Leveraging Physical and Virtual On-Aircraft Sensors to Inform Maintenance Practices

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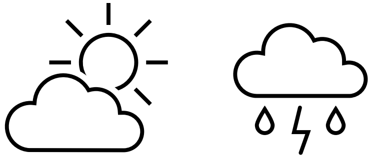
C2024-20921, Machine Learning for Corrosion Management

AMPP 2024, New Orleans, LA

6 March 2024

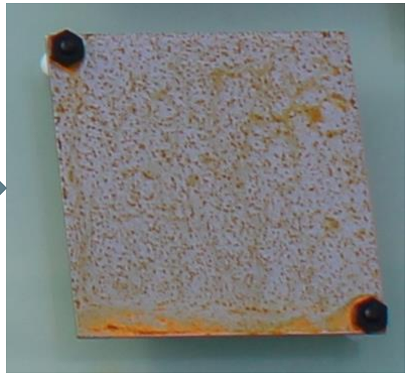
Atmospheric Corrosion

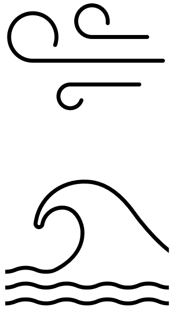


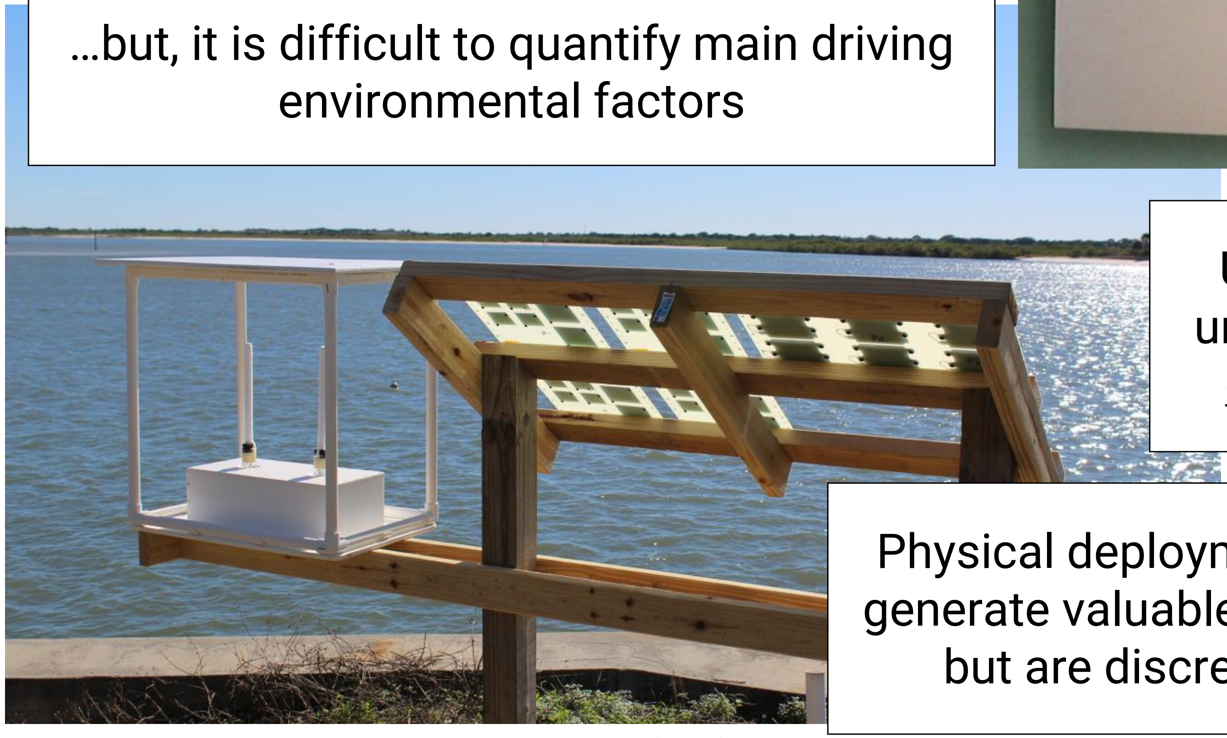
Atmospheric corrosion is known to occur...

…but, it is difficult to quantify main driving environmental factors

Atmospheric exposure







Understanding atmospheric corrosion rates under different climates can help characterize **<u>environmental severity & material severity</u>**

Physical deployments generate valuable data, but are discrete

Computational modeling can be used to complement existing databases

- Yoon, Y., J.D. Angel, and D.C. Hansen, *Corrosion* 72 (2016): pp. 1424–1432.
- “ISO 9223 Corrosion of Metals and Alloys - Corrosivity of Atmospheres - Classification, Determination and Estimation,” Reference number ISO (2012).
- Silver, N.A., and W. Gaebel, “Facilities Environmental Severity Classification Study Final Report” (2017), www.corrdefense.org.
- Kopitzke, S., “Characterizing Environmental Severity for Naval Air Stations” (2023), AMPP Corrosion Conference

Multi-Tiered Model, Robust to Available Data

Need robust model, capable of predicting corrosion based on available data…

At the minimum, environmental parameters capturing the ***wetness*** and ***saltiness*** are necessary

"Wetness" Parameters

- Relative humidity (RH)
- Air temperature
- Time of wetness

Local measurements and regional weather stations

"Saltiness" Parameters

- Annual salt accumulation
- Wind flux, direction
- Wave height, frequency
- Solution conductance

- Sanders, C. E., & Santucci, R. J. (2022). Experimental Design Considerations for Assessing Atmospheric Corrosion in a Marine Environment: Surrogate C1010 Steel. *Corrosion and Materials Degradation*, *4*(1), 1–17. https://doi.org/10.3390/cmd4010001
- Yan, L., Diao, Y., Lang, Z., & Gao, K. (2020). Corrosion rate prediction and influencing factors evaluation of low-alloy steels in marine atmosphere using machine learning approach. *Science and Technology of Advanced Materials*, *21*(1), 359–370. https://doi.org/10.1080/14686996.2020.1746196
- Pei, Z., Zhang, D., Zhi, Y., Yang, T., Jin, L., Fu, D., Cheng, X., Terryn, H. A., Mol, J. M. C., & Li, X. (2020). Towards understanding and prediction of atmospheric corrosion of an Fe/Cu corrosion sensor via machine learning. *Corrosion Science*, *170*. https://doi.org/10.1016/j.corsci.2020.108697

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Additional exposure considerations: sheltering, rainfall, exposure angle, sample geometry, etc.

- Sanders, C. E., & Santucci, R. J. (2022). Expe… ogate C1010 Steel. *Corrosion and Materials Degradation*, *4*(1), 1–17. https://do…
- Yan, L., Diao, Y., Lang, Z., & Gao, K. (2020). C… using machine learning approach. *Science and Technology of Advanced Materia…*
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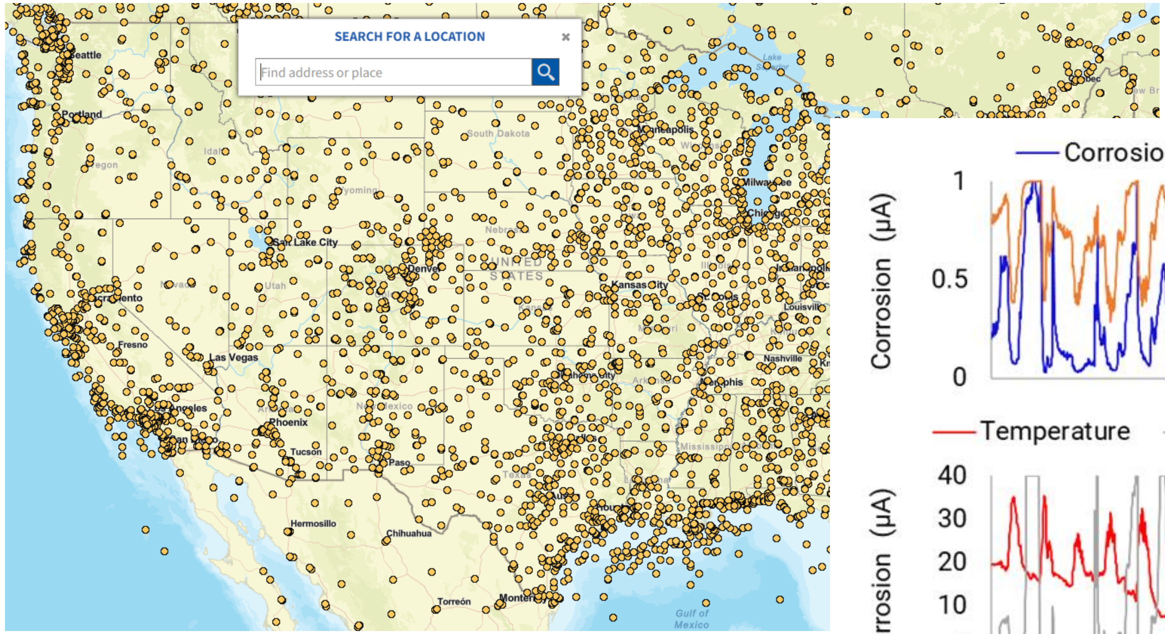
Data Acquisition of Environment and Corrosivity

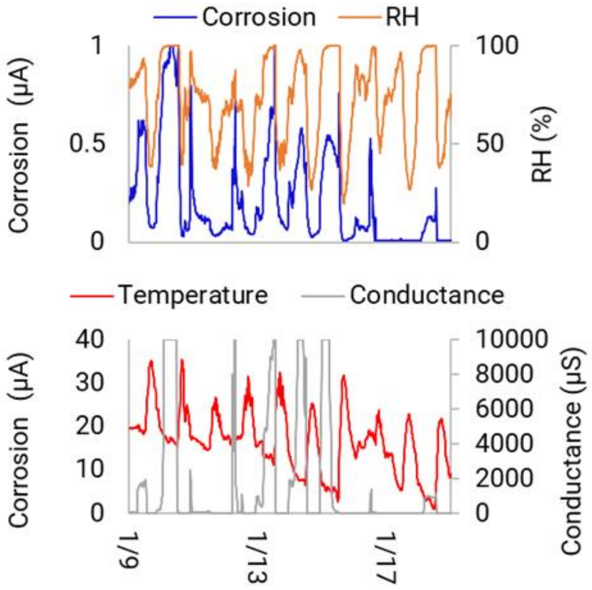
Weather and buoy stations

- Large database of historic measurements
- Well documented, over a range of global sites

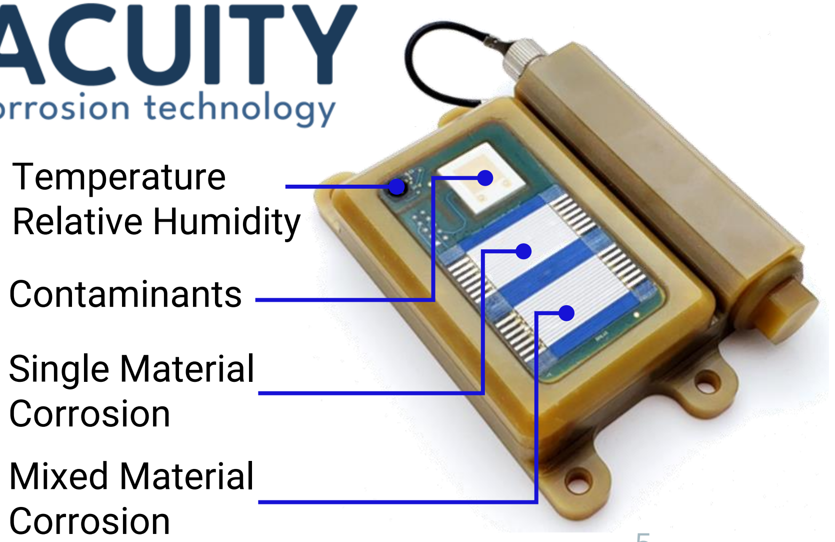
Real-time monitoring devices

- Capturing *real-time* corrosion with *local environment* monitoring
- Can differentiate adjacent conditions
- Durable for outdoor deployments in harsh conditions



