SMS SUMMIT 2024

SMS RESEARCH TOPICS

Breakout Session 1: Thursday, Aug. 1
11:00 AM—12:00 PM

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U.S. ARMY

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DISCOVERY: A CADRE OF SMS RESEARCHERS

ERDC

SMS LIFECYCLE

Discover

On-going work refining the art of asset management through algorithm and process development, data mining, and similar research efforts.

Develop

Taking new asset management practice discoveries and building tools that are leveraged by our industry partners.

Deliver

Provide Federal agencies assistance and guidance in the implementation of SMS tools and processes for maximum effectiveness.

Sustain

Application hosting, SMS Support helpdesk, and the various efforts required to provide SMS tools to Federal agencies.

SUSTAINMENT MANAGEMENT SYSTEM TCX

- Dr. Buddy Bartels
- Trevor Betz
- Rhoda Brucker
- Sam Dulin
- Mark Fisher
- Joel Groves
- Dr. Mike Grussing
- Seth Honningford
- Michael Johnson
- Matt Richards
- Brayden Riesberg
- Robert Skudnig
- Ryan Smith
- Clint Wilson
- Joseph Wittrock

CERL CONSTRUCTION ENGINEERING RESEARCH LABORATORY

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A Wealth of Information

With over 2 billion square feet of assets inventoried and assessed in SMS tools, there are millions of infrastructure asset data points available. This provides a wealth of information to gather insights for data-driven decisions and enables the SMS-TCX to continue refining metrics, algorithms, and optimization routines.

SOME RESEARCH QUESTIONS:

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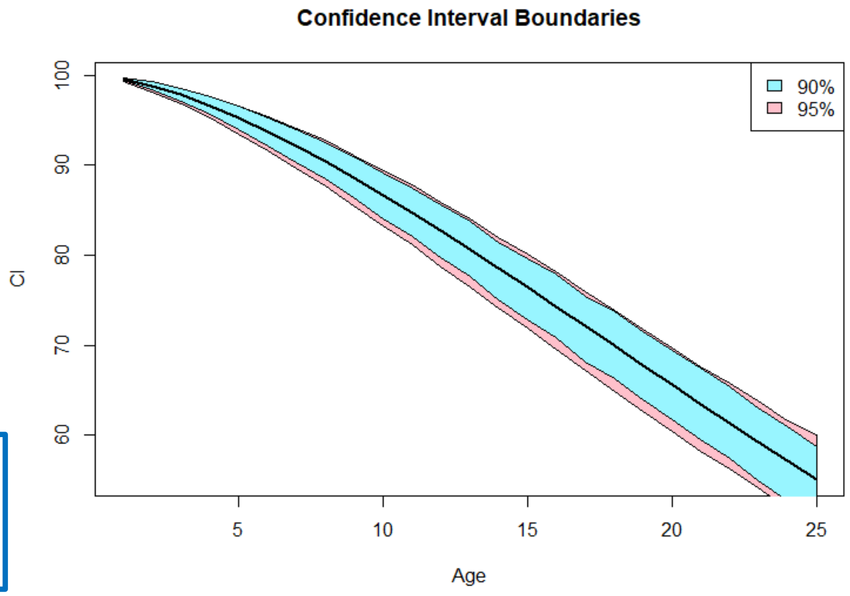
1. What does our previously collected inspection data tell us about ways to improved/adjust degradation models?
2. How do environmental factors like weather impact component service life?
3. How do we improve repair planning and investment prioritization?
4. Can we leverage SMS data to support better energy upgrade decisions?
5. How is degradation inter-related between systems and components?
6. Can SMS data and inspection comments be mined to target specific building issues ? (corrosion, mold)
7. How do we leverage the millions of images captured in BUILDER to support image recognition?
8. Can sensors be used to automate the inspection process?

QUESTION 1: DEGRADATION MODELS

IMPROVED MODEL UPDATES

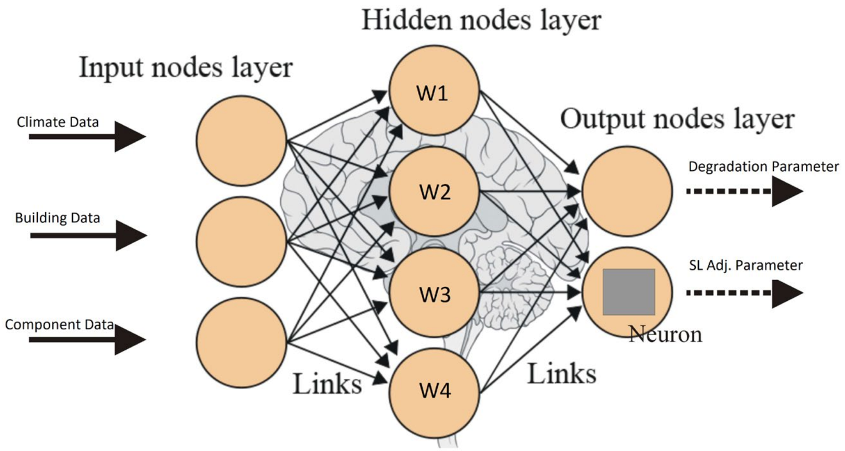
- Research Approach 1: apply uncertainty boundaries
  - Translates deterministic model to probabilistic model
  - If a component is within X% uncertainty, do not update model
  - Avoids "whipsawing" model with continuous updates after each inspection



