

Bayesian Modeling Coating Performance

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ABSTRACT

The research describes the effort to develop a predictive model for coating degradation and substrate corrosion on Army assets. The model incorporates the learning from field surveys of over 15,000 assets and 250,000 components; coating performance in standardized testing; and observations of coating condition as-applied to fielded items. The model outputs would provide a basis to (1) support a Commodity Manager to determine repaint intervals, optimizing expenditures and (2) develop new products / processes (impacting coating performance) increasing life of an asset protective coating system.

INTRODUCTION

Coating degradation on Army ground systems represents a significant maintenance cost and effort. The objective of this proposed work is to develop a predictive model for coating degradation and subsequent substrate corrosion on Army ground assets. Provided with a better understanding of the root causes, steps can be taken to reduce corrosion impacts on Army materiel.

Coating and corrosion condition on Army ground equipment is related to Stages of Corrosion (SoC) (Figure 1). These ratings are outlined in TB 43-0213 "Corrosion Prevention and Control for Army Ground Equipment." Data concerning materiel condition is gathered as part of standardized

inspections and the results of the inspections are a basis for recommended remedial preservation action.

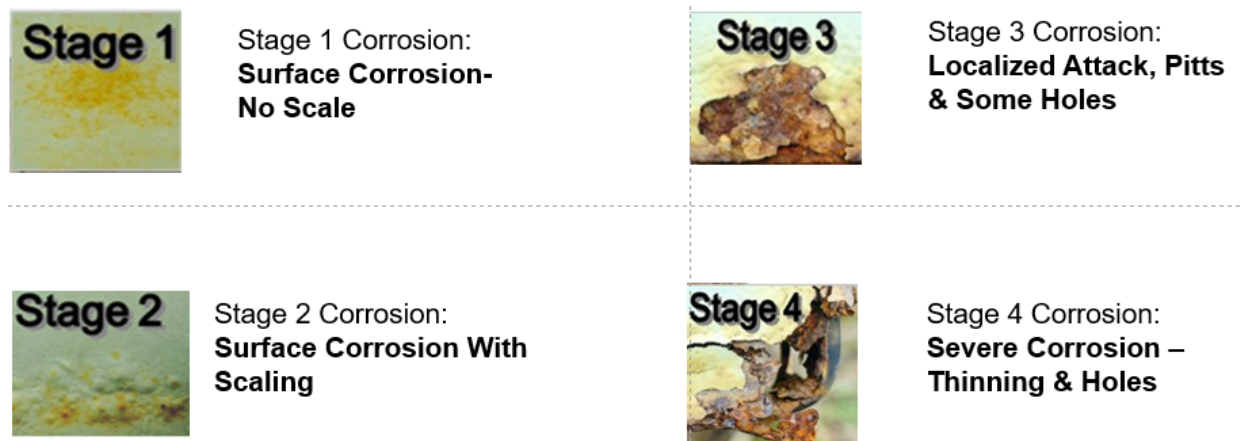


Figure 1: Stages of Corrosion

In general, Stage 1 corrosion conditions can be controlled by the application of Corrosion Inhibiting Compounds (CIC). Stage 2 and 3 corrosion can require both CICs and surface preparation / paint application. Stage 4 corrosion requires part repair / replacement in addition to recoating. Maintenance decisions for specific pieces of equipment are based on consideration of the occurrence of these various stages of corrosion on that gear.

The present effort seeks to develop a model explaining primary contributors to a recommended repair of CICs (only), CICs/spot paint [hereafter referred to as spot paint], or complete repaint [hereafter repaint]. The modeling effort seeks to combine a series of data to create the explanation. Primary sources of performance data include:

- Army Research Laboratory (ARL) data concerning the performance of Army standard chemical agent resistant coating (CARC) systems. This includes knowledge of the development of the original and current CARC systems, laboratory and field exposures of test samples, demonstration projects at various Logistics Readiness Centers (LRCs) and depots and monitoring of field demonstration assets.
- Field inspection data from the Army TACOM-sponsored ground vehicle survey efforts. This program began in 2015 and to date has inspected over 15,000 assets, identified over 250,000 parts having corrosion and coating damage, and contains over more than 400,000 photographs of corrosion and coating damage on parts.

The laboratory data describes coating and material performance under controlled conditions. The extent of coating loss and corrosion on actual assets represents the results of highly uncontrolled conditions. Establishing the relationship between asset condition and “expected” coating performance must consider additional factors. The present effort seeks to include influences of:

- The actual exposure environment. The corrosivity of equipment stationed in proximity to salt water would be expected to be worse than equipment located at a Fort in the arid southwest of the country.

- The use of the equipment. Inherent to a large inventory of assets to train and operate, some assets are used more than others. This places a larger strain on these assets due to impact from road debris, cargo carrying, soldiers entering / exiting the vehicle, etc. Furthermore, in the operation of equipment, specific components can be more subject to physical damage, exacerbating corrosion tendencies.
- Part complexity and quality of paint application. Army equipment is fabricated from sub-parts, each with their own physical complexity. It is difficult to achieve a high-quality paint system on complex, bolted, or faying surfaces as compared to a flat “test panel.”