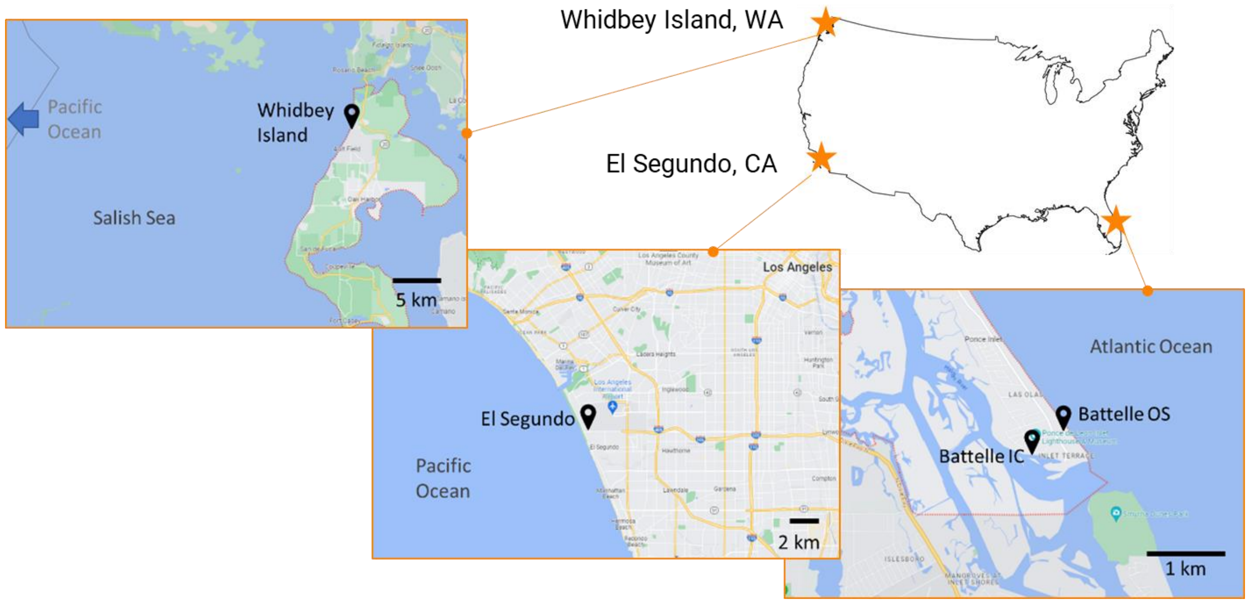


corrosion technology



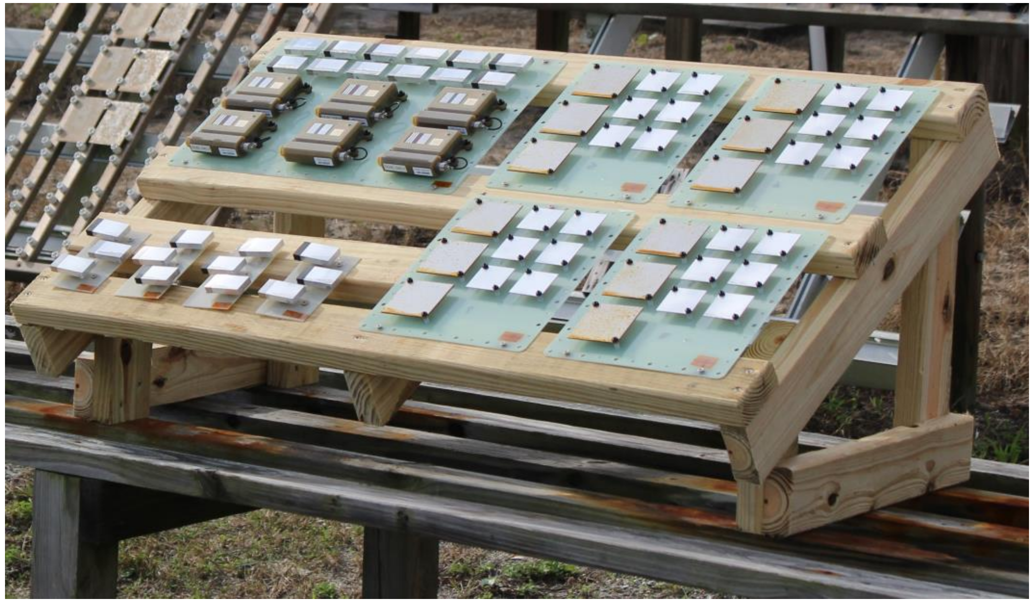
Agnew, L. (2023). Atmospheric Environment Severity Monitoring for Corrosion Management. *AMPP* C2023-19464

Database for Modeling Uses Four Distributed Sites



Environment and Corrosivity Data Streams

- Outdoor deployments of sensing devices and witness coupons
- Wet chloride candle measurements
- Weather station and buoy environments (NOAA)



- Friedersdorf, F., & Agnew, L. (2023). Use of Environment and Corrosivity Monitoring to Characterize Base and Airframe Severity. *NATO STO-MP-AVT-373*.
- Agnew, L., Avance, V., Clark, B., & Friedersdorf, F. (2023). Atmospheric Environment Severity Monitoring for Corrosion Management. *AMPP* .

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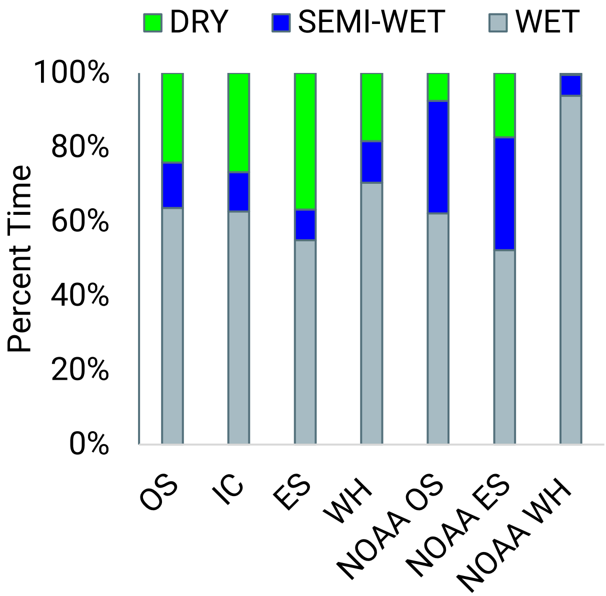
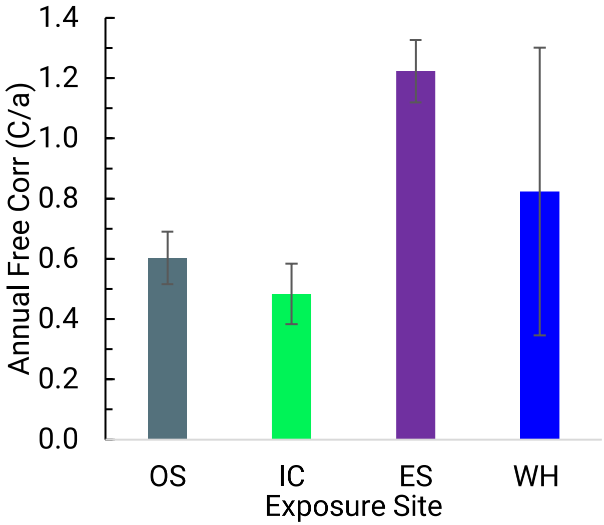
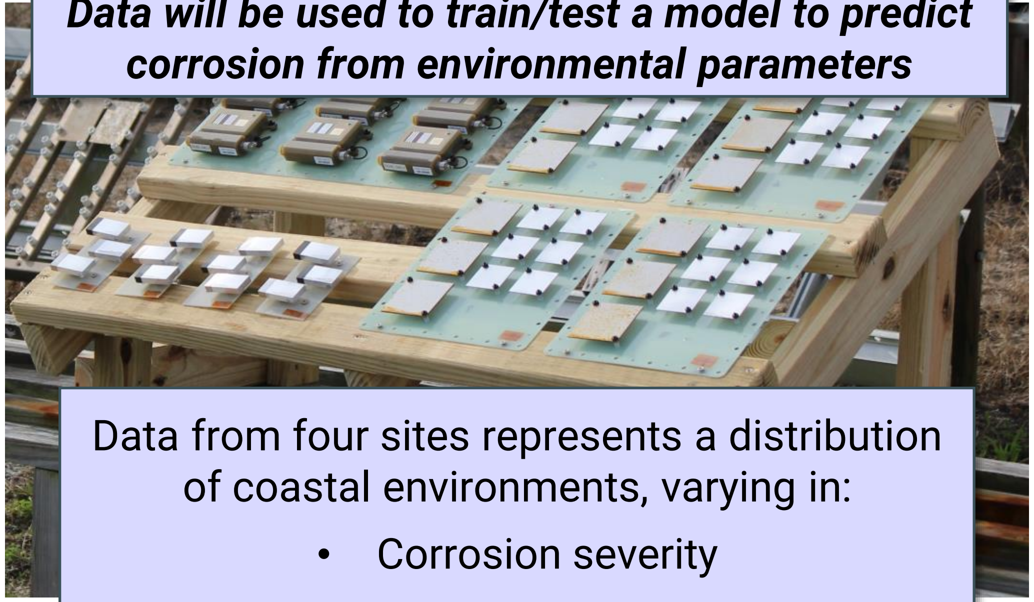




Data will be used to train/test a model to predict corrosion from environmental parameters



Data from four sites represents a distribution of coastal environments, varying in:

- Corrosion severity
- Salt deposition
- Time of wetness (TOW)

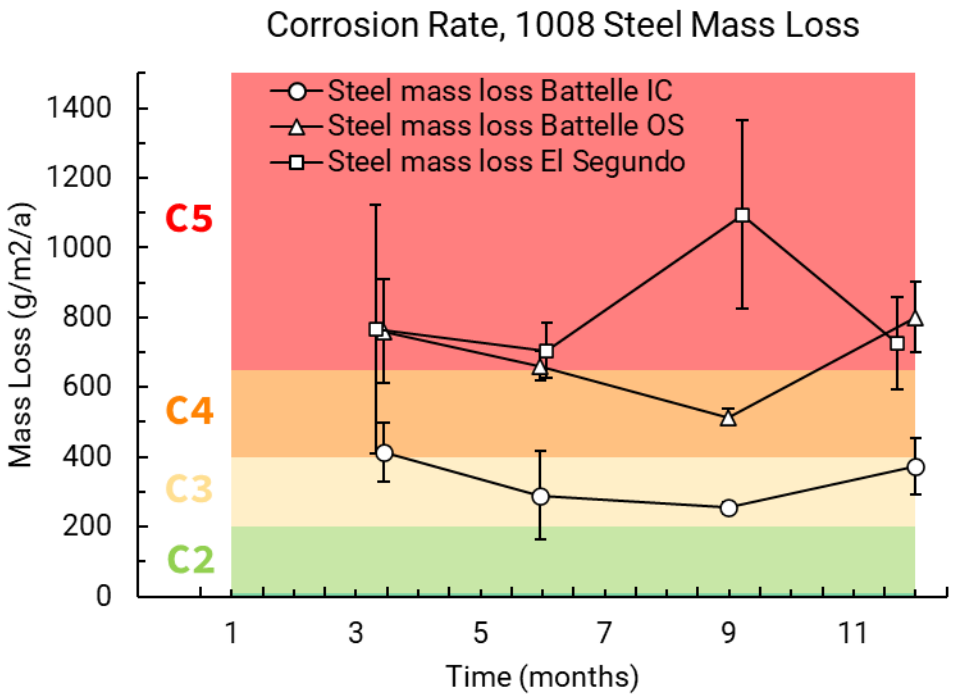
- Friedersdorf, F., & Agnew, L. (2023). Use of Environment and Corrosivity Monitoring to Characteriz
- Agnew, L., Avance, V., Clark, B., & Friedersdorf, F. (2023). Atmospheric Environment Severity Monit