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

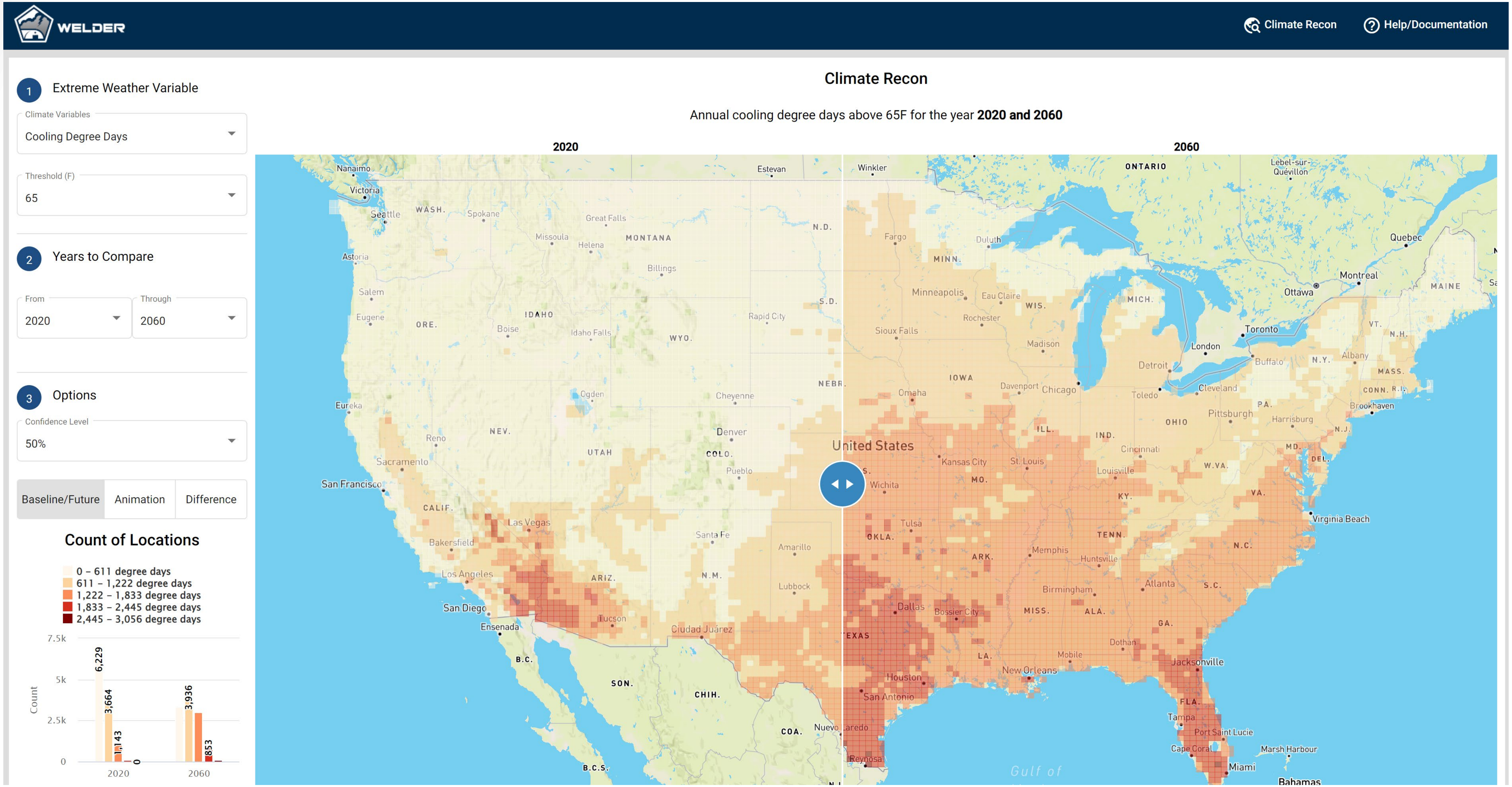
Betz, T., El-Rayes, K., Grussing, M. and Bartels, L., 2023. Optimizing facility maintenance planning under uncertainty. *Journal of Building Engineering*, *77*, p.107479.

- 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

QUESTION 2: WEATHER IMPACTS



CLIMATE EFFECTS MODELING

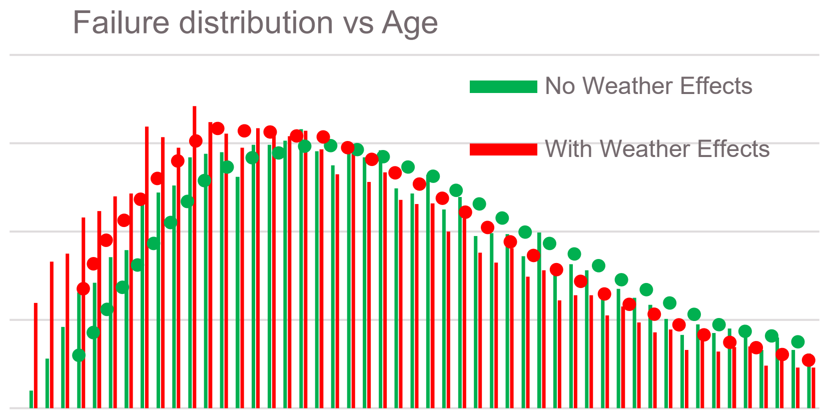
Building Components
Foundation
Super Structure
HVAC
  Rooftop AC Unit
…

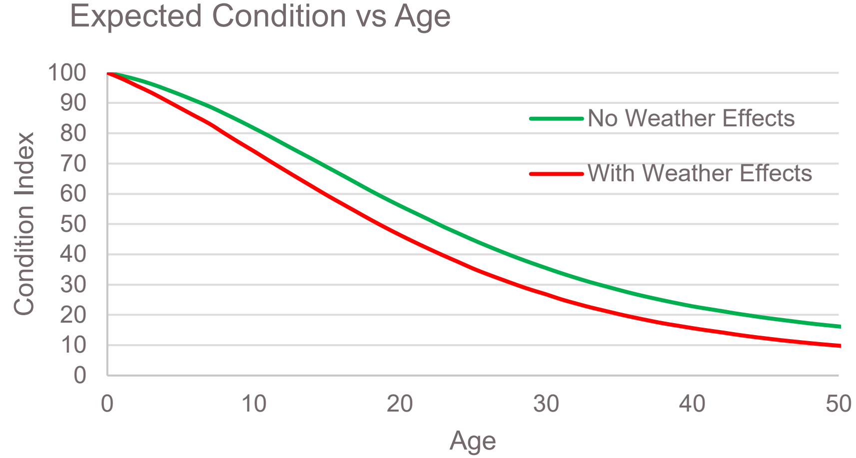
Hazard Events → **Stressors**

Severe Storm
Extreme Heat
…

Excessive Wind
Increased CCDs
Increased Temp Intensity
…

Damage/Distress Mode	Damage Type	Damage Effect	Weather Variable
Equipment Damage due to excess Wind	Abrupt	Condition Loss / Failure	CDDs
Accelerated HVAC equipment degradation due to increases demand	Gradual	Service Life Reduction	Annual Days above 100
HVAC Equipment failure due to prolonged run-time	Abrupt	Condition Loss / Failure	Wind Speed





Larsen, P., Grussing, M., Bercos-Hickey, E., Bidner, C., LaCommare, K., Landers, K., ... & Wehner, M. (2024). Weather effects on the lifecycle of US Department of Defense equipment replacement (WELDER). *Building and Environment*, *259*, 111639.

Betz, T., El-Rayes, K., Johnson, M., Mehnert, B., & Grussing, M. (2023). Machine learning model to predict impact of climate change on facility equipment service life. *Building and Environment*, *234*, 110192.

