

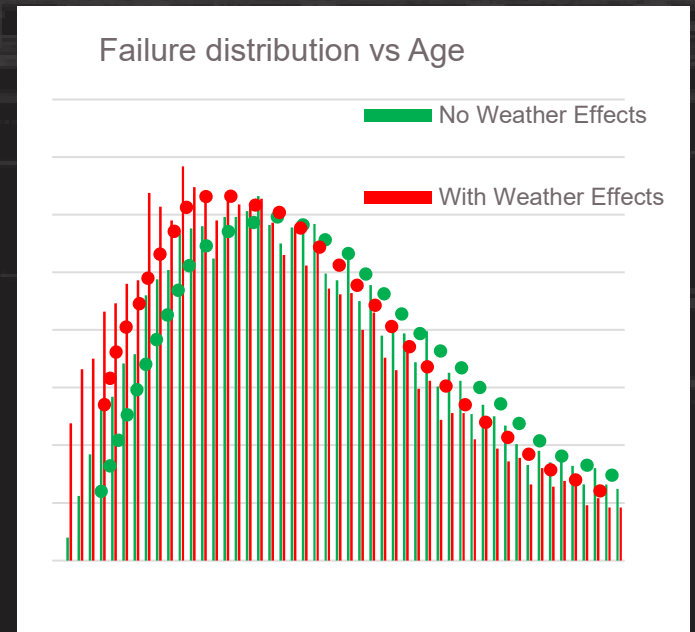
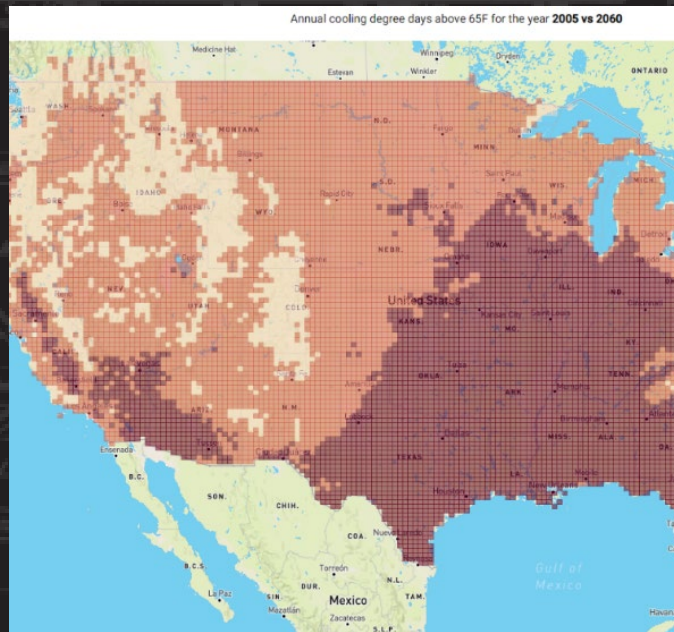
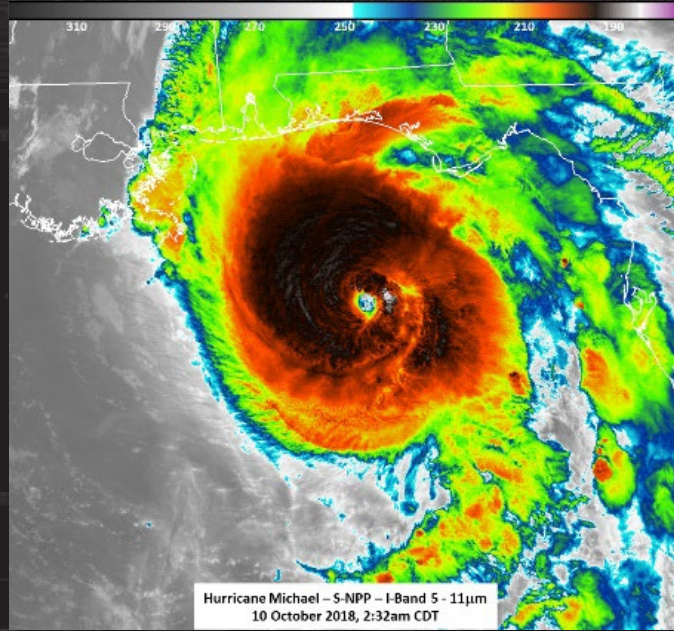