Quantifying Tiered Salt Accumulation Parameters

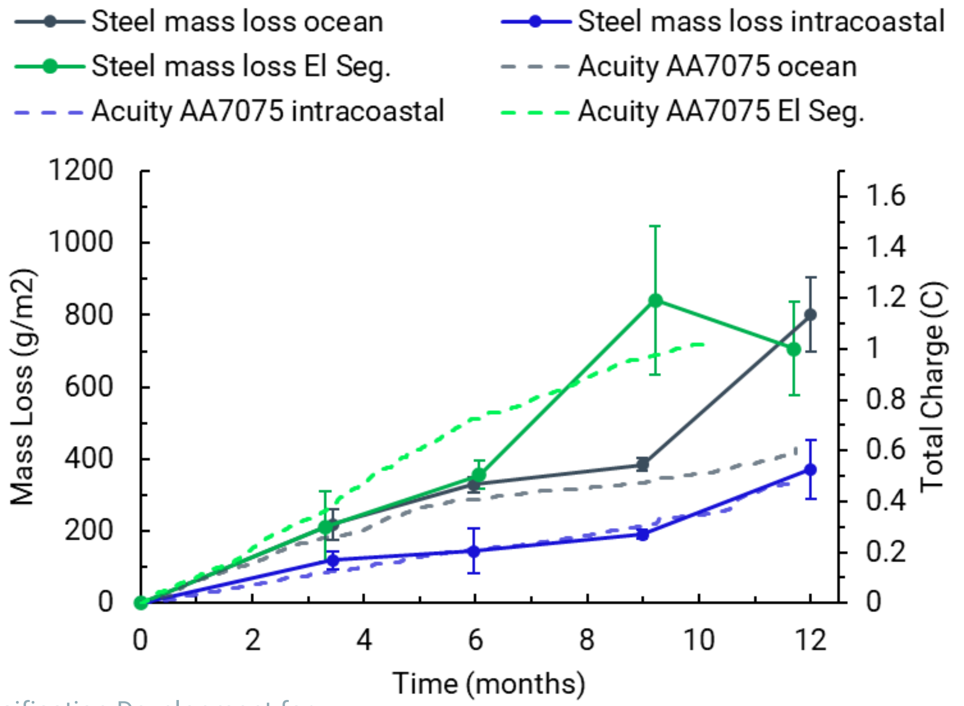
“Saltiness” Parameters

- **Annual salt accumulation**
- Wind flux, direction
- Wave height, frequency
- Solution conductance

Combination of wet candle measurements and severity rankings



Corrosion Rate
Free AA7075 and steel mass loss



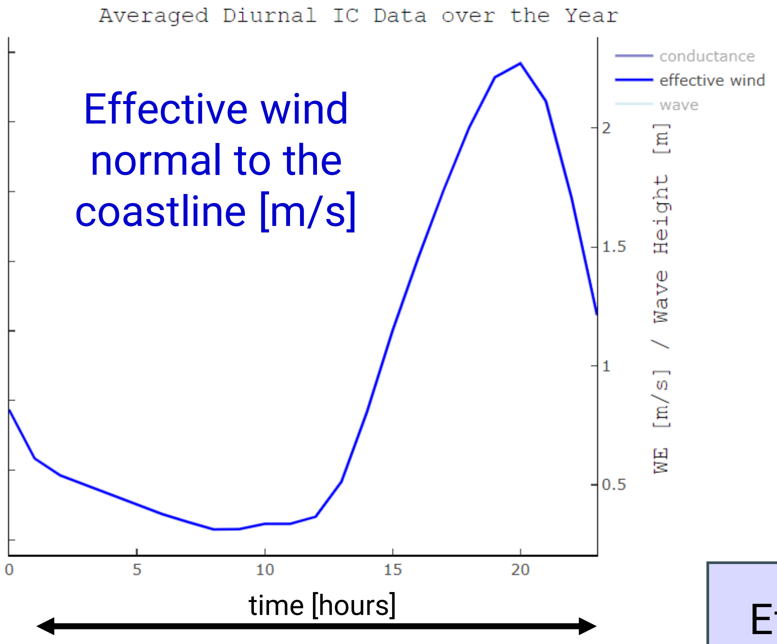
Agnew, L., Marshall, R., Avance, V., Clark, B., & Friedersdorf, F. (2024, January). Environment Severity Classification Development for Aerospace-Relevant Materials. *Materials Performance (MP) Corrosion Prevention and Control Worldwide*, 56–60. www.densona.com

Quantifying Tiered Salt Accumulation Parameters

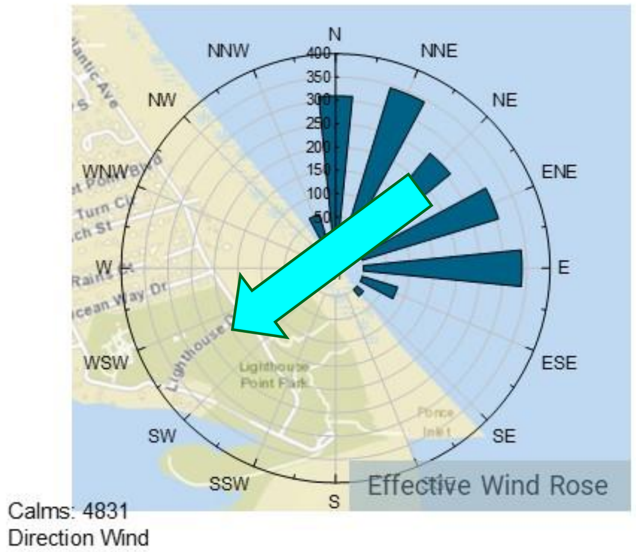
"Saltiness" Parameters

- Annual salt accumulation
- **Wind flux, direction**
- **Wave height, frequency**
- Solution conductance

- Calculation of effective wind
  - Measured wave height



Averaged diurnal cycle over the year



Effective wind occurs on a diurnal cycle

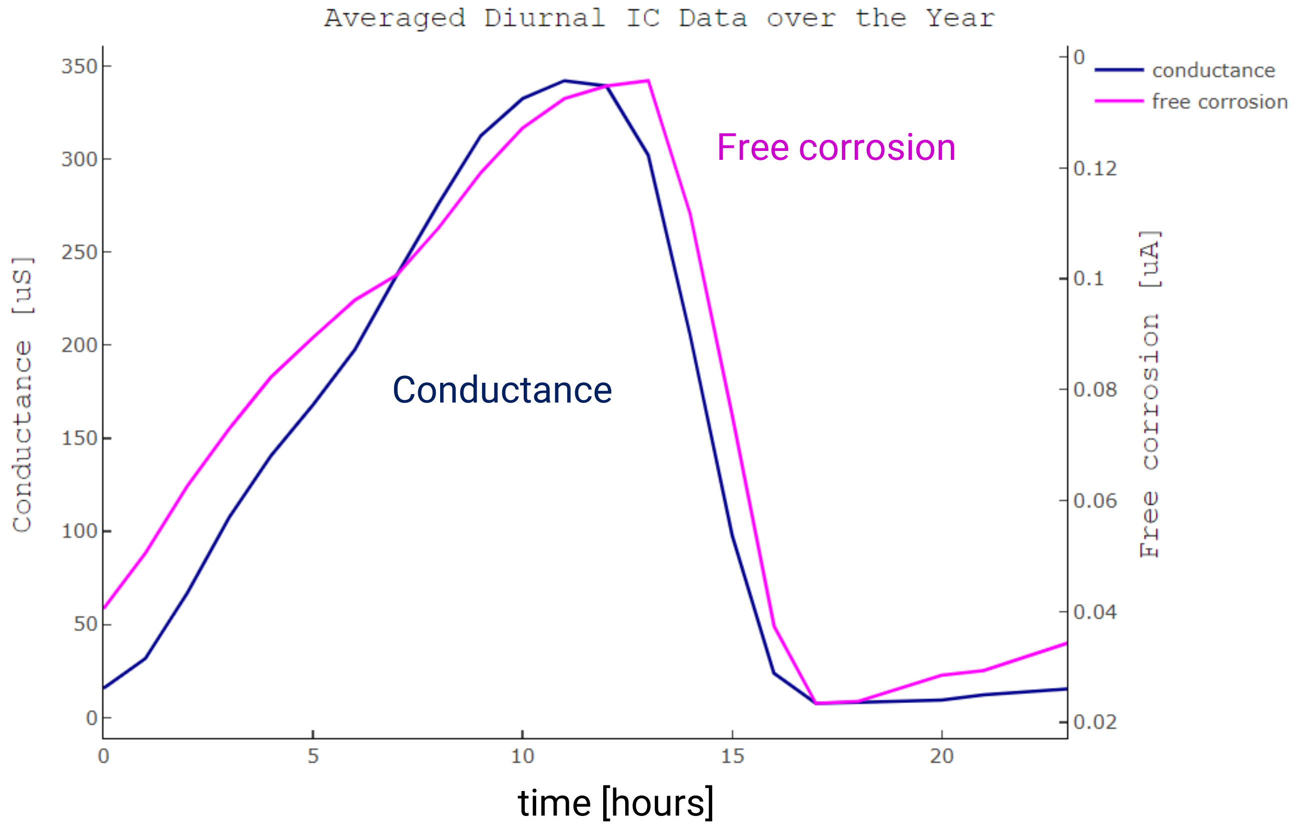
Quantifying Tiered Salt Accumulation Parameters

"Saltiness" Parameters

- Annual salt accumulation
- Wind flux, direction
- Wave height, frequency
- **Solution conductance**

Diurnal solution conductance trends are strongly correlated with corrosion rates…