QUESTION 3: OPTIMAL INVESTMENT DECISIONS

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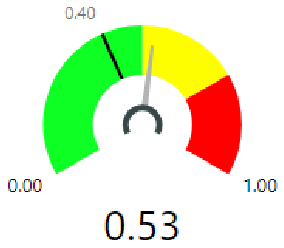
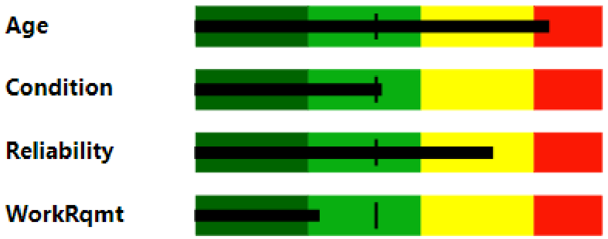
Facility Level Details

RPUID	Number	Name	Catcode	Catcode Descrption	Components	PRV	CRV	Age	EffAge	Condition	Repair
299710	3762	ENLISTED UPH	72111	ENLISTED UPH	186	$24,717,049	$45,988,650	24.33	21.92	75.38	$12,667,098

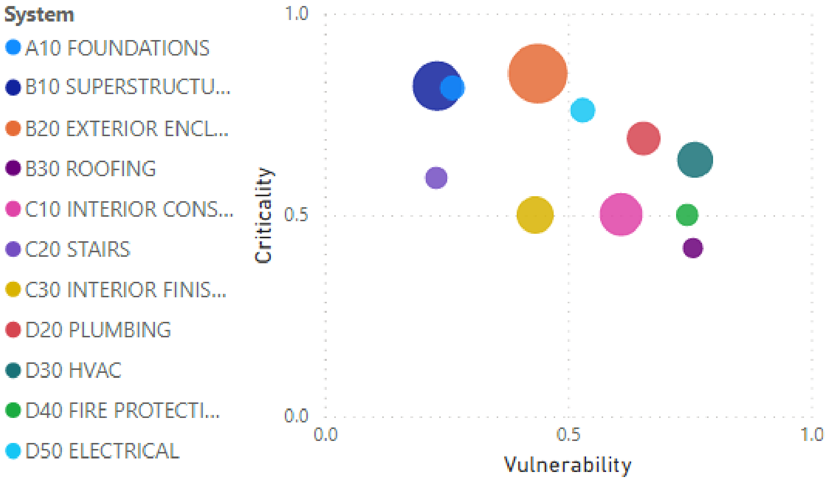
Risk Likelihood Score



Risk Likelihood Components



System Level Risk Posture



System Level Details

System	Criticality	Vulnerability	Components	CRV	Age	DLU	EffAge	SLU	Proj_CI	AccumDet	Repair	AccumRepair
A10 FOUNDATIONS	0.82	0.26	3	$1,324,343	43.00	0.43	42.08	0.42	90.00	0.17	$44,006	0.03
B10 SUPERSTRUCTURE	0.82	0.23	12	$8,897,173	36.33	0.36	36.13	0.36	90.00	0.17	$295,641	0.03
B20 EXTERIOR ENCLOSURE	0.85	0.44	38	$13,711,033	25.95	0.75	22.79	0.63	84.47	0.26	$1,088,471	0.11
B30 ROOFING	0.42	0.76	3	$523,692	23.00	0.96	20.01	0.82	60.00	0.67	$42,487	0.58
C10 INTERIOR CONSTRUCTION	0.50	0.61	20	$6,206,140	26.50	0.85	23.77	0.72	70.50	0.49	$3,128,289	0.38
C20 STAIRS	0.59	0.23	1	$1,019,592	43.00	0.34	46.56	0.37	90.00	0.17	$33,880	0.03
C30 INTERIOR FINISHES	0.50	0.43	26	$4,460,765	18.12	0.52	18.99	0.50	73.85	0.44	$1,125,563	0.27
D20 PLUMBING	0.69	0.66	21	$3,396,018	26.81	1.07	21.08	0.77	71.90	0.47	$960,622	0.32
D30 HVAC	0.64	0.76	23	$4,103,367	18.65	0.87	18.04	0.81	57.83	0.70	$5,158,019	0.67
D40 FIRE PROTECTION	0.50	0.75	2	$894,248	14.50	0.73	14.50	0.73	60.00	0.67	$530,532	0.86

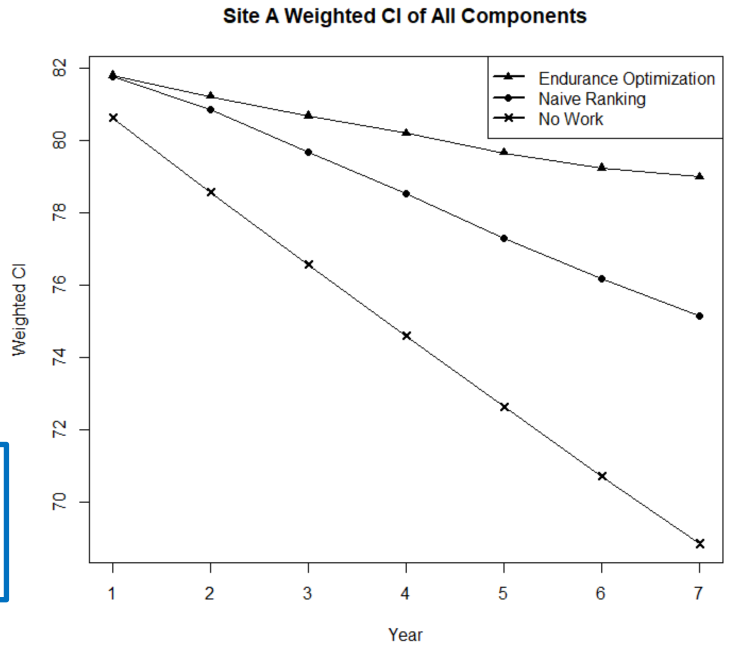
MORE OPTIMAL REPAIR PLANNING

- 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

Bartels, L.B., Betz, T.S. and Grussing, M.N., 2024. Measuring and Optimizing for Infrastructure Endurance. *Journal of Performance of Constructed Facilities*, *38*(4), p.04024024.



Prioritizing repair based on rate of degradation slows overall decline

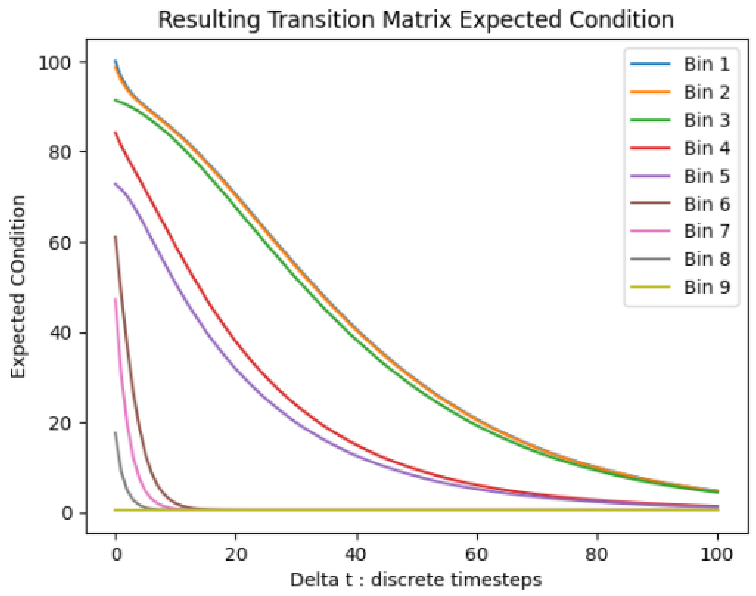
- Research Approach 2: multi-year decision-making
  - Measure the relationship between near-term and medium-term decision combinations
  - Fund the decision combinations between components that have the best impact over the entire multi-year period

Betz, T., El-Rayes, K. and Grussing, M., 2024. Multiyear Facility Maintenance Optimization. *Journal of Performance of Constructed Facilities*, *38*(2), p.04024005.