SMS SUMMIT 2024

SMS RESEARCH

ON-GOING RESEARCH IN SMS

DATA ANALYTICS AND MODELING



U.S. ARMY



US Army Corps
of Engineers®



ERDC
ENGINEER RESEARCH & DEVELOPMENT CENTER

RESEARCH INVOLVES MANY TEAM MEMBERS



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- Robert Skudnig
- Ryan Smith
- Clint Wilson
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- Seth Honningford
- Brayden Riesberg



SOME RESEARCH QUESTIONS:



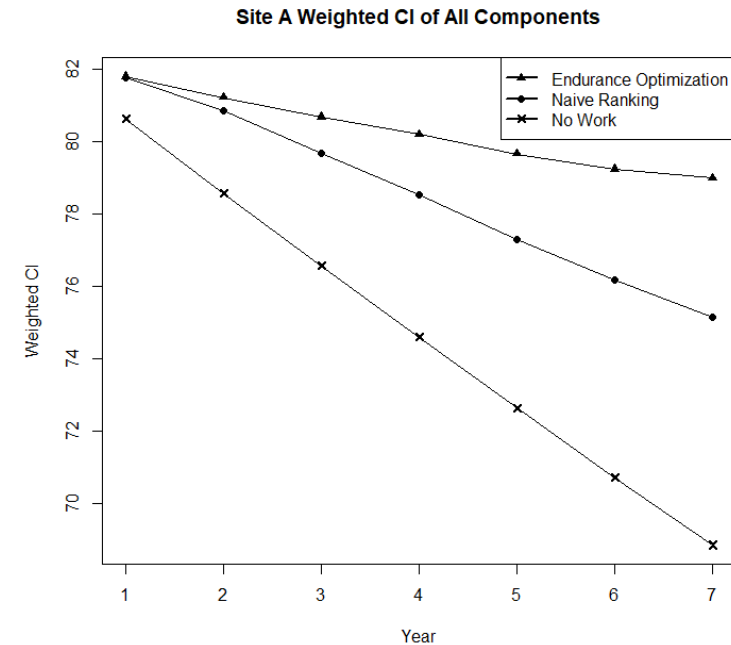
1. How do we make more optimal repair plans?
2. Can SMS help make decarbonization decisions?
3. How can we make improved model adjustments?
4. Can degradation be correlated to other component types?
5. Can SMS be used to identify other problem areas? (mold, corrosion)
6. Other topics: image recognition, mdi, pca, nlp, Markov modeling



MORE OPTIMAL REPAIR PLANNING



- **Research Approach 1:** make repair decisions based on rate of degradation
 - “Endurance” measures the rate of degradation and time until failure
 - Fund those components that have the least runway until failure
 - Year-over-year decisions



Prioritizing repair based on rate of degradation slows overall decline

- **Research Approach 2:** multi-year decision-making
 - Measure the relationship between near-term and medium-term decision combinations
 - Fund the decision combinations between components that have the best impact over the entire multi-year period

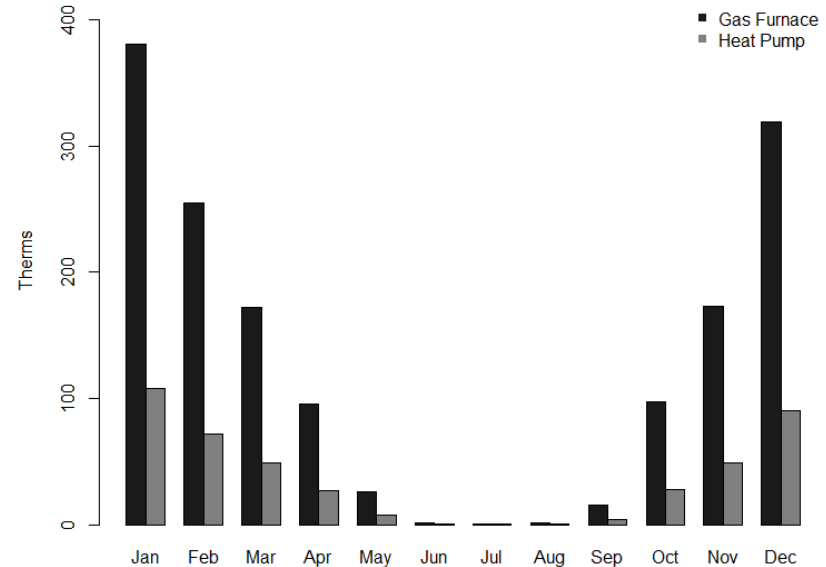
Component	Year 1	Year 2	Year 3	Cost	Impact
1	do nothing	repair	do nothing	\$11,871	0.178
2	repair	do nothing	do nothing	\$6,697	0.057
3	do nothing	do nothing	do nothing	\$0	0.000
...
102	do nothing	do nothing	do nothing	\$0	0.000