Measurement from real-time sensing device



Quantifying Tiered Salt Accumulation Parameters

"Saltiness" Parameters

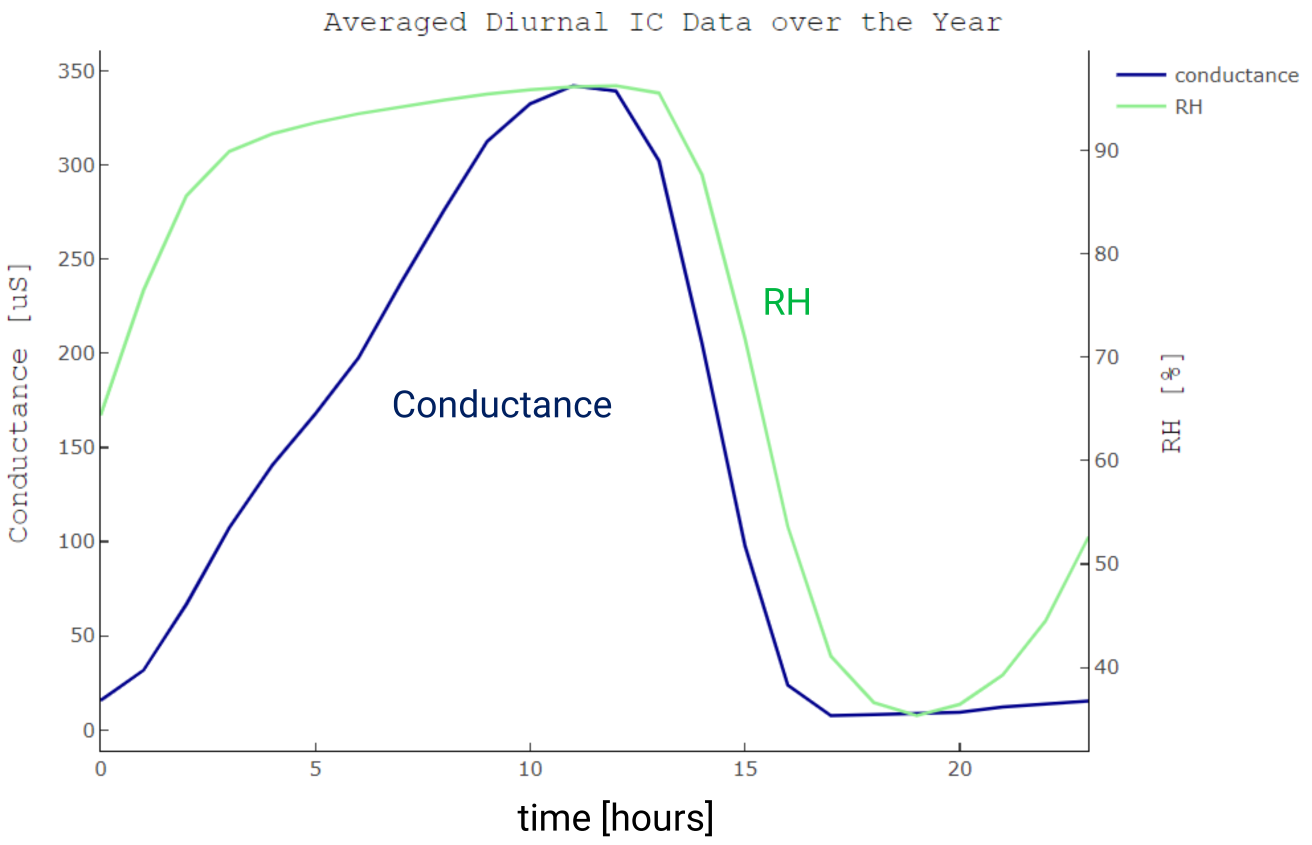
- Annual salt accumulation
- Wind flux, direction
- Wave height, frequency
- **Solution conductance**

Diurnal solution conductance trends are strongly correlated with corrosion rates…

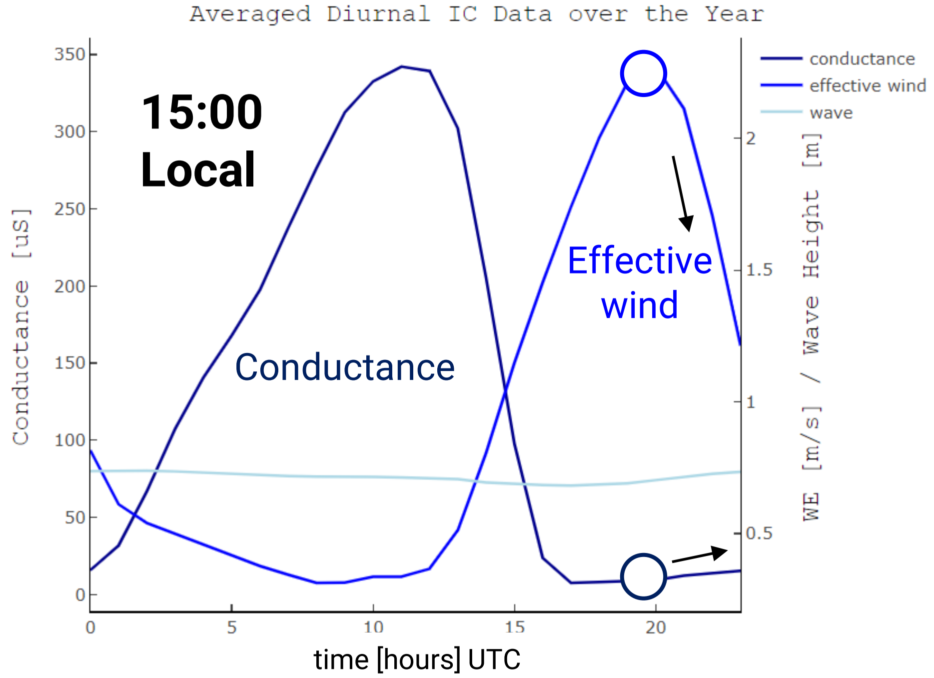
… and RH

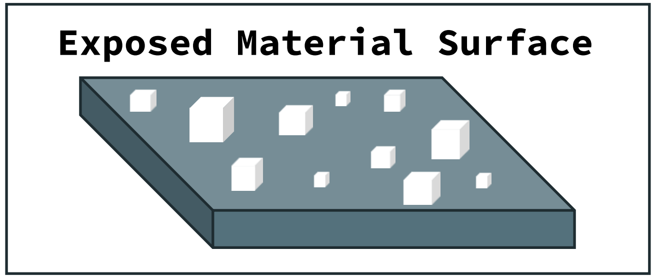
Indicates that conductance is a strong representation of contaminants on the surface

Measurement from real-time sensing device



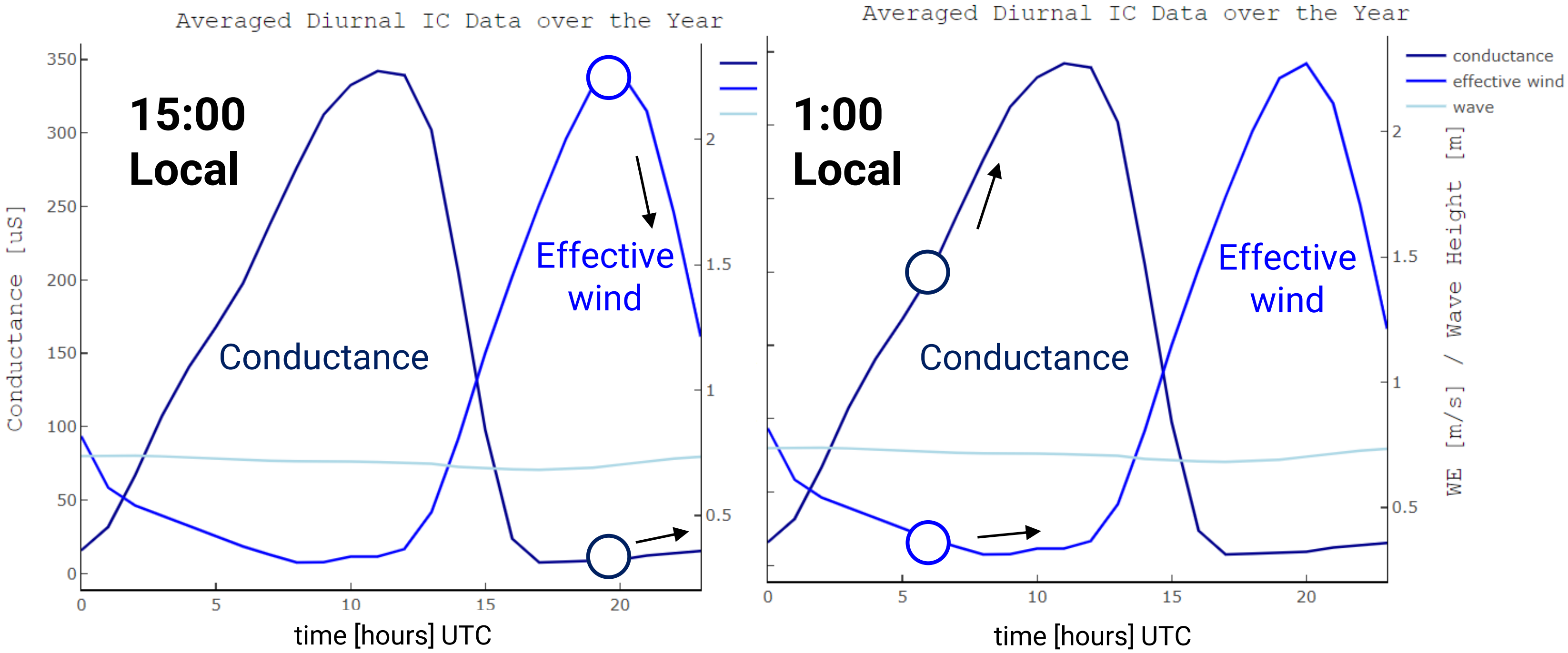
Delayed Corrosion Response from Salt Deposition

