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## **Developing A Likelihood-Based Modeling Approach To Predict Atmospheric Corrosion Rates Using Corrosion Sensor Technologies**

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### **ABSTRACT**

The current approach to corrosion severity prediction is to use long-term averages of environmental parameters (such as relative humidity, temperature, and pollutants), geographic features (such as coastal proximity), and witness coupon corrosion rates for indicator materials to classify an environment into one of a small number of severity categories. However, recent work has revealed that brief changes in environmental conditions—even those lasting only a few hours—can significantly affect total corrosion damage, and long-term averages of environmental conditions are not sufficient to accurately predict cumulative corrosion damage. Recent improvements in corrosion sensing technology have made corrosion sensors a possible replacement for—or at least an enhancement to—the severity classification approach. Recent modeling efforts have demonstrated that greater prediction accuracy is achieved using corrosion rate models trained under constant salt loads, such as those in between precipitation events. Thus, this paper first describes a novel likelihood-based salt load identification algorithm to improve long-term corrosion rate predictions across events that change surface salt loading densities by tracking salt loading characteristics on the sensor. The developed likelihood-based salt load identification algorithm is then used to weight corresponding corrosion rate prediction models trained using data collected from laboratory exposures of corrosion sensors for which the salt loading was controlled and periodically changed. The improvement in the corrosion rate and total corrosion damage predictions across exposures are evaluated for multiple sensors, salt loading densities, and exposures.

**Key words:** Atmospheric Corrosion, Corrosion Sensors, Atmospheric Corrosion Modeling

## INTRODUCTION

The prevention, mitigation, and repair necessitated by the damaging effects of corrosion costs companies and government agencies an estimated \$5.2 trillion annually, representing 3.4% of the global GDP. In order to minimize costs associated with repair or replacement necessitated by corrosion-induced damage, entities decide maintenance schedules and select materials based on the expected corrosion severity of the design environment. In most cases, highly corrosion resistant alloys or coatings are more expensive than systems with limited corrosion protection, so companies and government agencies must balance their desire for long service lives with the high up-front cost of durable materials or frequent maintenance. Estimates of the corrosion severity or corrosiveness of an environment inform decisions about what degree of corrosion resistance is necessary and determine how frequently inspections, repairs, cleanings, or other maintenance services need to be performed. By improving estimates of corrosivity at specific field locations, users could make better decisions regarding materials, coating systems, and maintenance schedules, thus decreasing the overall lifetime operating costs of assets and equipment in the field.

### Corrosion Severity Prediction and Corrosion Sensors

The widespread, industry-accepted approach to corrosion severity prediction is to use long-term averages of environmental parameters (such as relative humidity, temperature, or atmospheric pollutants), geographic features (such as coastal or industrial proximity), and witness coupon corrosion rates of a small number of indicator materials to classify an environment into one of a small number of severity categories. Locations in the high severity categories are assumed to have higher corrosivities, and thus materials can be expected to have higher corrosion rates in those environments than in less severe locations that have lower corrosivities. Recent work has demonstrated that using long-term averages of environmental conditions is not sufficient to accurately predict corrosion rates or total corrosion damage. These findings revealed that brief changes in environmental conditions—even those lasting only a few hours—can significantly affect total corrosion damage (1-3).

Recent improvements in corrosion sensing technology have made corrosion sensors a possible replacement for—or at least an enhancement to—the severity classification approach. These new sensors have the ability to concurrently measure atmospheric conditions (e.g., relative humidity and temperature), electrochemical properties dependent on the amount and type of salt deposited on the surface, and corrosion rates with high frequency (multiple times per hour). The high frequency of measurements from the sensors is particularly innovative since corrosion rates are typically measured by weighing panels before and after exposure to determine their mass loss after a given period, often 3 months, making exposures expensive, difficult, and very time consuming. While the sensors provide a much richer data set, the sensing element used for corrosion rate measurements corrodes during the measurement period, so its lifetime is limited. A typical lifetime for the corrosion rate sensing element is one to two years. After this, the electrodes needed to measure corrosion rate have been consumed by corrosion, but the other measurement devices on the sensor remain active and fully functioning.