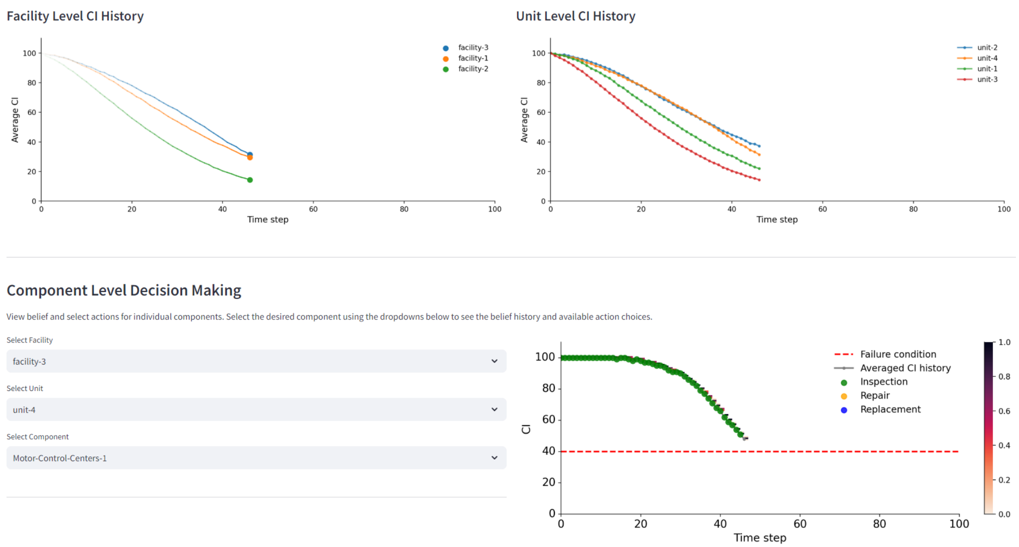
Component	Year 1	Year 2	Year 3	Cost	Impact
1	do nothing	repair	do nothing	$11,871	0.178
2	repair	do nothing	do nothing	$6,697	0.057
3	do nothing	do nothing	do nothing	$0	0.000
…	…	…	…		…
102	do nothing	do nothing	do nothing	$0	0.000

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



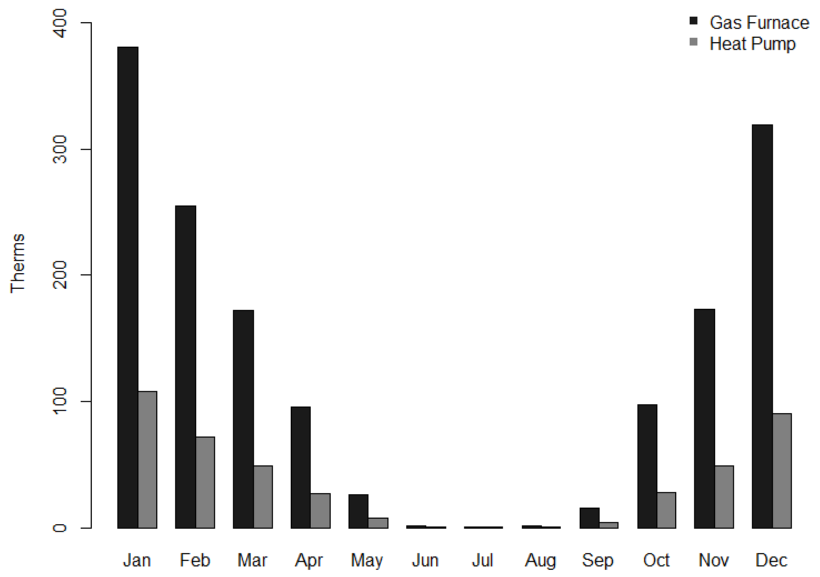
Vora, M., Thangeda, P., Grussing, M.N. and Ornik, M., 2023. Welfare Maximization Algorithm for Solving Budget-Constrained Multi-Component POMDPs. *IEEE Control Systems Letters*, *7*, pp.1736-1741.

QUESTION 4: ENERGY ANALYTICS

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

Betz, T., El-Rayes, K. and Johnson, M., 2024. Optimizing the Decarbonization of a Geographically Dispersed Building Portfolio. *Building and Environment*, p.111767.