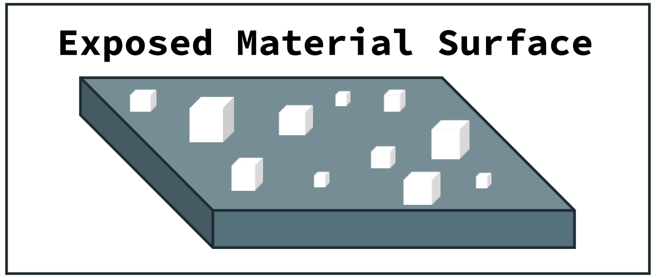


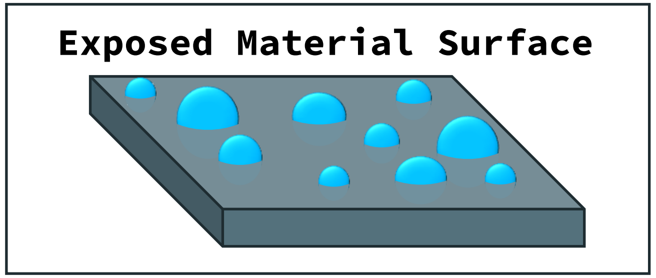


Sea-breeze winds and wave height contribute to salt deposition

Delayed Corrosion Response from Salt Deposition



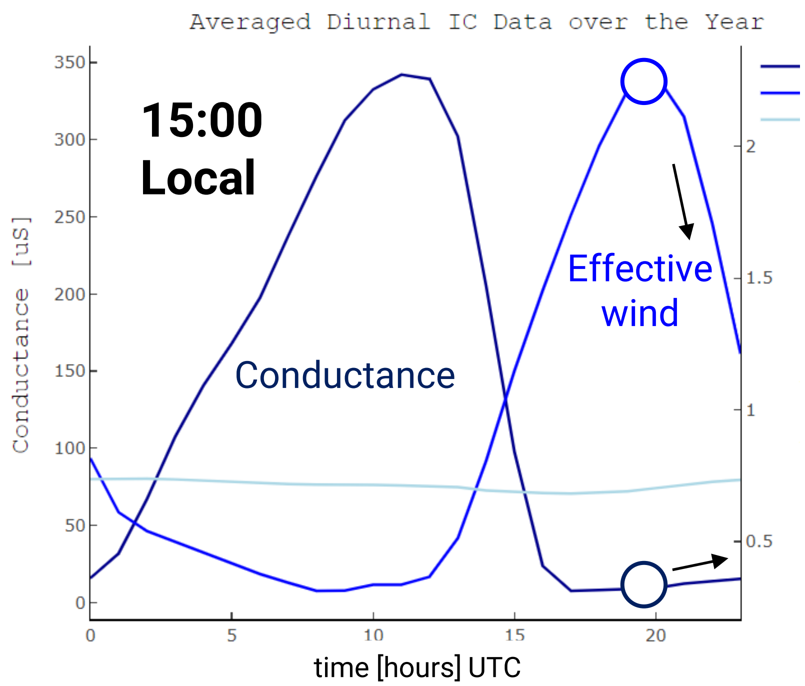


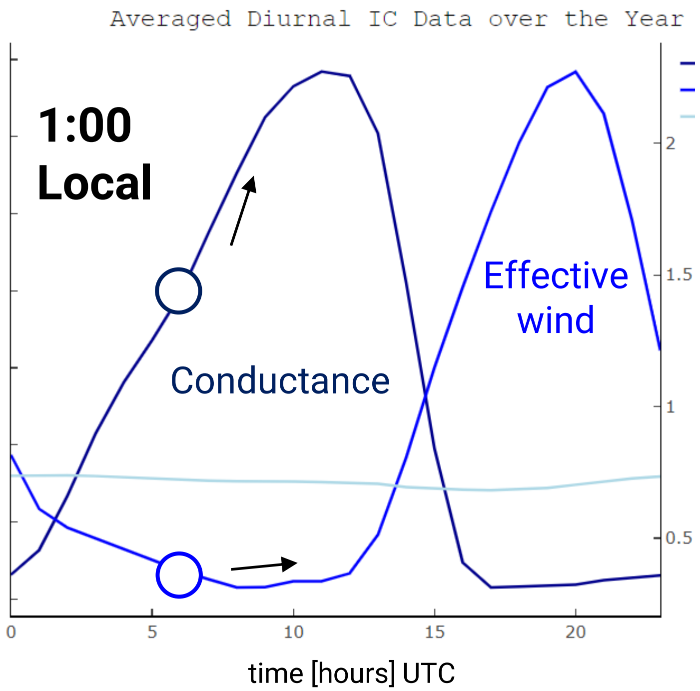


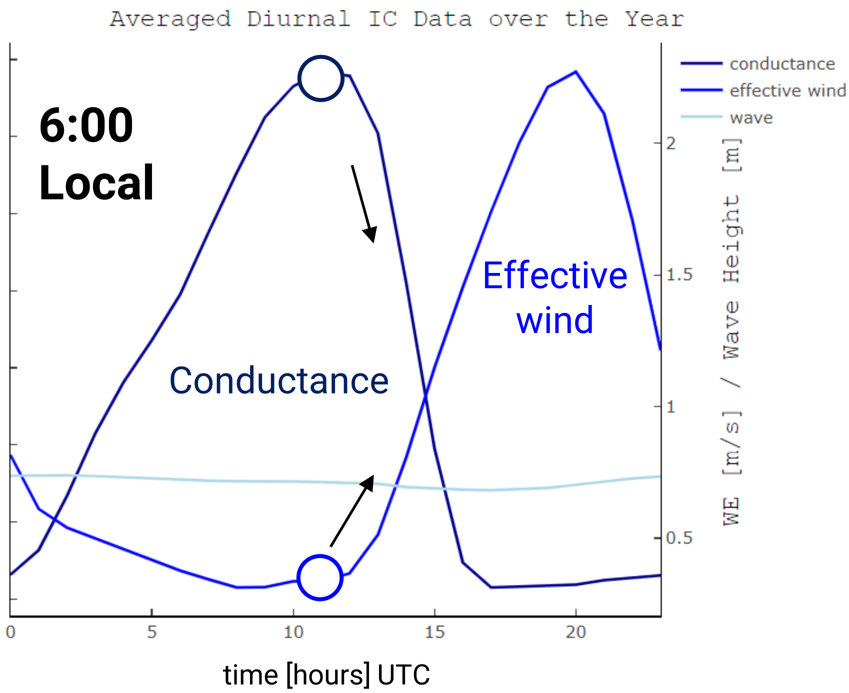
Sea-breeze winds and wave height contribute to salt deposition

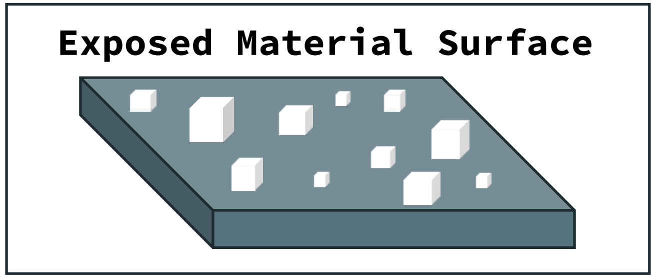
- Overnight RH results in deliquescence of salt into electrolyte droplets
  - No additional salt deposition

Delayed Corrosion Response from Salt Deposition









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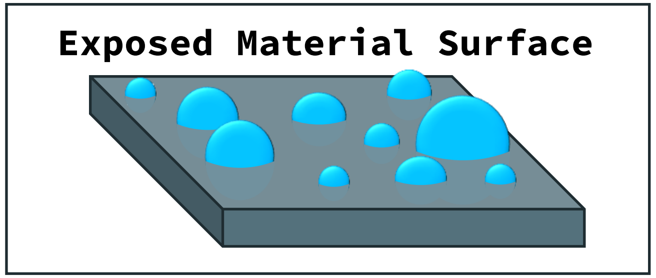

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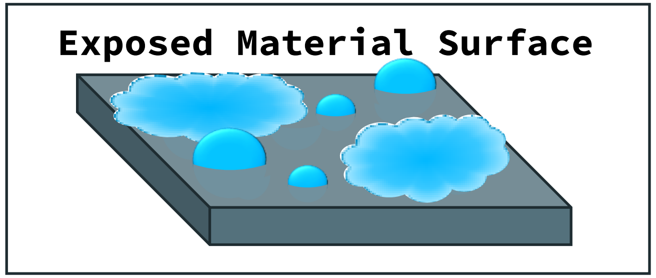
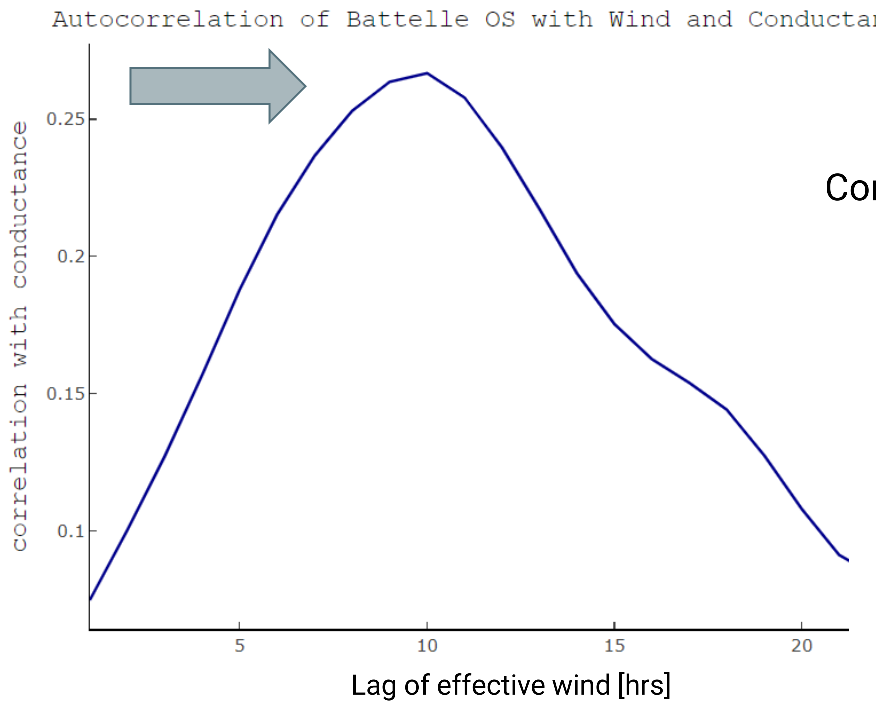
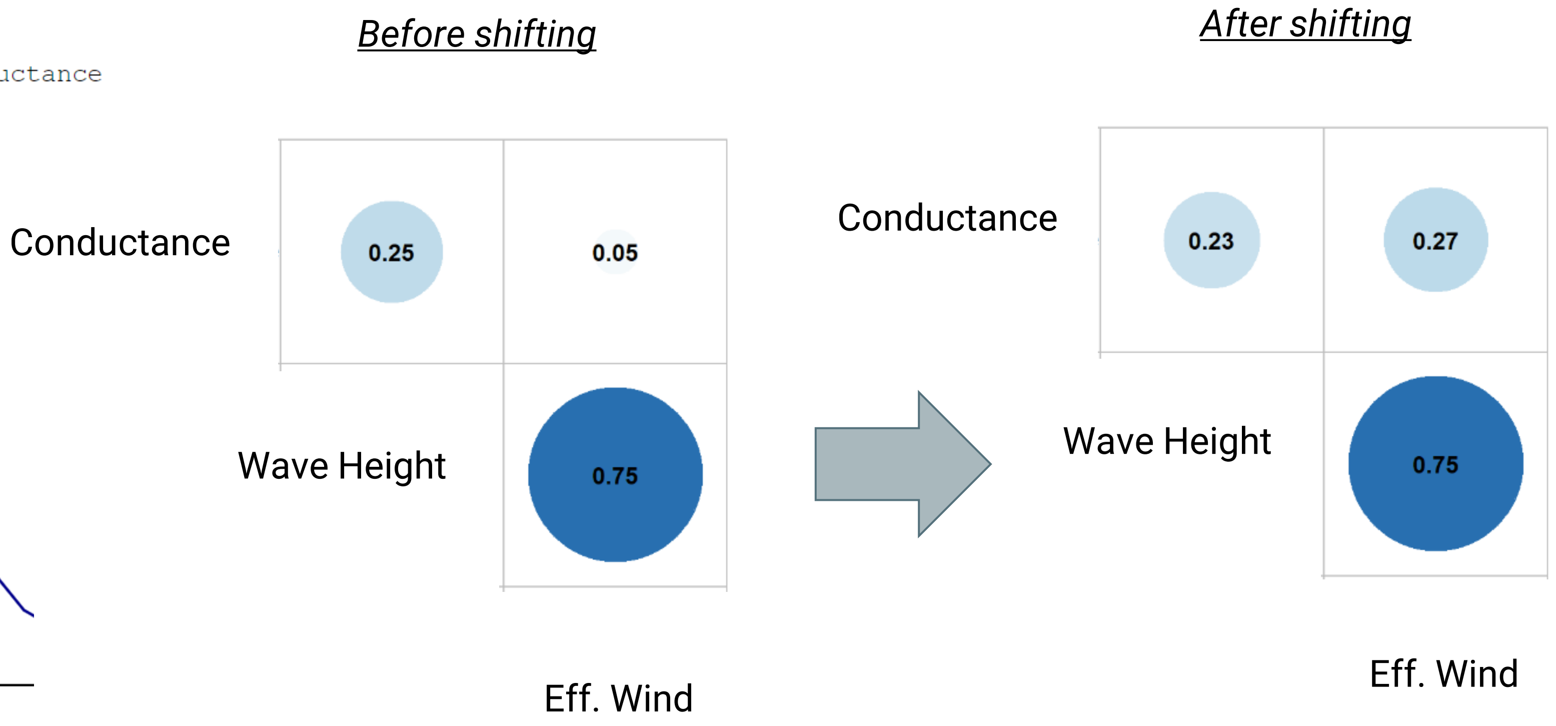


