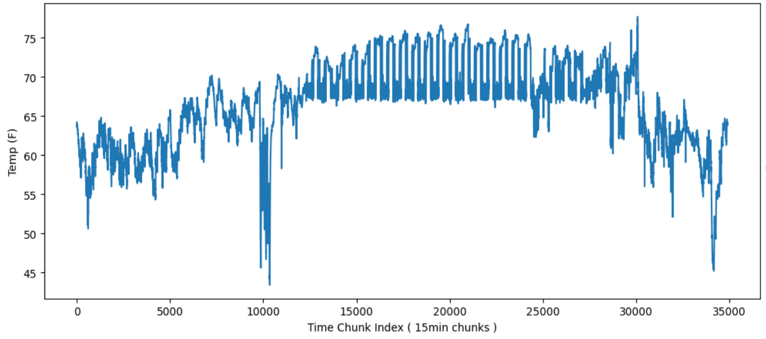
	Inventory	Assess	Predict	Work Planning	Forecast
Traditional Methods	Physical data collection of building components	Inspectors physically getting eyes on inventory	SMS condition prediction algorithms only adjusted by physical inspections	Generated from standards and policy thresholds for condition and remaining service life	Long-term version of Work Planning
SMS Process	Inventory	Assess	Predict	Work Planning	Forecast
Automated Enhancements		Sensor data creating inspection points OR Creating inspection requirements / flags	Supplemental algorithms to SMS model OR Standalone condition prediction for certain sensors	Creating 'inspection required' work	Developing sensor specific trends to forecast instead of standard SMS curves

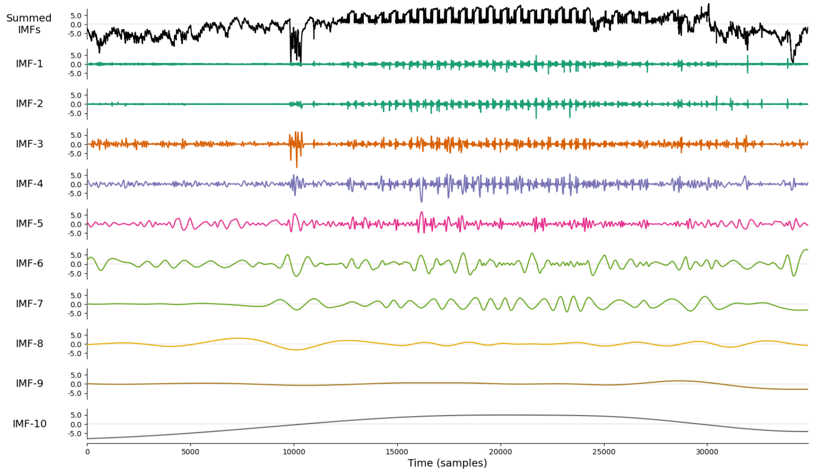
Methodology



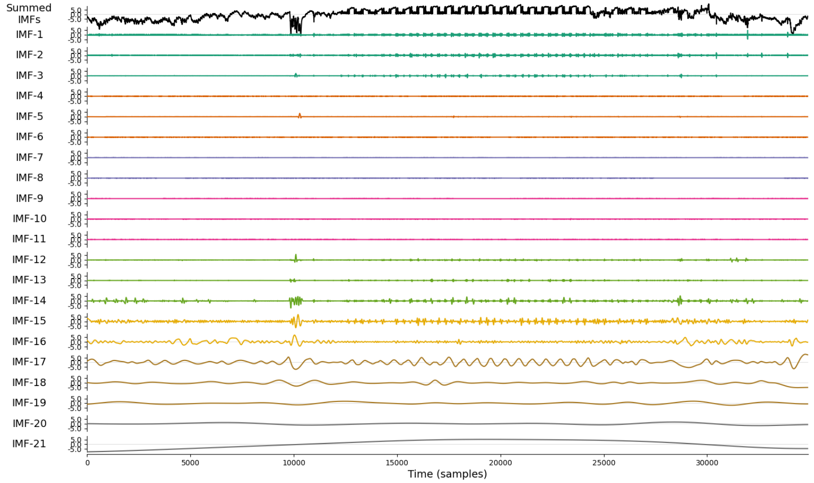
- Empirical Mode Decomposition (EMD)
- Temperature prediction neural network
- Unsupervised Anomaly Detection
- Runtime frequency analysis
- Deviation Metric development and correlation
- Unsupervised Condition Assessment