Estimated energy use between design alternatives

$$Maximize\ [X] * [R]$$

$$s.t.$$

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

$$\frac{\Sigma[X]*[C]}{\Sigma[X]*[S]} \leq PB_{max}$$

$$[X] = binary$$

Mathematical optimization can define component replacement for minimum ROI

QUESTION 5: COMPONENT/SYSTEM INTERACTIONS

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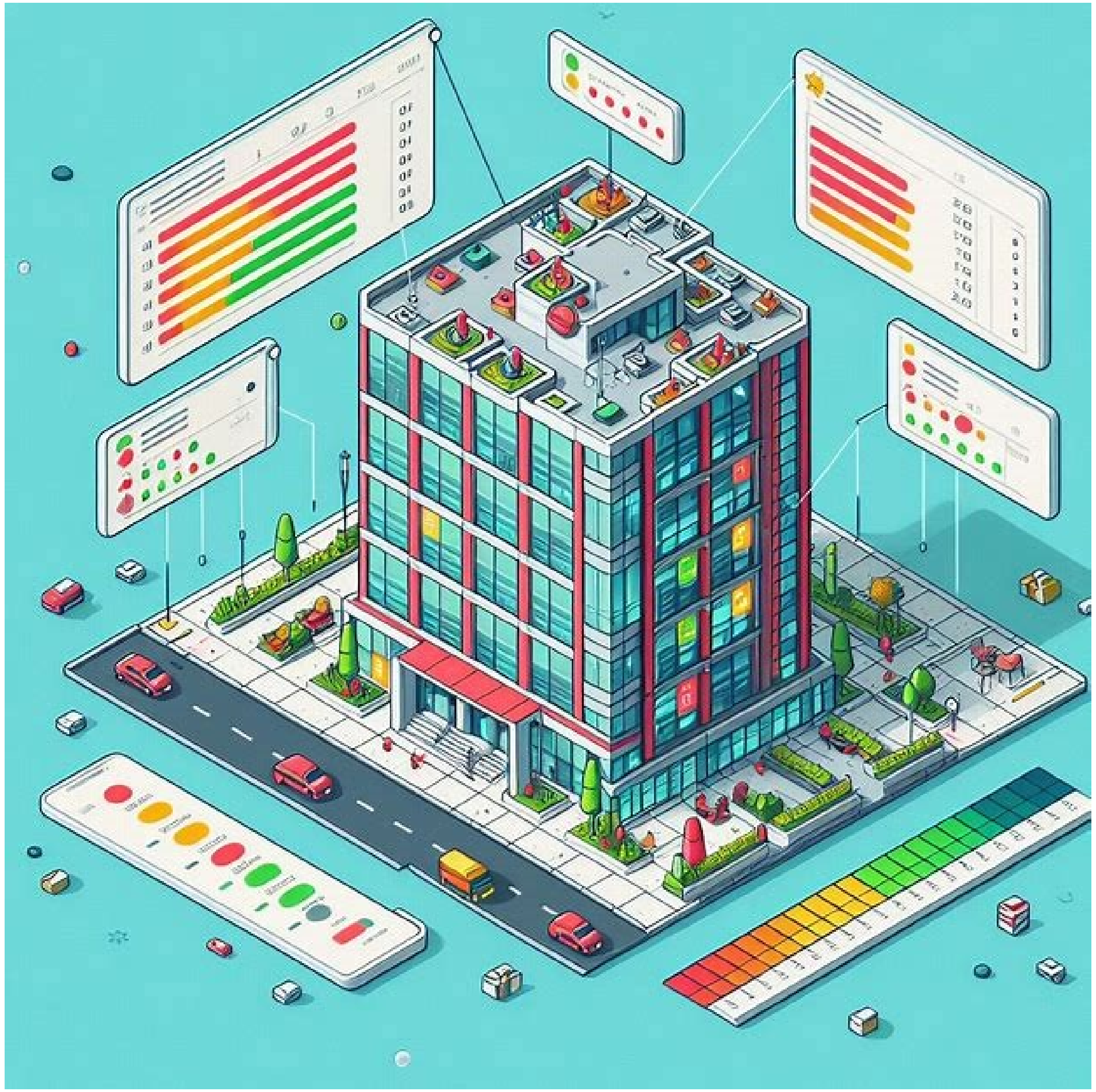
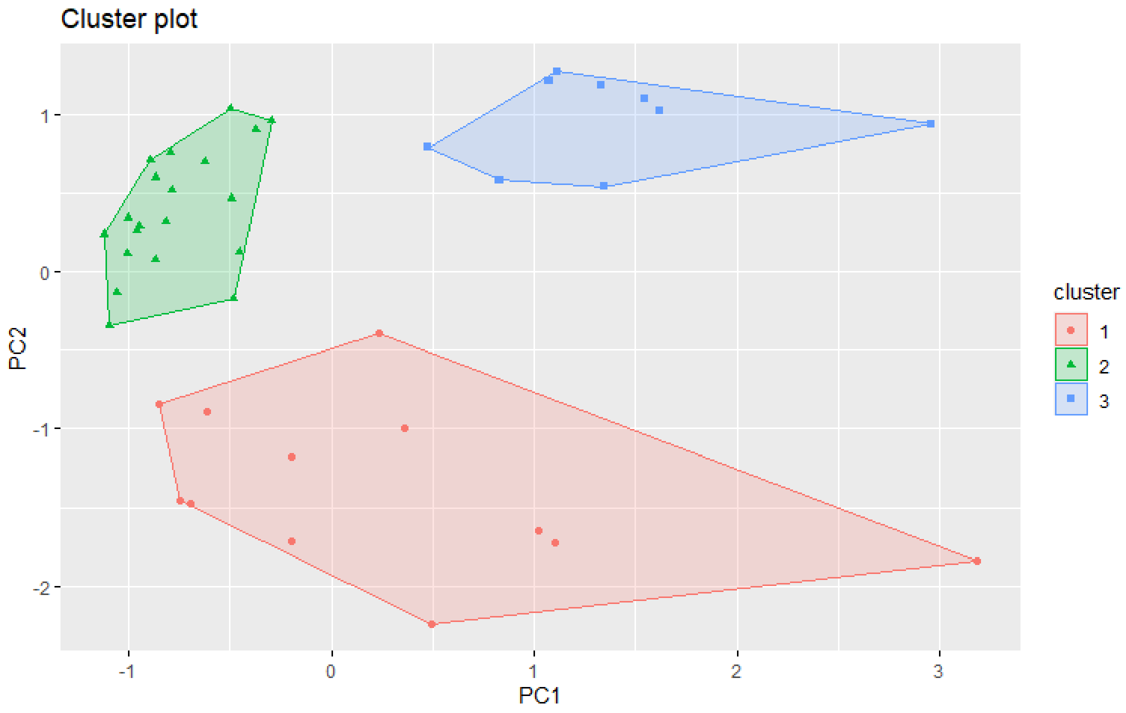
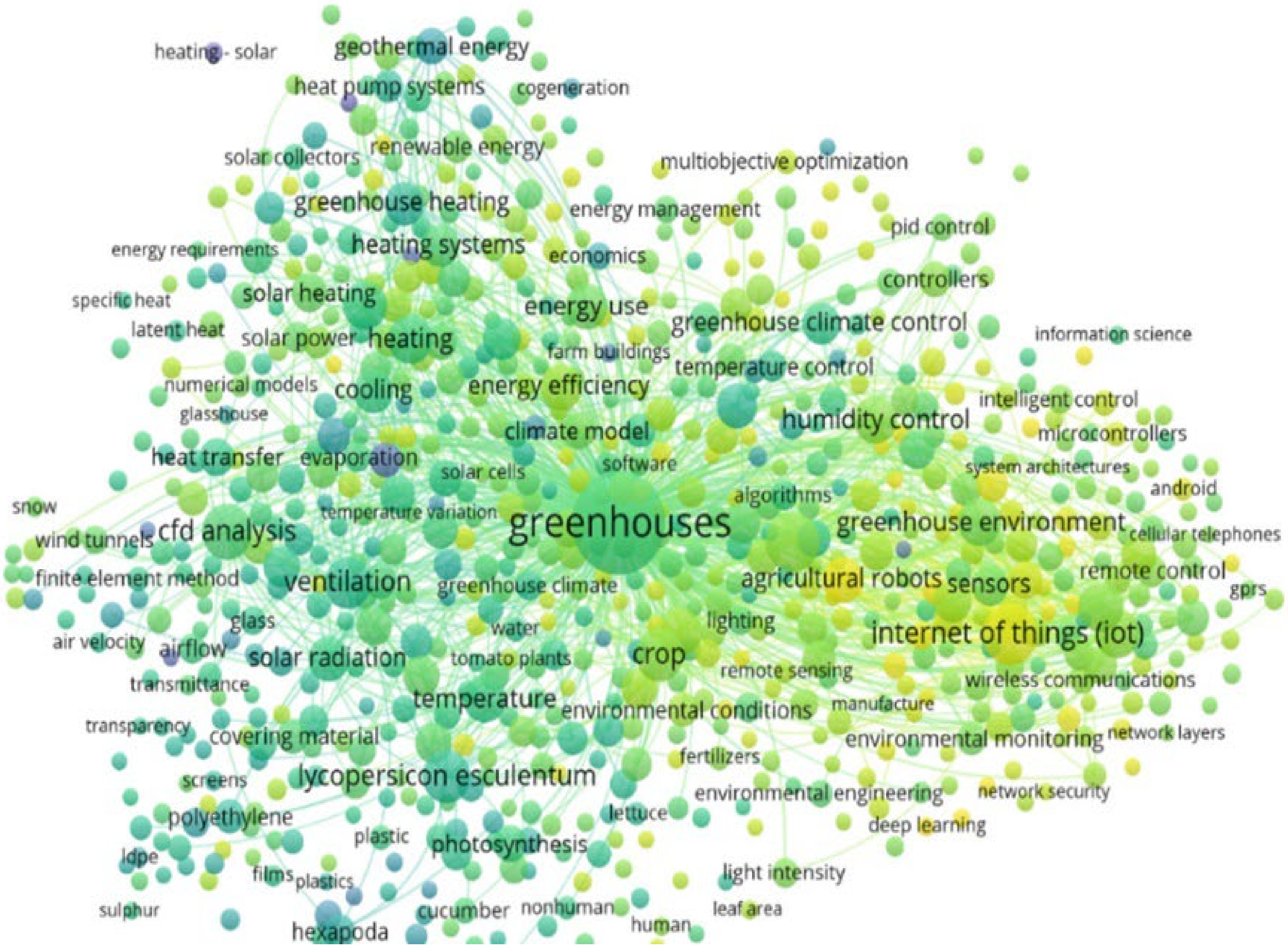