Sufficient electrolyte coverage enables electrochemical corrosion reactions

Shifting Effective Wind Increases Correlations

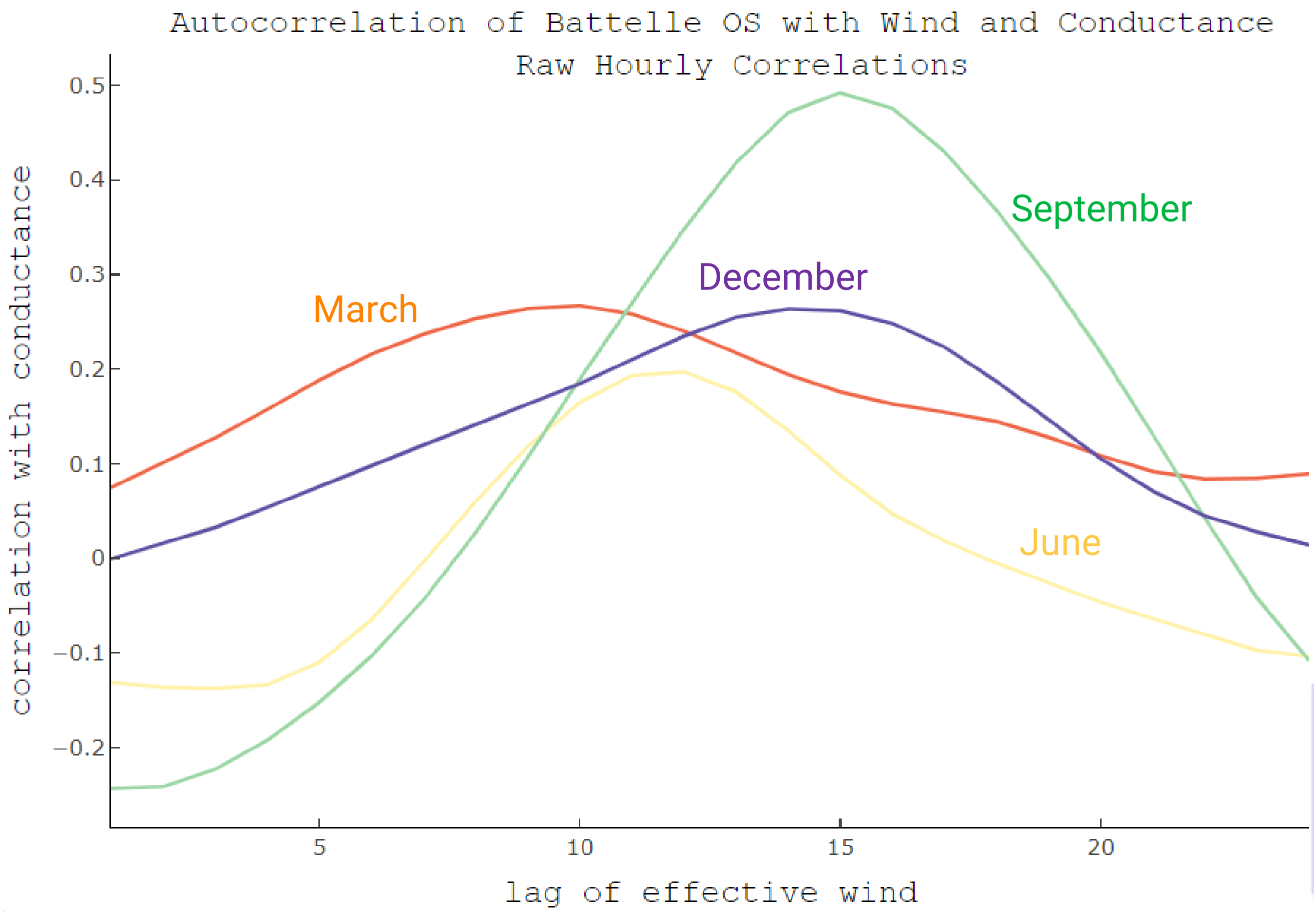


A correlation matrix run with each "lagged" hour of the wind determined optimum shifting



Shifting the wind increases the correlation with conductance, and correspondingly, corrosion

Shifting is Dependent on Months/Seasons



The shifting is dependent on the month/season

Therefore, a single-month of data will be used in the model going forward

Random Forest Model Constructed to Predict Corrosion Rates

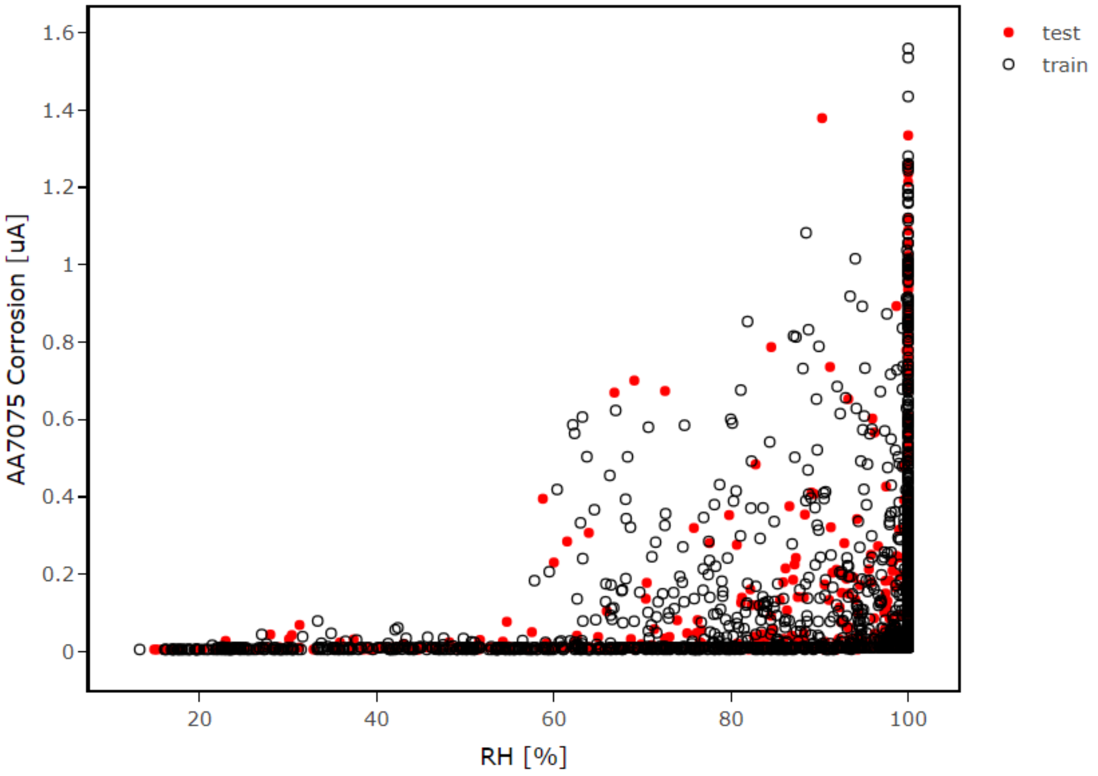
Database of environment and corrosivity parameters *(single month)*

Tiered wetness and saltiness parameters

75% of training data

Optimize RF parameters

25% of testing data



Training/testing split was well distributed among the AA7075 free corrosion rate and RH

Tiered Predictions of Free Corrosion on ***Testing Data***

Environmental Input Parameters

Weather Station	Sensor
Temperature	Temperature
RH	RH
Distance to seacoast	Conductance
Effective wind	
Wave height	

Wet Candle
Annual salt accumulation

Tiered Input Features	R^2 of AA7075 Free Corrosion Prediction	RMSE [uA]

Reminder – input features are ***location independent***, as the model was trained/tested on a dataset with four different locations

Corrosion predictions are at an ***hourly resolution***

Root Mean Squared Error (RMSE)

Tiered Predictions of Free Corrosion on ***Testing Data***

Environmental Input Parameters	
Weather Station	Sensor
Temperature	Temperature
RH	RH
Distance to seacoast	Conductance
Effective wind	
Wave height	
Wet Candle	
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Tiered Input Features	R^2 of AA7075 Free Corrosion Prediction	RMSE [uA]
NOAA T, RH, and static salt	0.65	0.52

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Weather Station	Sensor
Temperature	Temperature
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Distance to seacoast	Conductance
Effective wind	
Wave height	
Wet Candle	
Annual salt accumulation	

Tiered Input Features	R^2 of AA7075 Free Corrosion Prediction	RMSE [uA]
NOAA T, RH, and static salt	0.65	0.52
NOAA T, RH, shifted wave, shifted wind, distance to the coast	0.73	0.46

Tiered Predictions of Free Corrosion on ***Testing Data***

Environmental Input Parameters

Weather Station

- **Temperature**
- **RH**
- Distance to seacoast
- Effective wind
- Wave height

Sensor

- Temperature
- RH
- **Conductance**

Wet Candle

- Annual salt accumulation

Tiered Input Features	R^2 of AA7075 Free Corrosion Prediction	RMSE [uA]
NOAA T, RH, and static salt	0.65	0.52
NOAA T, RH, shifted wave, shifted wind, distance to the coast	0.73	0.46
NOAA T, RH, and conductance	0.69	0.50

Tiered Predictions of Free Corrosion on ***Testing Data***

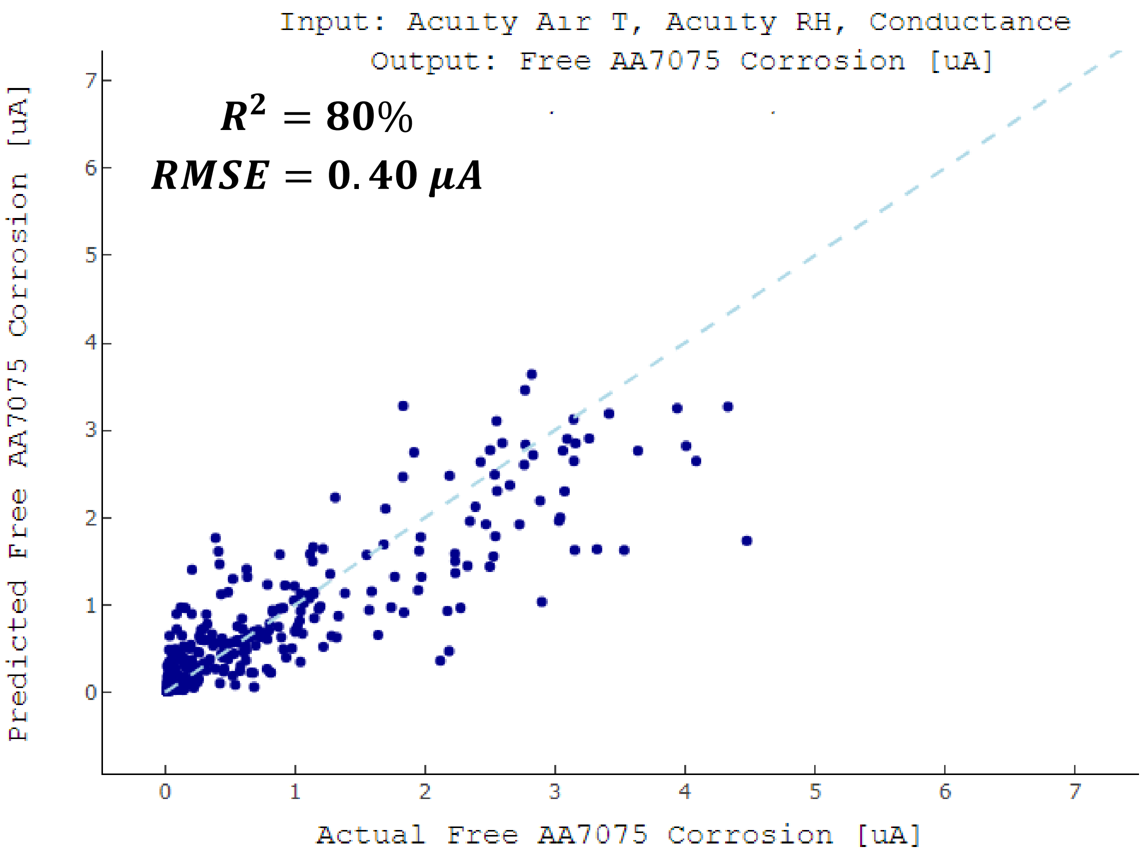
Environmental Input Parameters	
Weather Station	Sensor
Temperature	**Temperature**
RH	**RH**
Distance to seacoast	**Conductance**
Effective wind	
Wave height	
Wet Candle	
Annual salt accumulation	