Pre-Processing





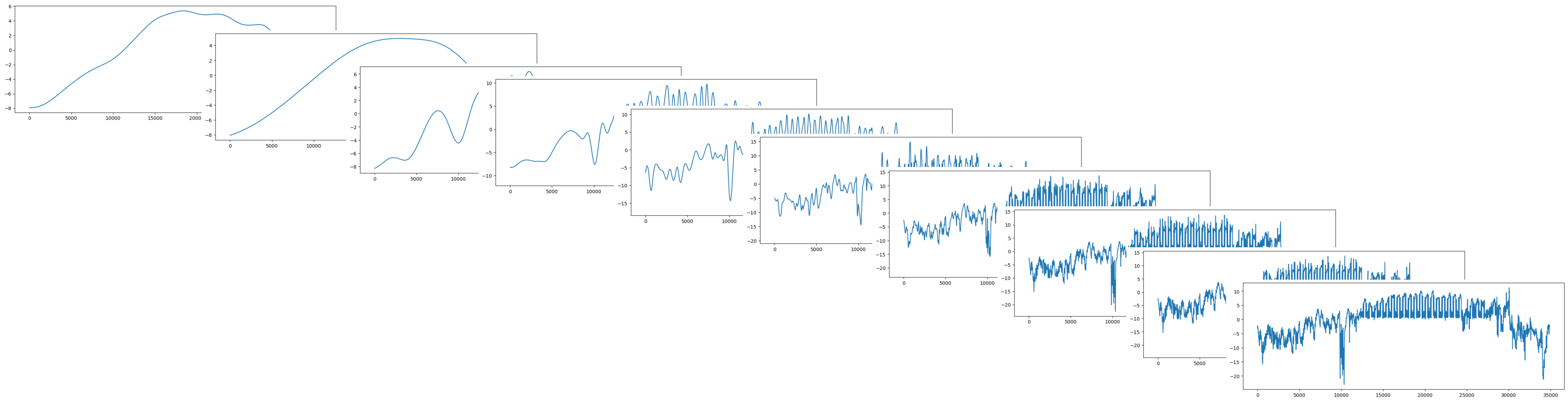
Empirical Mode Decomposition (EMD) breaks a signal down into oscillatory components, called Intrinsic Mode Functions (IMFs)

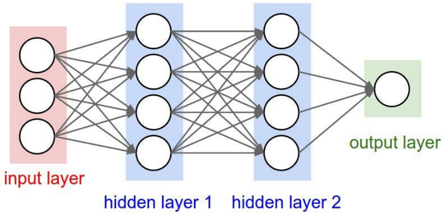


Complete Ensemble EMD (CEEMD) first adds a small amount of noise to the data before using an EMD algorithm. This helps separate the information of different frequencies into distinct IMFs, however it has the downside of adding noise to the signal.

Turning IMFs into Neural Network Inputs

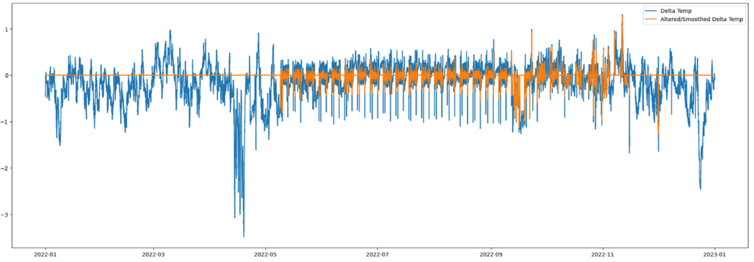
- The final IMF (with the lowest frequency information) is called the "Residual"
- Starting with the Residual, we add on the IMFs one by one. At each step, our sum is a time series input.
- Each step is a neural network input





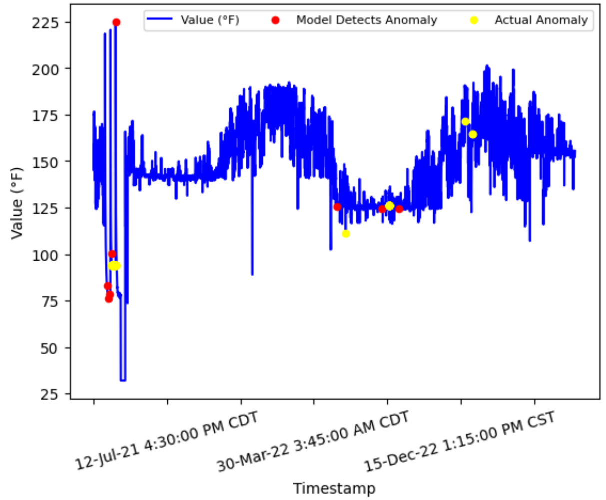
ML / Neural Network Processing

Temperature prediction neural network



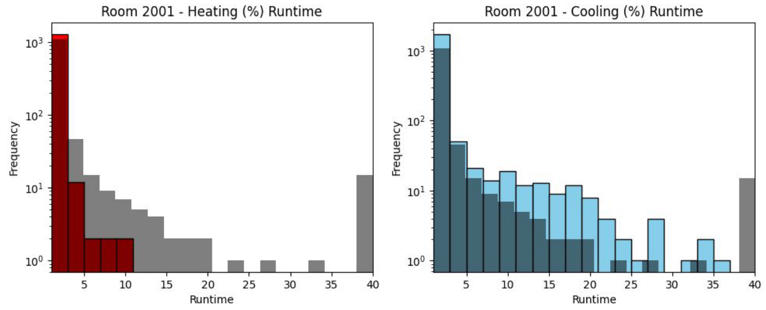
- Develop model that can use sensor data to predict temperature
- We define the Delta Temperature as the difference between the Actual Temperature and the Room Temperature.
- We take a rolling mean over the Delta Temperature and set it to 0 whenever the system is off.