CLUSTERING OF COMPONENTS

- 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



QUESTION 6: TEXT ANALYTICS AND NLP



CAN SMS PROVIDE INSIGHT INTO PROBLEMS?

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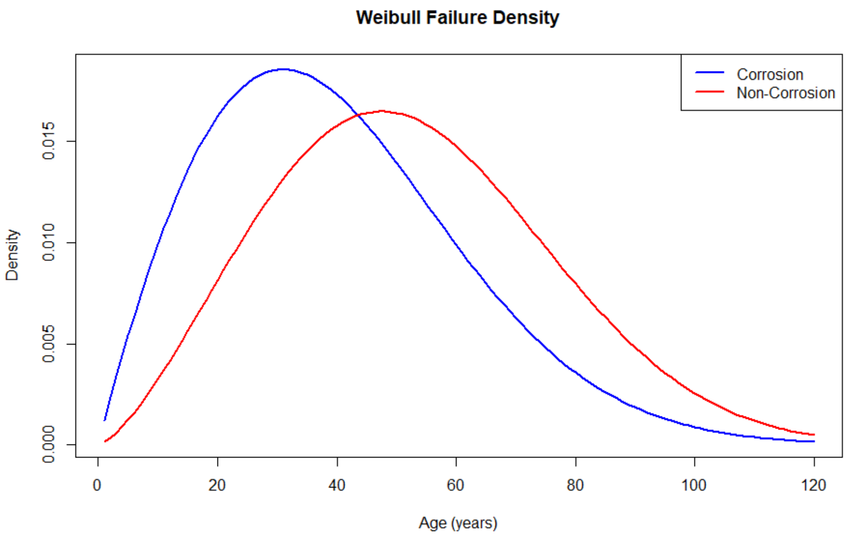
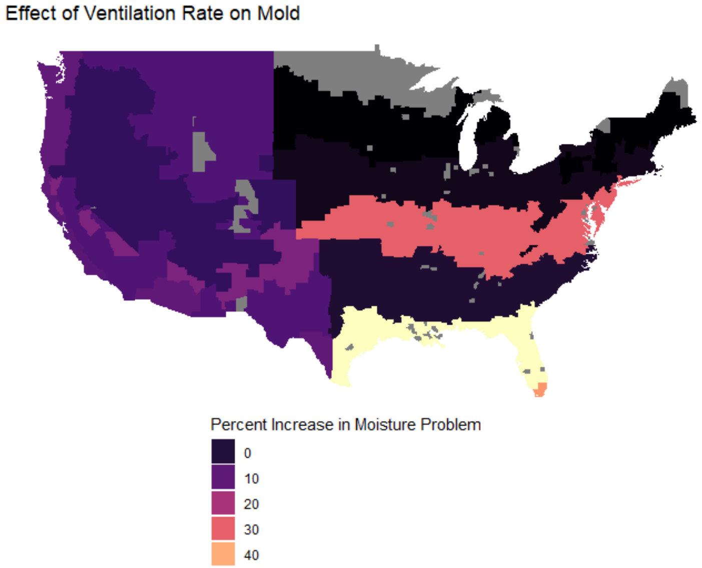
- Research Approach 1: Corrosion
  - Can inspection comments identify patterns in risk features?
  - Is it possible to estimate the impact (in terms of $ or service life)?



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.

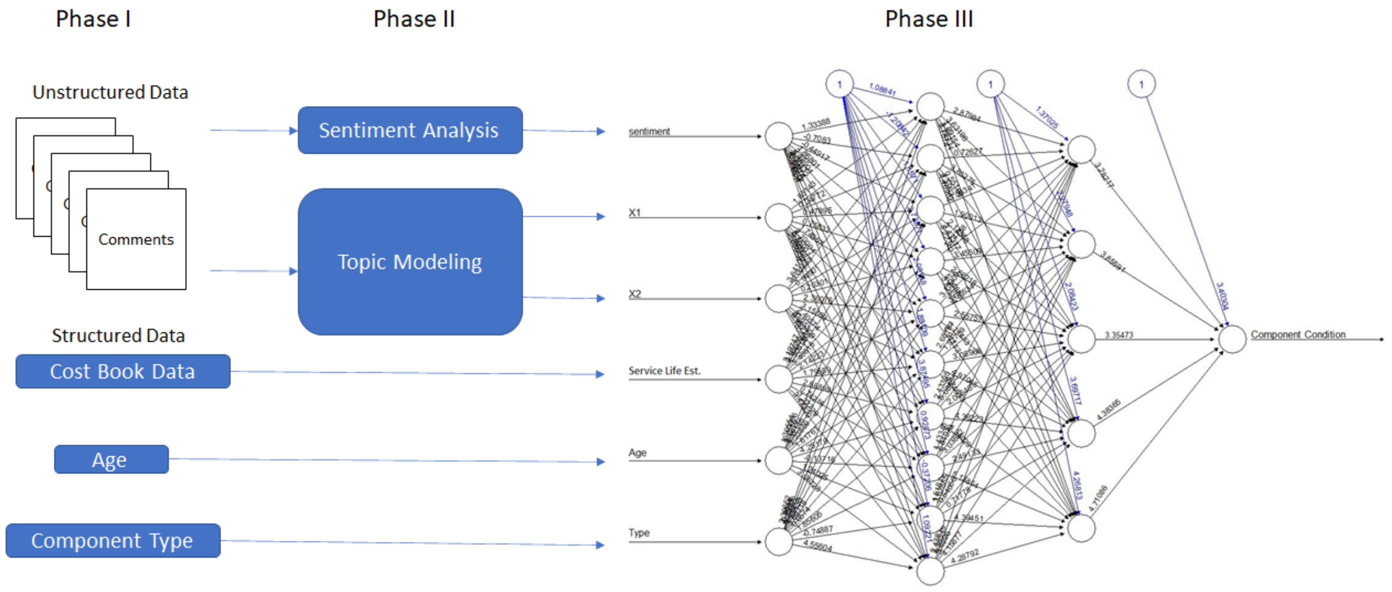


Moisture problems may be correlated with climate zones

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)