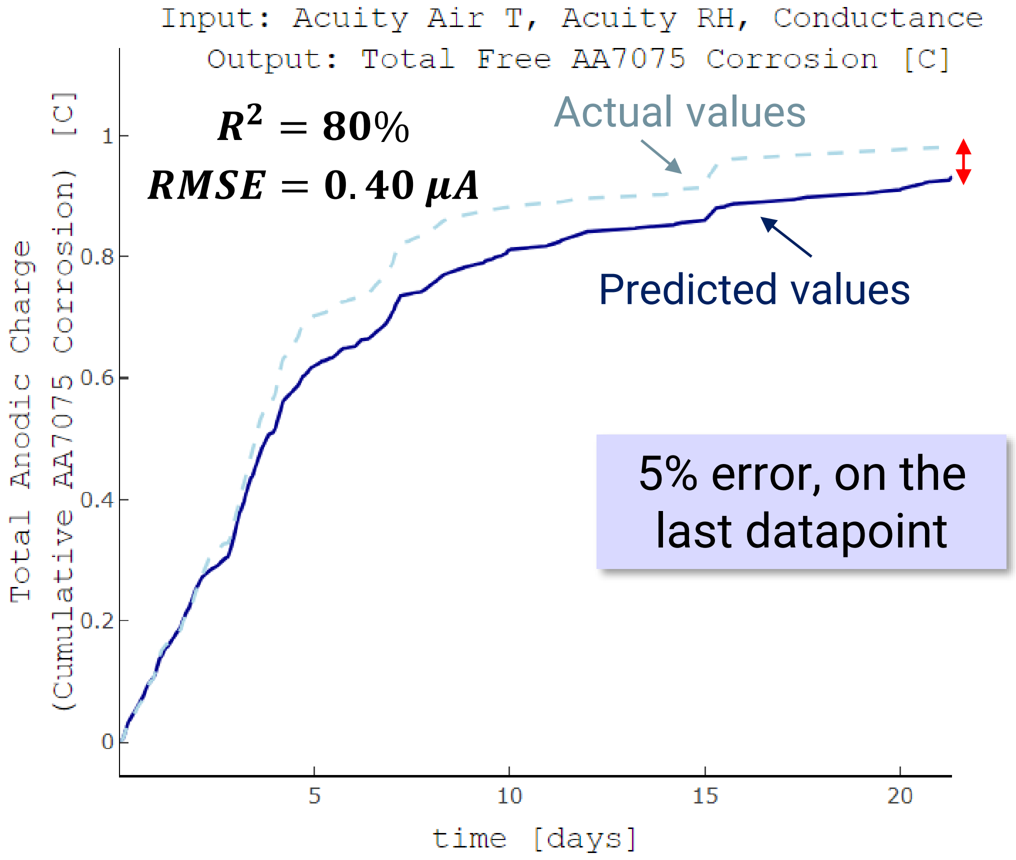
Best performing model includes *local* measurements

	R^2 of AA7075 Free Corrosion Prediction	RMSE [uA]
NOAA T, RH, and static salt	0.65	0.52
NOAA T, RH, shifted wave, shifted wind, distance to the coast	0.73	0.46
NOAA T, RH, and conductance	0.69	0.50
Acuity T, RH, and conductance	0.80	0.40

Shifted wind and wave parameters are demonstrated as effective proxies for salt deposition, while static annual values are less effective

Machine Learning Prediction of Corrosion from Environmental Parameters





5% error, on the last datapoint

Over the month, the corrosion rates are slightly underpredicted, but track well with actual values

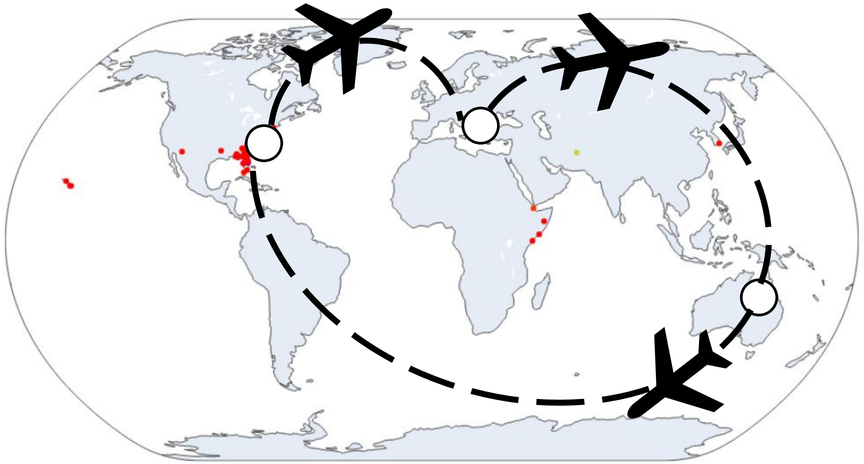
Practical Implications of Predictions

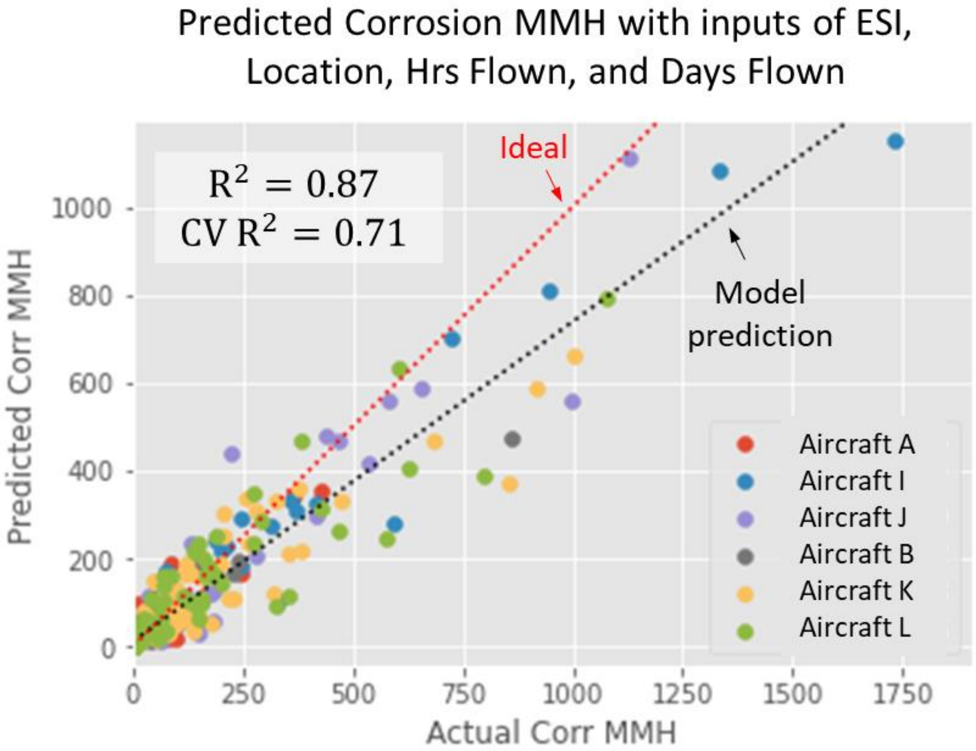
Two main uses,

in the context of aircraft maintenance,

for corrosion predictions from weather parameters

Using the model to track aircraft severity, through different *locations*





Strong prediction of corrosion maintenance manhours (MMH) **based on tracked environmental severity**

Translating Model to New Locations for Asset Tracking

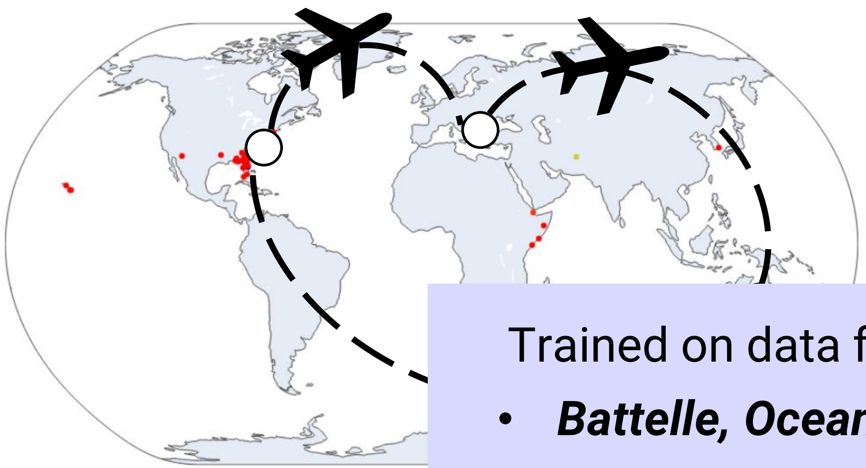
Two main uses,

in the context of aircraft maintenance,

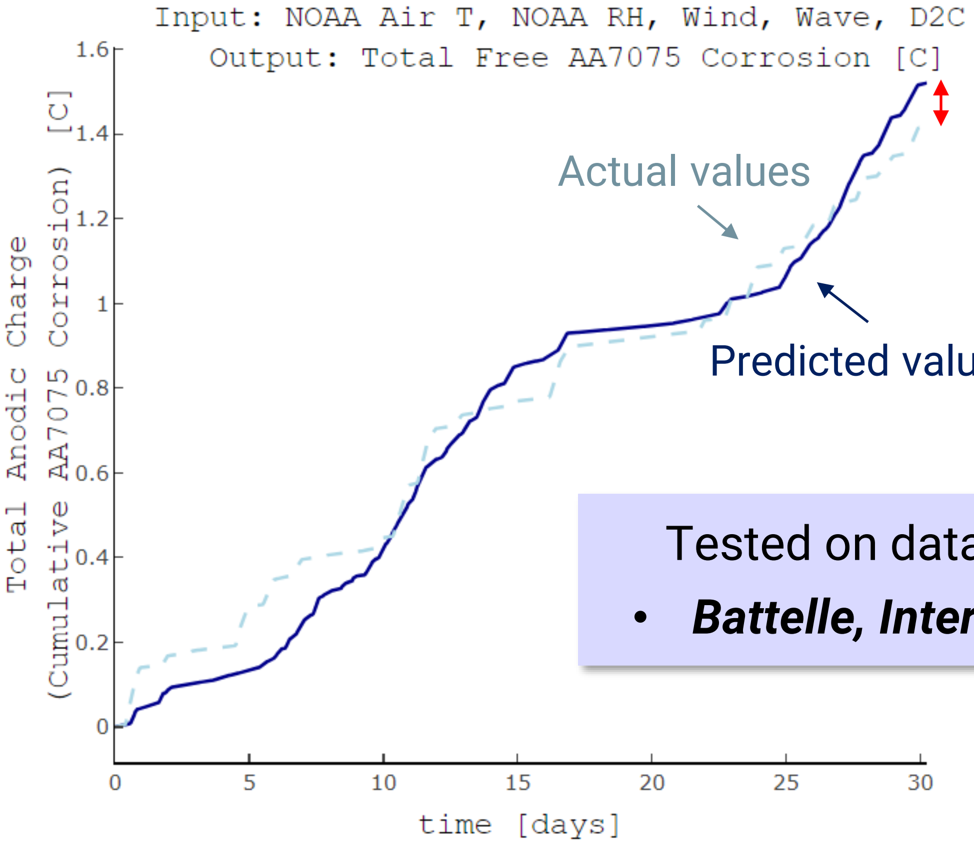
for corrosion predictions from weather parameters