SMS AND DECARBONIZATION DECISIONS



- How do we decide which components to replace for the largest decarbonization impact?
- Two problems:
 - Alternative energy modeling is expensive! (as much as \$20k-\$30k per facility)
 - Short-fuse money sometimes becomes available, but does not give organizations enough time for full-scale energy modelling
- Combine:
 - SMS equipment data
 - Weather data
 - Energy Information Agency data
- This can quickly give rough estimates of design alternatives (e.g., heat-pump vs. fuel-fired furnace)
- Optimization routines select the components to replace for the biggest impact



Estimated energy use between design alternatives

$$\text{Maximize } [X] * [R]$$

s.t.

$$\Sigma[X] * [C] \leq B_{max}$$

$$\frac{\Sigma[x]+[c]}{\Sigma[x]+[s]} \leq PB_{max}$$

$$[X] = \text{binary}$$

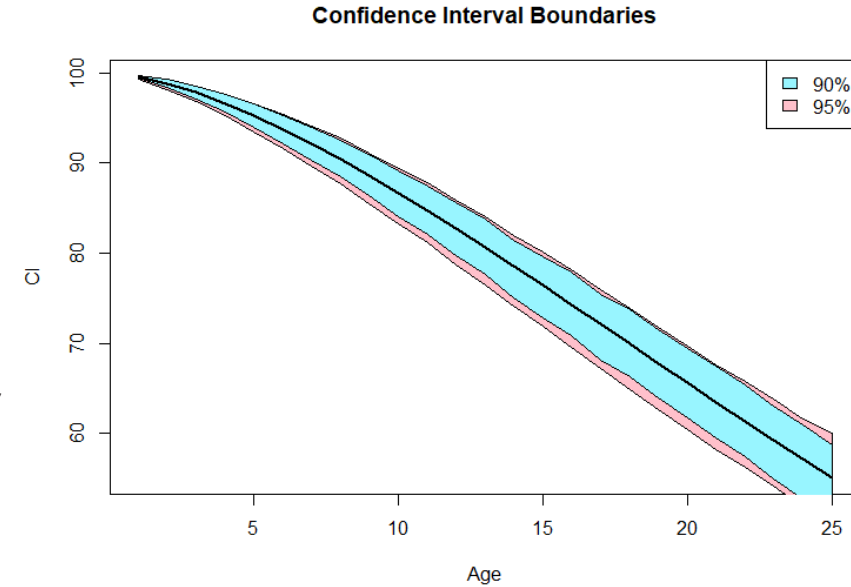
Mathematical optimization can define component replacement for minimum ROI