QUESTION 7: IMAGE PROCESSING

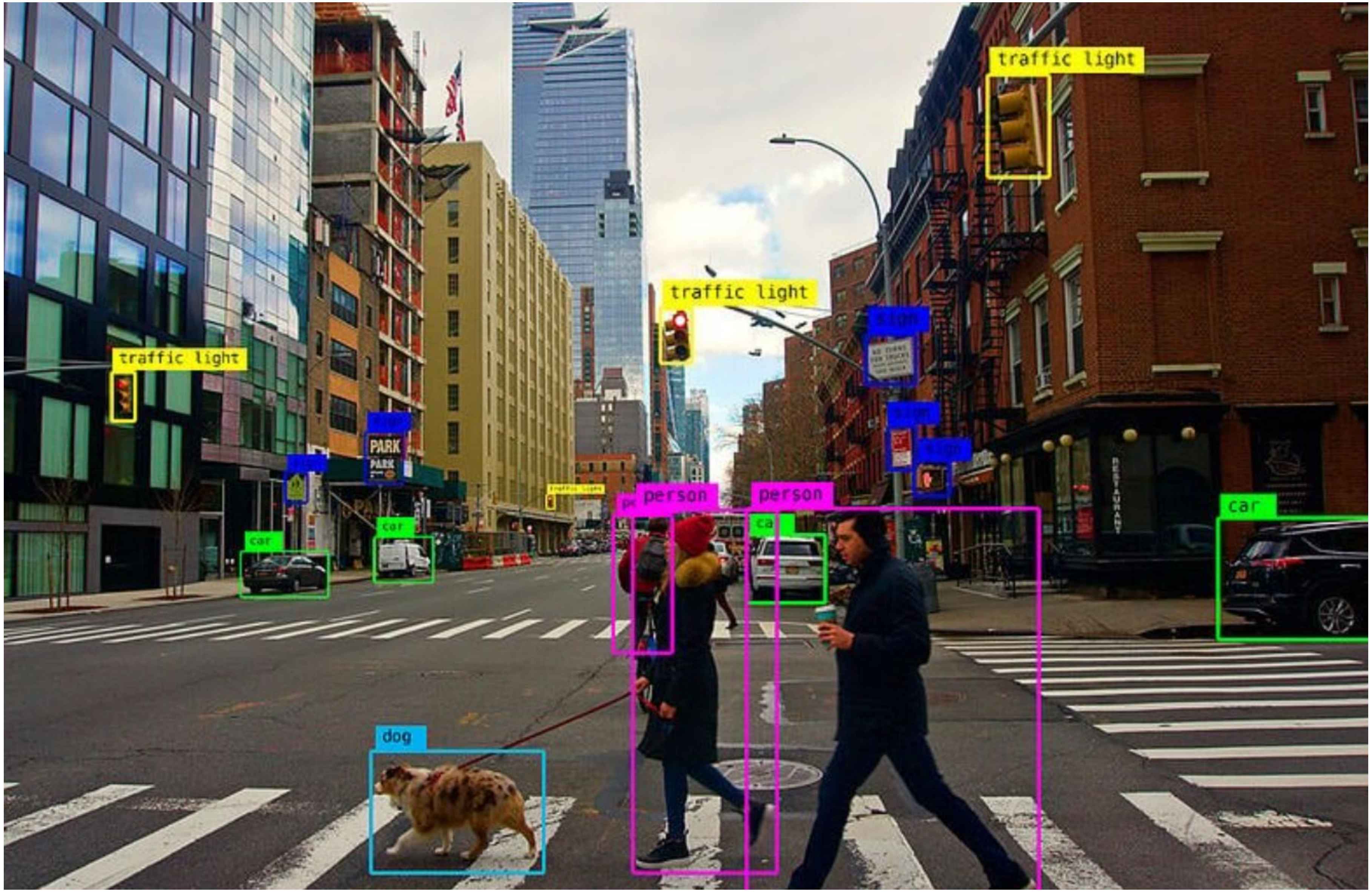
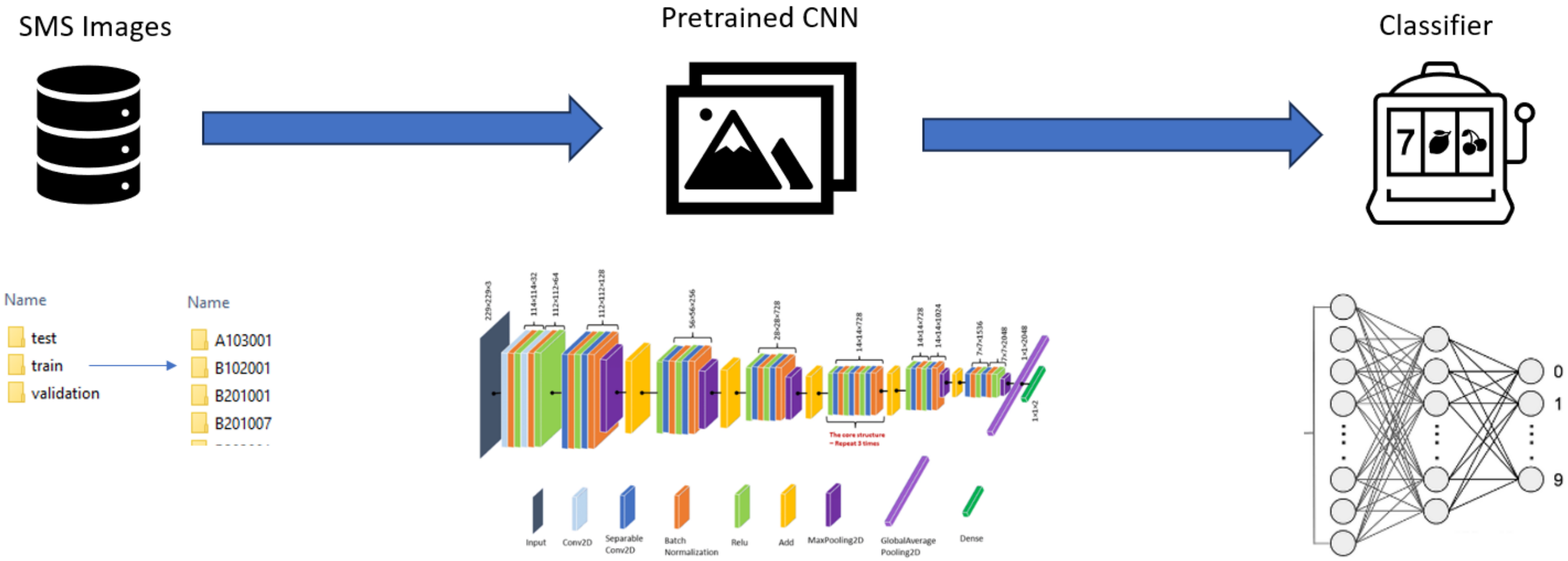