7% error, on the last datapoint

Using the model to track aircraft severity, through different *locations*



Trained on data from
- ***Battelle, Oceanside***
- ***El Segundo***
- ***Whidbey Island***



Tested on data from
- ***Battelle, Intercoastal***

Practical Implications of Predictions

Two main uses,

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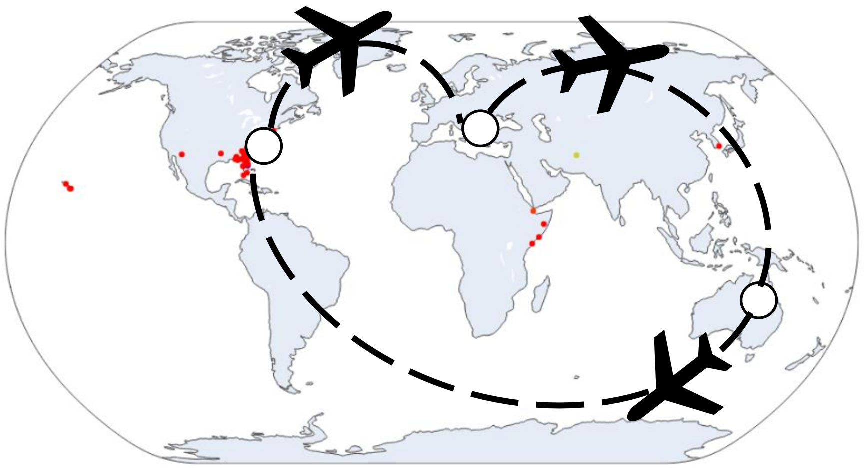
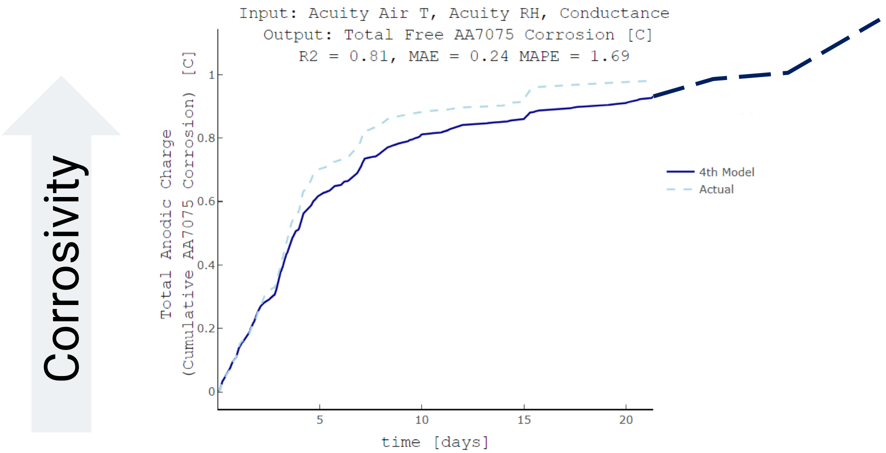
for corrosion predictions from weather parameters

Using the model to track aircraft severity, through different *locations*

Expanding to different timeframes *(forecasting)*

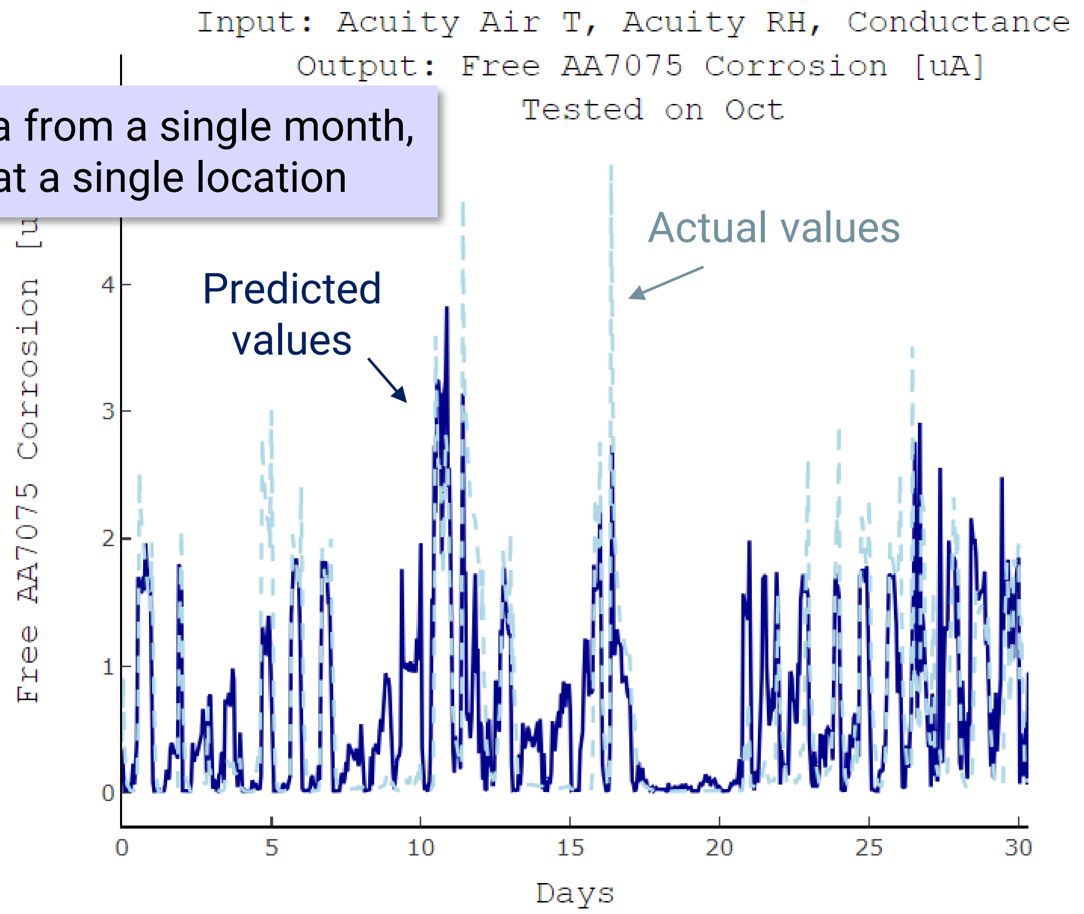


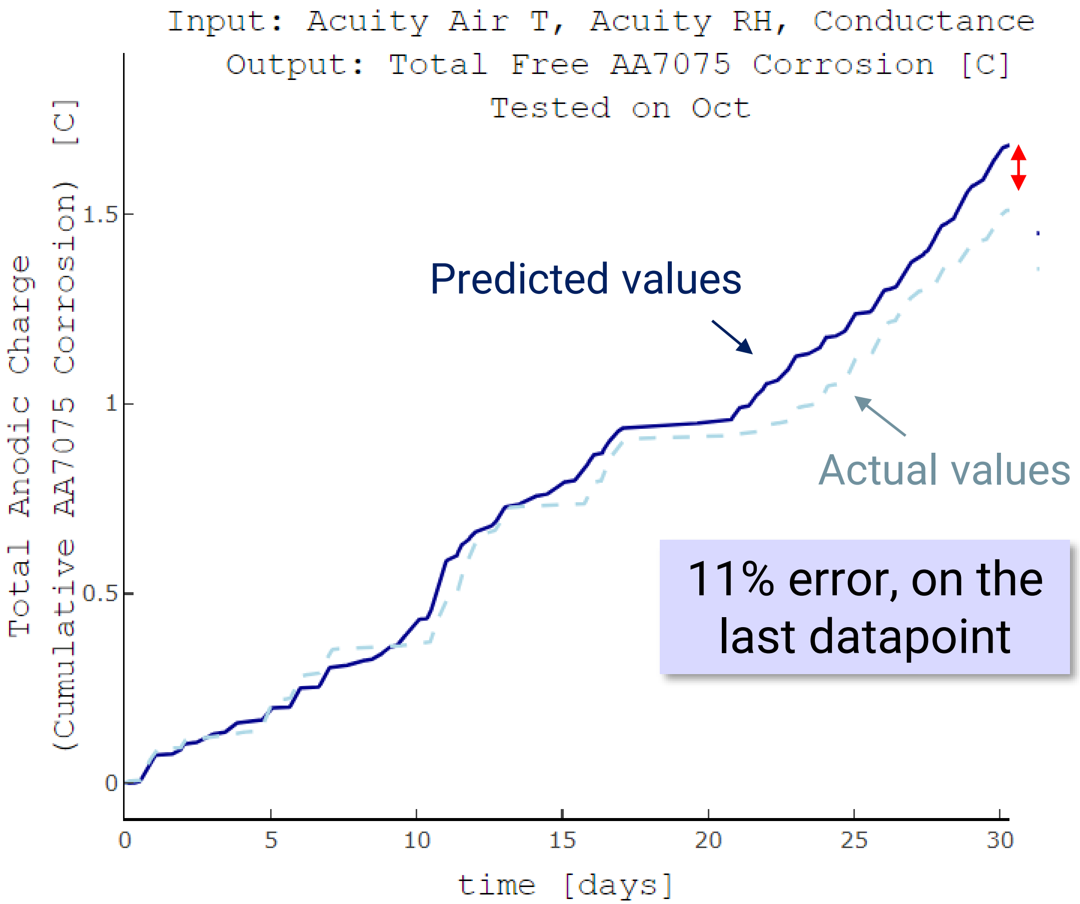


Can demonstrate this by testing the established model on a completely new month…

Forecasting Example

Data from a single month, at a single location





11% error, on the last datapoint

Despite a new month (new values), corrosion rate and cumulative corrosion track with actual values, demonstrating initial robustness

Conclusions

- Real-time monitoring devices and NOAA measurements were successfully leveraged to train and test machine learning models to **predict hourly-resolved corrosion rate**
- A tiered model approach was developed to determine the relative feature importance of specific environmental parameters
- Local environment measurements provided the best model approximation, in contrast to static annual average values
- Effective wind and wave height, when temporally scaled, represented the delivery mechanisms of salt deposits and accumulation
- The model was demonstrated to be translated to *new locations* and to new *time frames,* for **aircraft tracking and forecasting applications**, respectively
- *Next Steps*
  - *Apply to galvanic corrosion, with more comprehensive dataset*

Acknowledgements & Disclaimer

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The contributions from collaborators at QTEC Aerospace, Sikorsky, and the University of Dayton Research Institute (UDRI) are gratefully acknowledged

QTEC AEROSPACE

SIKORSKY A LOCKHEED MARTIN COMPANY

University of Dayton Research Institute

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Questions?

- Real-time monitoring devices and NOAA measurements were successfully leveraged to train and test machine learning models to **predict hourly-resolved corrosion rate**
- A tiered model approach was developed to determine the relative feature importance of specific environmental parameters
- Local environment measurements provided the best model approximation, in contrast to static annual average values
- Effective wind and wave height, when temporally scaled, represented the delivery mechanisms of salt deposits and accumulation
- The model was demonstrated to be translated to *new locations* and to new *time frames,* for **aircraft tracking and forecasting applications**, respectively
- *Next Steps*
  - *Apply to galvanic corrosion, with more comprehensive dataset*