Over the last 20 years, three major data sources have been collected and used by several research efforts to train corrosion models as functions of atmospheric parameters [4-6]. First, earlier studies used atmospheric variables and corrosion rates gathered from literature prior to 1993 [5,6]. Then, the International Organization for Standardization (ISO) sponsored the CORRAG program and collected long-term atmospheric and mass loss data from dozens of exposure sites over a wide variety of locations and environments [4]. Most importantly, the CORRAG program attempted to acquire all data using the same techniques. Most recently, the US Department of Defense collected corrosion data from exposure racks across dozens of military installations [7]. Like the CORRAG program, all the data were generated in a consistent manner (although differently from the CORRAG study). Materials studied include zinc, copper, and various alloys of aluminum and steel, with individual regression models being

developed for each material [4-7]. In general, the regression models resulting from these efforts were developed to predict corrosion rate over a one-year period and were then extended to longer-term rates using an exponential function [4, 6]. Common parameters used as model inputs include average relative humidity ( $RH$ ), average chloride levels, average sulfate levels, and total time of wetness ( $RH > 80\%$ ) over the exposure period. Several models also included the number of rainy days that occurred over the exposure period, with one model incorporating mass loss of the previous exposure as an input parameter [7]. Several of these models were successful at predicting corrosion rate over both short- and long-term exposures, but were limited to a specific site location. In other words, any attempt to use one location's model to predict corrosion at other exposure sites resulted in very poor fits [3-7].

Regression models attempting to unify the large data sets across different global regions met varying degrees of success depending on the material. An  $R^2$  value (i.e., the coefficient of determination) is a value between 0 and 1 that summarizes the accuracy of the model. The global regression model with the highest prediction capability for short-term corrosion rates was for steel alloys where  $R^2$  values reached 0.83. Models to predict the short-term corrosion rates for aluminum were significantly worse, with  $R^2$  values  $< 0.6$  [4.5]. Moreover, long-term corrosion damage predictions were significantly worse than for one-year predictions, with the highest  $R^2$  values reaching only 0.39 for zinc. There was no ability to predict long-term damage for aluminum [3, 4]. For steel, the most recent one-year models developed by the Air Force have achieved a slightly improved  $R^2$  value of 0.86, however, this model is more computationally intensive (up to 16 independent parameters) [8]. Additionally, the Air Force model performs poorly when coastal environments are included among the training data. This latter fact is important to note since most corrosion damage occurs in coastal locations.

A number of factors have been identified as being responsible for the relatively poor fits. In many cases, the ways in which environmental variables are measured vary widely across different studies. This is particularly true for chloride and sulfate measurements indicating salt composition. Another significant attribute accounting for poor model fits is that some atmospheric parameters were measured at locations that are not in the direct vicinity of the corrosion samples. The most important factor compromising previous models, however, is the use of average values of environmental parameters such as  $RH$  across long durations. For aluminum corrosion to occur, for example, deposited salts must be present under conditions where the  $RH$  is high: both the deposited salts and the high humidity are necessary. The use of average values cannot account for the specific times when these two events occur simultaneously. Given the relatively poor ability of current modeling approaches to predict corrosion, a new paradigm is needed to be able to predict the cumulative damage effects of exposure.

### Gaussian Process Modeling and Importance of Salt Load Identification

In a previous research effort by the authors, a more flexible modeling approach was pursued to capture the relationship between environmental parameters ( $RH$ , air temperature, surface temperature, and conductivity) as measured by corrosion sensors. The data were naturally variable and are large in volume as the sensor can collect measurements ranging from every 30 seconds (i.e., during accelerated testing) up to 30 minutes (i.e., for long-term field exposures). Several candidate flexible modeling approaches were considered (e.g., high-order polynomial regression, artificial neural networks), however, it was determined that a Gaussian process (GP) modeling approach was well-suited for modeling the sensor data due to the following considerations:

- Because they are non-parametric, GP models are particularly suitable when non-linear and interacting relationships between input parameters are present. This means that the GP modeling approach does not require the user to prescribe the model form with respect to the model inputs as is typically the case when using regression models.
- GP models can predict both the expected value and the variance at a prediction point based on proximity to observed training points. Note that this particular feature of the GP model makes it possible to develop the likelihood-based model weighting approach for identifying and tracking salt loading density. This connection will be shown in the following section detailing the methodology.