IMPROVED MODEL UPDATES

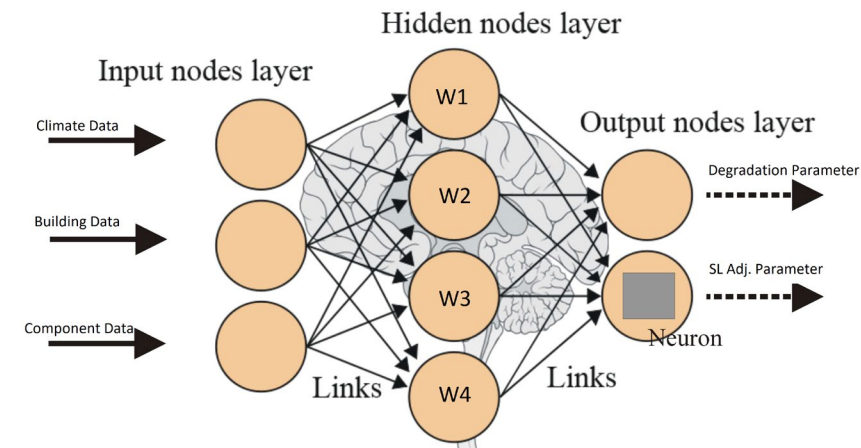


- **Research Approach 1:** apply uncertainty boundaries
 - Translates deterministic model to probabilistic model
 - If a component is within X% uncertainty, do not update model
 - Avoids “whipsawing” model with continuous updates after each inspection



If an inspection falls within a reasonable confidence boundary, there is no need to update the model

- **Research Approach 2:** Use ML to assign parameters
 - Can incorporate more relevant features (climate, FAC, etc.)
 - Capable of modeling non-linearities



ML is used to predict the degradation and beta parameters

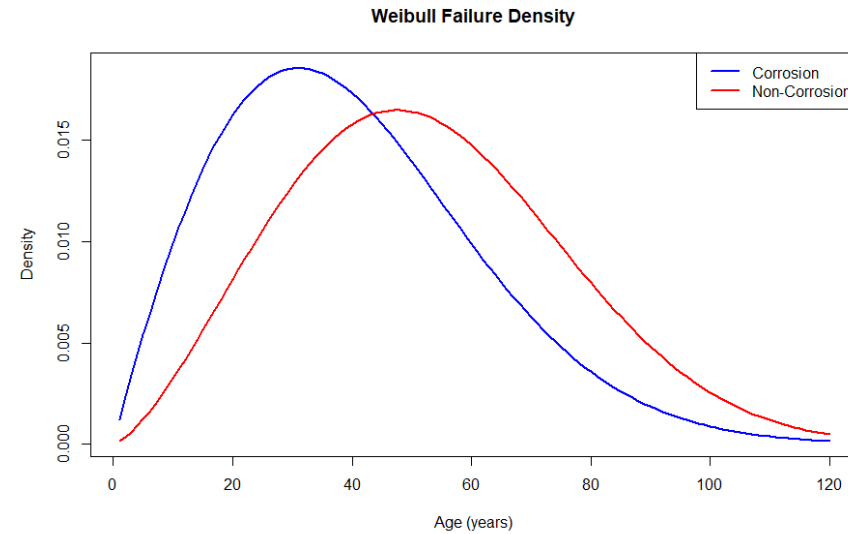


CAN SMS PROVIDE INSIGHT INTO PROBLEMS?



• Research Approach 1: Corrosion

- Can inspection comments identify patterns in risk features?
- Is it possible to estimate the impact (in terms of \$ or service life)?

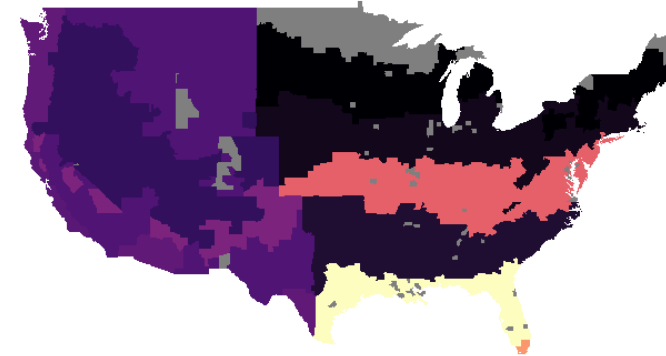


Failure probability density may change if a component experiences corrosion

• Research Approach 2: Mold

- Can a model assign a mold severity risk indicator?
- Looks at variables like climate, ventilation levels, building type etc.