Presently, the corrosion model is not complete. This discussion focuses on the field inspection data analysis shaping the development of the model.

MODELING

Bayesian Belief Network

The present program seeks to use a Bayesian Belief Network (BBN) approach to resolve the relationship between the maintenance decisions to apply CICs, spot paint, or complete repaint of an asset and the various root causes and drivers of coating deterioration and corrosion. A BBN captures relationships between variables, typically displaying these in a graphical format, Figure 2.

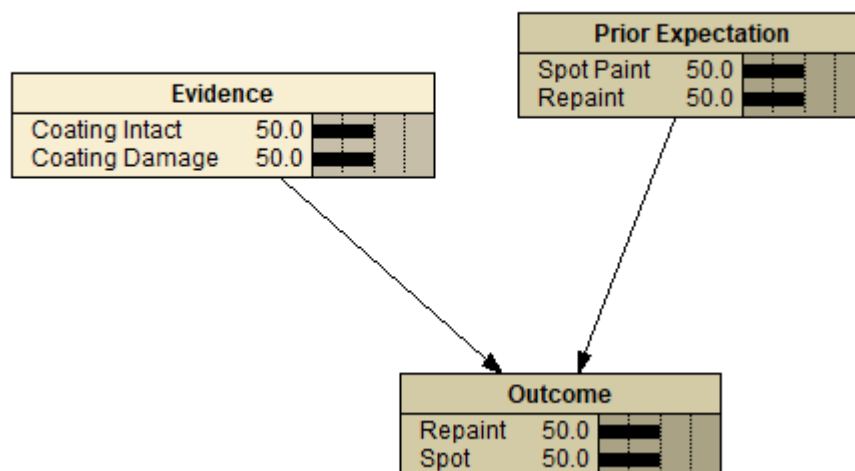


Figure 2: Simple BBN

The mathematics within the relationships can be derived from Bayesian probability. Simply, Bayes' Theorem provides an update on the probability of a hypothesis based on the accumulation of additional specific evidence.

This may be more fully expressed as:

$$P(\text{Hypothesis} | \text{Evidence}) = \frac{\text{Likelihood}(\text{Evidence} | \text{Hypothesis}) * \text{Prior Probability}}{\text{Probability}(\text{Evidence})} \quad \text{eq. (1)}$$

Where:

- $P(\text{Hypothesis} \mid \text{Evidence})$ is the probability that the hypothesis is true, given the specific evidence.
- Likelihood ($\text{Evidence} \mid \text{Hypothesis}$) is the likelihood value of a specific piece of evidence being associated with the specific hypothesis.
- Prior Probability is the expected probability in the absence of any evidence.
- Probability (Evidence) is the sum of all probabilities of sources of the evidence.

Using a common example, your hypothesis that it might rain may be strengthened if you have the advantage of a weather forecast, but only if there is a link between the forecast (“the evidence”) and actual rain (“the hypothesis”). If the meteorologist forecasted it to rain every day, it would certainly be correct on some days, but the abundance of “evidence” would overwhelm the usefulness of the forecasts.

As another example, consider that we are trying to associate a specific maintenance classification (e.g., CIC application, spot painting, or repainting) with predictions of coating performance on a ground vehicle asset. We may have a hypothesis that repainting is associated with the percentage of a vehicle surface area that is corroding. The theorem suggests that the higher the likelihood of specific evidence being associated with a hypothesis, the more probable that the hypothesis is true. We can then investigate if the percentage of a vehicle area corroding is associated with one of the hypotheses outcomes (CIC, spot painting, or repainting). In the present discussion, the “evidence” characterizing the factors leading to the maintenance classifications comes from analysis of the Army survey data.

Army Survey Data Analysis

The Army ground vehicle survey data contains identifying information concerning each asset included in the inspections. The visual inspection process divided each asset into six (6) views: front, back, driver side, passenger side, roof, and underbody. In each view, inspectors took note of deteriorating parts. Deterioration included examples of paint delamination and corrosion. Corrosion was rated for each part following the stages of corrosion. A part rating included both the stage of corrosion and the percentage of the part surface area exhibiting that stage. Conceivably, a part could have an indication of no corrosion or an indication of all four stages of corrosion, each assigned an estimated surface area as a percentage of the total surface. Other observations, such as mechanical damage or faded paint, were also noted. At the conclusion of the 15–20-minute inspection per asset, the inspector noted a recommendation for further repair. Relevant to the modeling are recommendations for maintenance via CICs, spot painting, and repainting. (Other issues, such as the need for metal repair or items needing more detailed inspection, were also captured.)

The maintenance recommendation was based on a visual assessment of the comprehensive condition of multiple parts and conditions on the vehicle—it was not a recommendation based on a fixed algorithm. This is a common experience where the inspector is considered a trained expert in making such recommendations. An initial challenge in the modeling effort was to gain an understanding of the drivers of such distinctions, and in turn, the controlling factors influencing the drivers.