- Depending on settings for data noise, the GP model can either directly interpolate all training data (i.e. data from a deterministic computer simulation) or smooth the prediction across noisy observations (i.e. data from laboratory or field experiments). When a prediction point is near a training point, the GP's predicted variance will be comparatively low and increases as one moves further from the training points. Thus, the predicted variance is intuitively dependent on both the noise present in the training data and the location of a prediction point relative to the training data.

As with all modeling frameworks, it is necessary to formulate an approach for prediction (i.e., the consideration of inputs, outputs, and the range of applicability of the models). In the case of the corrosion sensor data, there were two primary prediction schemes to consider:

- Global prediction— in this approach, a GP model would be trained over all data within an exposure and not account for varying salt loading characteristics on the sensor. This would be the most analogous to previous sensor modeling efforts. The inputs would be readings from the durable sensing elements (*RH*, air temperature, surface temperature, conductivity on a gold interdigitated electrode (IDE)) and predict the consumable sensing element for corrosion rate, i.e. the polarization resistance on the material-specific IDE.
- Salt load-specific prediction – This approach first considers that the salt loading density on the sensor surface might be a known quantity. If this is the case, then a GP model for corrosion rate for that material trained on data collected under that particular salt loading condition could be directly used. The inputs and outputs of the model would be the same as in the global modeling approach, however, an array of the available models would be employed to predict corrosion rate throughout an exposure with varying salt loads.

Figure 1 compares these two prediction approaches and illustrates their performance on total corrosion damage predictions over time. It is observed that the prediction that considers salt load as known tracks much more consistently with the total corrosion damage as computed directly from the corrosion rate sensor data. Note that this exposure encompasses nine different salt loads in monotonically increasing amounts as shown in Figure 2, the details of which will be discussed in the methodology section. In contrast, Figure 1 shows that while the global approach captures the natural fluctuations of low and high corrosion rates during low and high humidity as is evident by the prediction plateaus and subsequent corrosion rate increases, Figure 2 demonstrates that the actual corrosion rate prediction itself under different salt loading densities is inaccurate as is evident by the corrosion rate prediction  $R^2$  values.

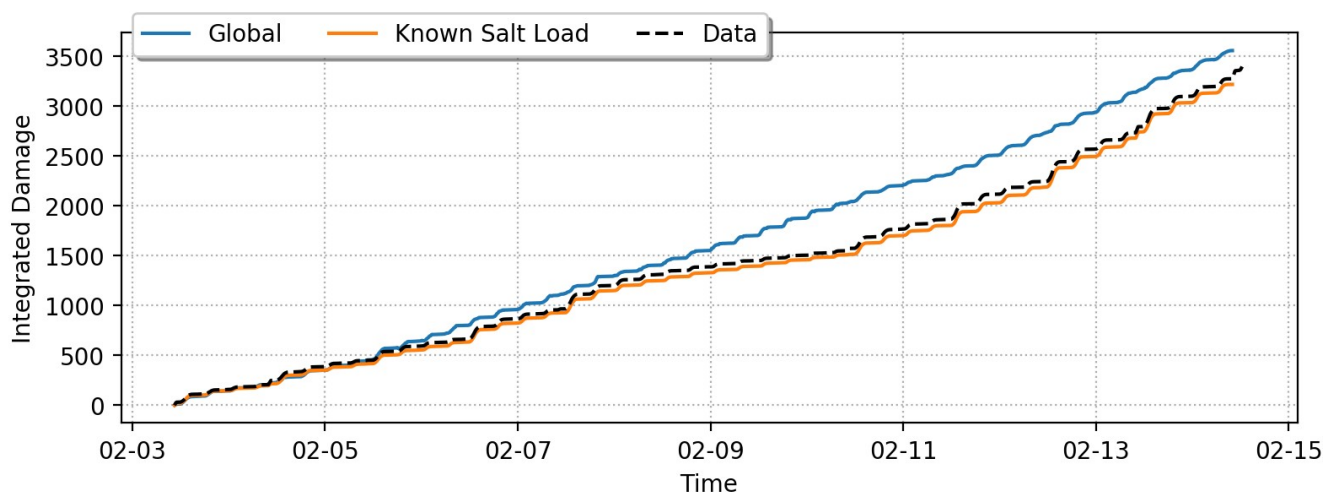


**Figure 1: Comparison of global GP prediction approach for corrosion rate to one where salt loading density is known throughout the exposure and salt load specific GP models are used**