Effect of Ventilation Rate on Mold



Percent Increase in Moisture Problem



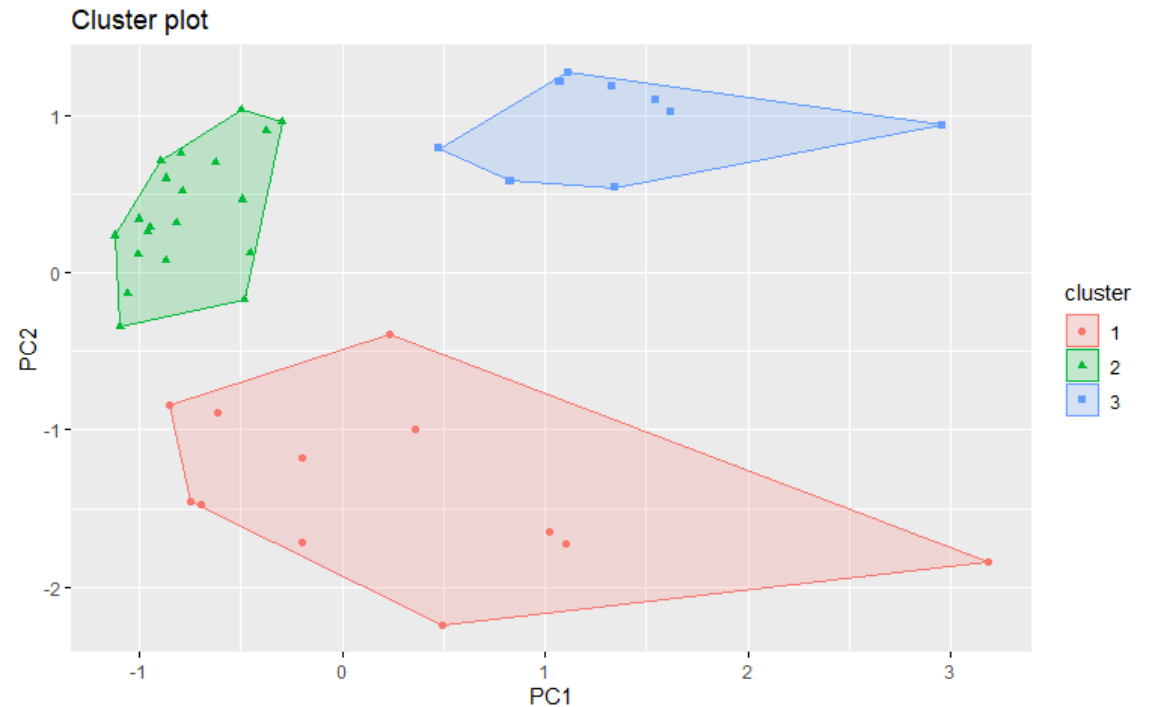
Moisture problems may be correlated with climate zones



CLUSTERING OF COMPONENTS



- Can components be clustered into groups that experience similar degradation?
- This may provide a path to infer degradation without inspecting every component
- Combines features into “principal components” to reduce the number of variables
- Clusters defined by similarity in the new principal component space