IMAGE RECOGNITION

- Use SMS images to classify inventory or assign degradation
- Transfer learning neural network
  - Use existing pre-trained model
  - Add SMS-specific layers
- In initial stages of feasibility



QUESTION 8: SENSOR INTEGRATION

ERDC/CERL SR-01-23

Construction Engineering Research Laboratory

US Army Corps of Engineers®
Engineering Research and Development Center

Operations and Maintenance Engineering Technology

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

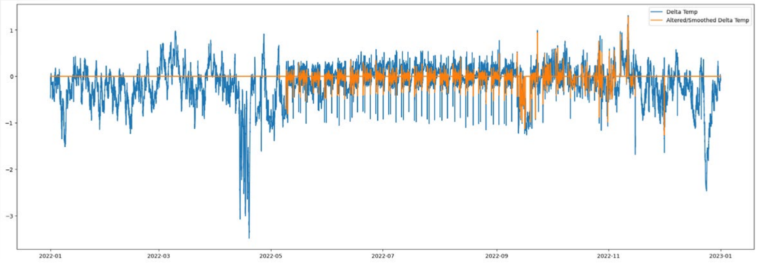
March 2023
Revised November 2023

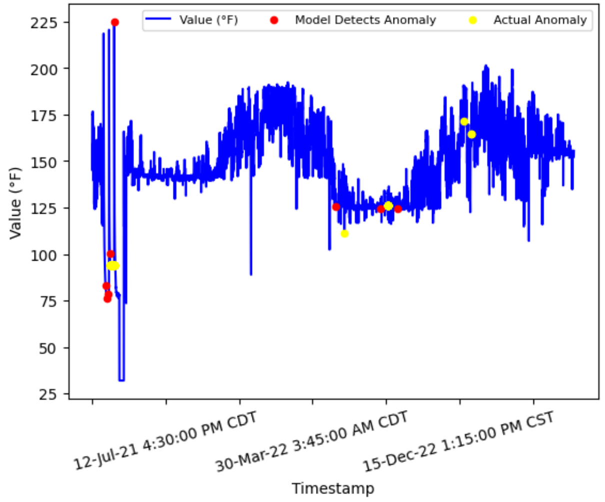
DRAFT

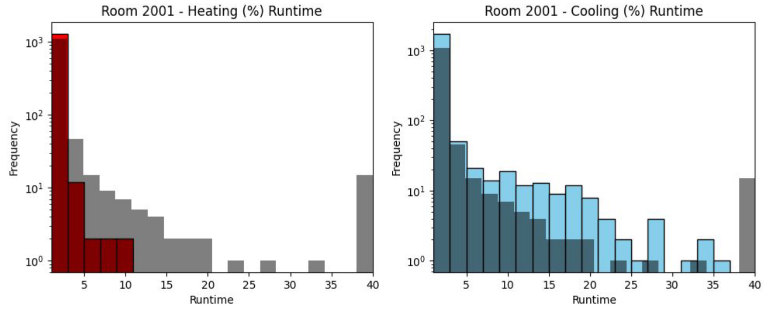
DRAFT NOT APPROVED FOR PUBLIC RELEASE; distribution is limited to authors.

ML / NEURAL NETWORK PROCESSING

Unsupervised Anomaly Detection





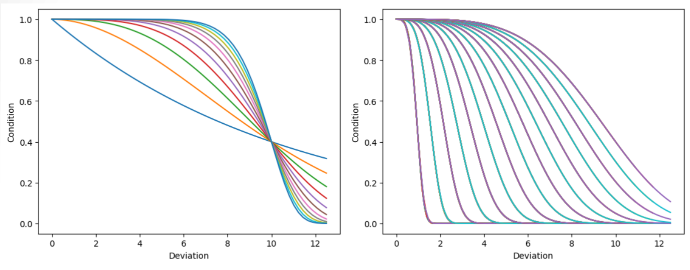


- Develop model that can use sensor data to predict temperature
- We define the Delta Temperature as the difference between the Actual Temperature and the Room Temperature.
- We take a rolling mean over the Delta Temperature and set it to 0 whenever the system is off.

- "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

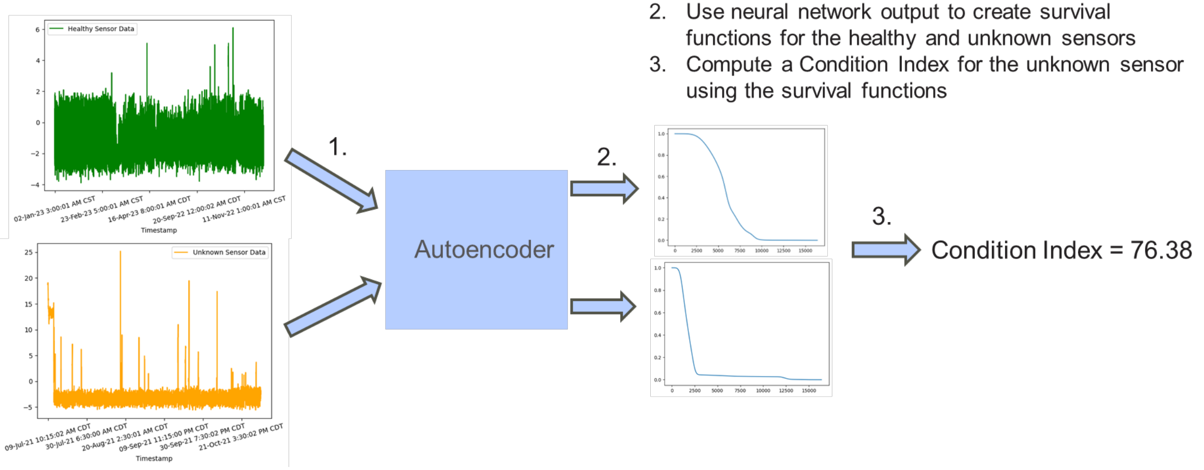


Room	deviation	Condition			
		alpha = 2	alpha = 3	alpha = 4	alpha = 5
1	449	82	91	96	98
2	524	77	87	93	96
3	600	71	81	88	92
4	618	70	80	87	91
5	650	67	77	84	89
6	679	65	74	81	87
7	761	58	66	73	78
8	840	51	57	62	67
9	938	44	46	48	50
10	994	40	40	40	40

- 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.

FUTURE DISCOVERY

Ideas / Discussion from the audience on other areas of research:

- Generative AI
- Advanced Assessment Techniques
- Auxiliary used of SMS Data
- Others?

Questions / Discussion

THANK YOU!

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