Unsupervised Anomaly Detection



- Convolutional Neural Network with Spectral Residuals (CNN-SR)
- Long Short-Term Memory Neural Network (LSTM) detection.

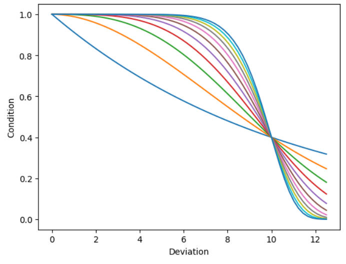
Runtime frequency analysis

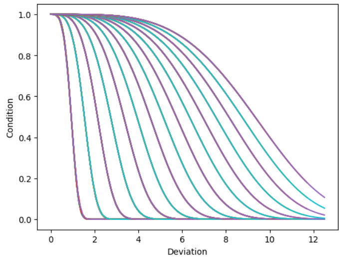


- “How much time does the machine need in order to change the room temperature to its thermostat setting?”
- “How much time does a machine need to in order to complete its task?”

Metric Correlation to Condition

Deviation Metric development and correlation



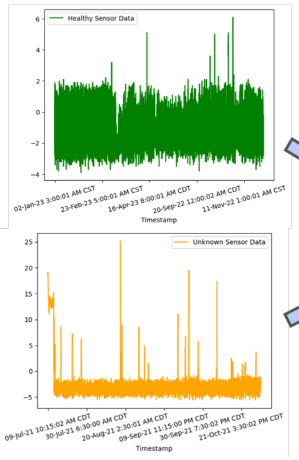


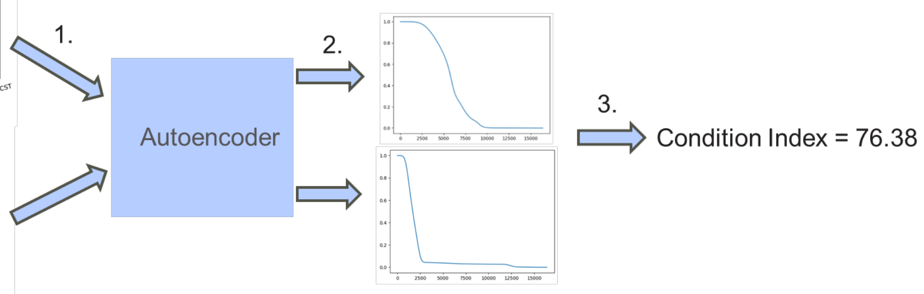
Room	deviation	Condition			
		alpha = 2	alpha = 3	alpha = 4	alpha = 5
1	449	82	91	96	98
2	524	77	87	93	96
3	600	71	81	88	92
4	618	70	80	87	91
5	650	67	77	84	89
6	679	65	74	81	87
7	761	58	66	73	78
8	840	51	57	62	67
9	938	44	46	48	50
10	994	40	40	40	40

- Deviation of a newer component would be closer to 0 and a Weibull distribution can be used to forecast deviation
- Terminal deviation functions similar to the “design life” concept
- Requires training the model with new equipment

Unsupervised Condition Assessment

Steps:
1. Input healthy and unknown sensor data into autoencoder neural network
2. Use neural network output to create survival functions for the healthy and unknown sensors
3. Compute a Condition Index for the unknown sensor using the survival functions





- The algorithm does not need inspection data, only sensor data.
- Work for assessing long and short-term equipment health.
- Can assess the global and local condition index for a piece of equipment.

Way Forward and Next Steps

- Finalization of Tech Report

- **Potential Future Research/Implementation**
  - Hands-on training data for new equipment to better train neural networks / ML
  - Expanding analysis to more components that match up to Tyndall sensor list
  - Adapt CERL BAS neural network to new Tyndall points as we start acquiring USAF data
  - Pilot study with other COTS solutions / vibration sensor technology
  - Research inspection cost savings
  - Develop flow diagram of sensor data usage
    - Flagging components that require a physical inspection
    - Trends which automatically create inspection points
    - Trends which supplement SMS condition prediction
  - Verification and Validation for methodology processes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A Method Comparison of Algorithms for Predicting Equipment Condition Ratings in the Enterprise Sustainment Management System using Building Automation System Data

A Case Study at Tyndall AFB and the Engineering Research and Development Center, Version 1.0

Matthew E. Richards, Louis Bartels, PhD., Michael Grussing, PhD., Trevor Betz, Joseph Wittrock, Sam Dulin and Robert Skudnig

March 2023
Revised November 2023

DRAFT

DRAFT NOT APPROVED FOR PUBLIC RELEASE; distribution is limited to authors.

Summary

- Strategic – MDI
- Tactical – Reinforcement Learning
- Operational – Automated Condition Assessment

THANK YOU

Please take a few minutes to complete a short survey about this session. Your feedback will help us improve future programming for JETC.

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Beyond Condition Assessment: SMS for Strategic, Tactical, and Operational Intelligence

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