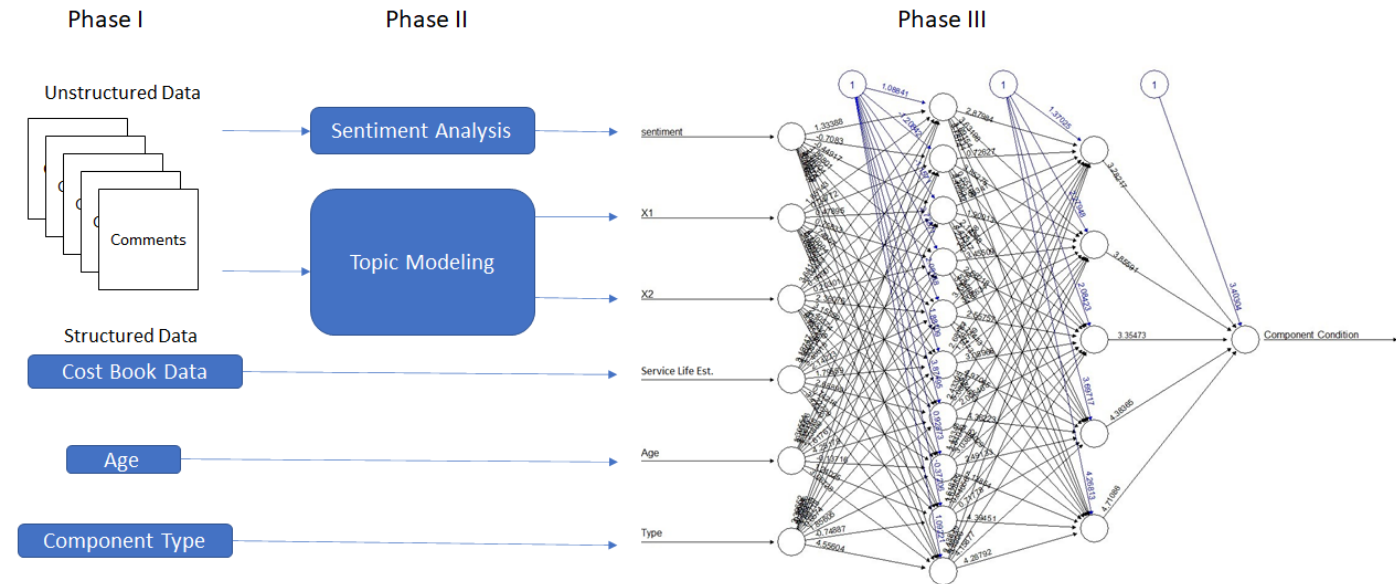




TEXT COMMENTS TO CONDITION



- A machine-learning model is used to associate text descriptions with condition scores
- This may have advantages in:
 - Streamlining inspections
 - Standardizing inspection scoring
 - Using text from a CMMS to assign scores
 - Integration with large language models (LLMs)

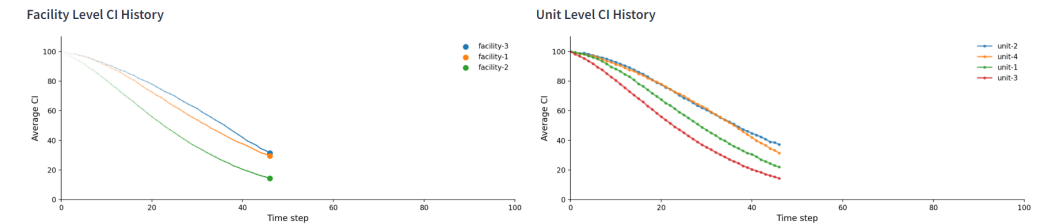
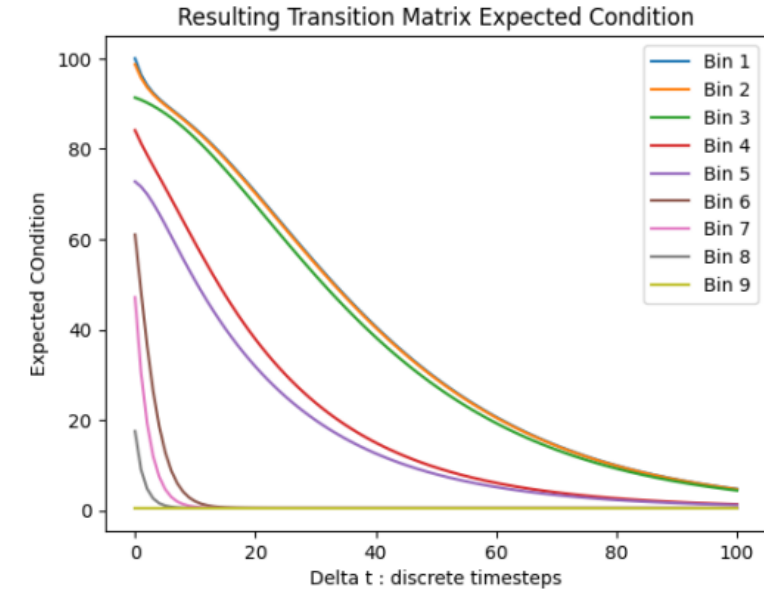




MARKOV MODELING



- **Research Approach 1: Reinforcement Learning**
 - Build state transition matrices from inspection data
 - Use RL to create optimal maintenance policies
- **Research Approach 2: InfraLib Dashboard**
 - “InfraLib” software library
 - Build state transition probabilities from component parameter values
 - User implements different maintenance policies in a dashboard to measure their impact



Component Level Decision Making

View belief and select actions for individual components. Select the desired component using the dropdowns below to see the belief history and available action choices.



