UNCERTAINTY QUANTIFICATION OF AND MASSIVE COMPUTING IN PROGNOSIS AND FLEET HEALTH MANAGEMENT

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ABSTRACT

This paper presents a novel approach to modeling corrosion-fatigue as originally introduced by Arinan Dourado and Felipe Viana. Their method utilizes a physics-informed neural network which combines the mathematical application of fracture mechanics to fatigue and data-driven layers that account for the effects of corrosion through manipulations of bias and weights. The focus material of this study is the Al 2024-T3 alloy used on aircraft fuselage paneling. This alloy is subjected to cyclical loadings and corrosion due to atmospheric qualities such as relative humidity, sulfur dioxide, and ozone. By developing a model that can accurately predict crack length over a large period of time, fleet management in the aerospace industry can improve its inspection efficiency, saving both time and money.

Keywords: Crack growth propagation, Paris' Law, and Walkers Model

NOMENCLATURE

K	Stress intensity
F	Dimensionless function of geometry
S	Nominal stress
a	Crack length
N	Number of cycles
da/dN	Cyclic growth rate
ΔK	Stress intensity range (SIF)
R	Stress ratio
m	Slope on log-log plot
C	Constant
γ	Material constant

1. INTRODUCTION

Many models that attempt to express the effects of corrosion through mathematical expression focus solely on the crack initiation stage where the effects of corrosion are most prominent. Oftentimes, models such as Paris' Law or Walker Models are used which do not account for the environmental or mechanical effects on crack propagation. However, those elements are crucial to accurately predicting crack growth as it pertains to numerous applications in modern aeronautics.

In the aerospace industry, aircrafts are constantly exposed to cyclical loadings as well as corrosion that can reduce their predicted life span. Loading greatly varies throughout a flight mission while corrosion has the greatest effect during takeoff and landing as corrosive elements are most concentrated near the ground. Landing location also impacts corrosion as different atmospheric solutions affect crack growth rate (CGR) as shown in Figure 1. Unfortunately, corrosion is often overlooked as a cause of wear when scheduling repairs and maintenance which can lead to costly future failures [10, 11]. Thus, making accurate predictions of corrosion-fatigue (CF) damage would allow the aerospace industry to perform improved management and prognosis of its fleet of aircrafts.

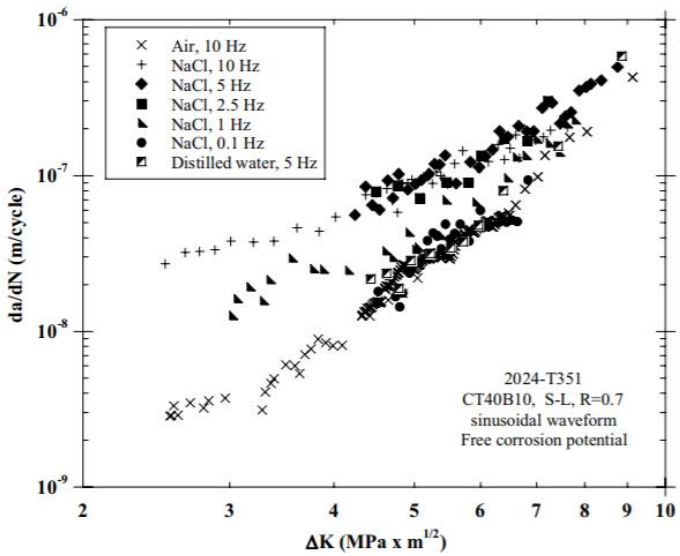

Figure 1. CGR vs Intensity Plot [5], higher CGR's for the same intensity when under corrosive environment.

2. BACKGROUND

Before proceeding with the investigation, some general concepts of corrosion-fatigue damage and neural networks should be introduced.

2.1 Corrosion-Fatigue Divisions

CF damage can be divided into 4 stages or regimes [1][2]:

- Surface film breakdown
- Pit growth
- Pit-to-crack transition
- Cracking

Among many alloys, there exists a passive film that protects the surface from corrosion. For aluminum, it is an oxide layer that is several nanometers thick [1]. Once the film is broken down, the exposed metal faces accelerated corrosion, leading to the formation of a pit. Pits are simply a loss of material or imperfections on a material's surface. Mechanical loads on the pit can lead to cracking which constitutes the pit-to-crack transition stage. Then, the small crack grows into a long crack until it has either been remedied or caused structural failure of the object. The overall life span of pit formation to long crack can be seen in Figure 2.

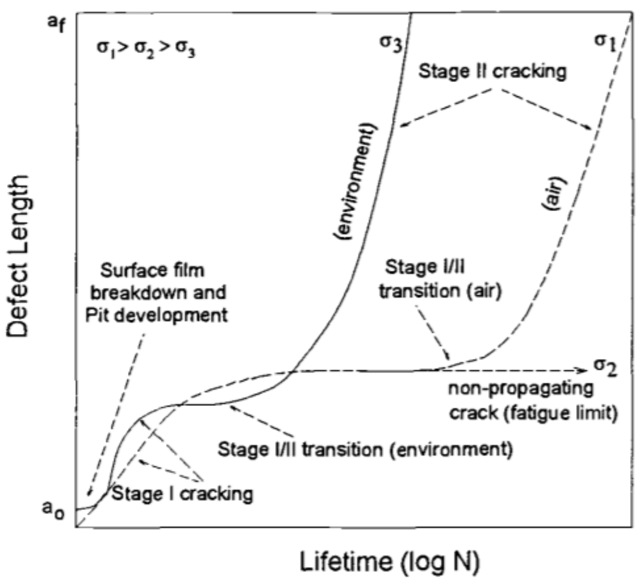

Figure 2. Schematic of defect development stages in air and an aggressive environment. [4]

Modeling of CF damage falls into categories [2]:

- Pit-to-crack-transition models
- Small and Long Crack Growth

These models are distinct because corrosion is most prominent in the initial stages while mechanical loading has the greatest affect after the formation of the pit. This does not mean that both corrosion and fatigue cannot occur simultaneously, but it helps simplify the already complex problem of modeling CF damage.

2.2 Neural Networks

In the brain, neurons are used to make connections in an organized manner. Neural networks are designed with layers of neurons wherein each acts as a function, taking multiple inputs and delivering a single output. In a simplistic multilayer perceptron (MLP) neural network, perceptrons are neurons that give an output of 0 or 1. The importance of the input is judged by a weight. The output is then determined by a threshold value known as a bias, as indicated by Equation 1.

$$\text{output} = \begin{cases} 0 & \text{if } \sum \mathrm{w_j} x_j \leq \text{threshold} \\ 1 & \text{if } \sum \mathrm{w_j} x_j > \text{threshold} \end{cases} \quad (1)$$

where w_j is the weight and x_j is the input.

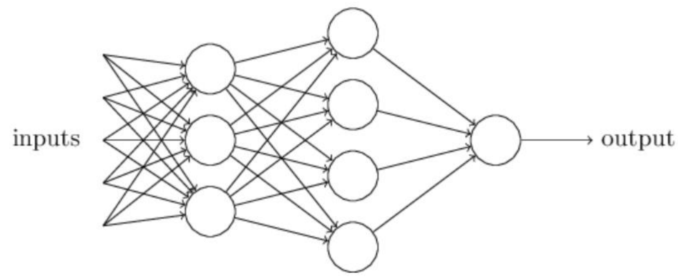

Figure 3. Simple Multilayer Perception Diagram [7] by Michael Nielson

Another type of neuron is a sigmoid neuron which differs by the fact that it can take an input between 0 and 1 and give a sigmoid curve (2) as an output which can be 0, 1, or any value in between. Layer of sigmoid neurons are also referred as an MLP.

$$\sigma(z) \equiv \frac{1}{1+e^{-z}} \quad (2)$$

Neural networks can be used to perform an array of complex actions such as recognizing handwritten numbers, images, or faces. In the context of this research, neural networking is being used to account for the complexity of corrosion damage while being guided by a physics-informed path.

3. Research Approach

Unlike most MLP, the Physics-Informed Neural Network (PINN) requires a by using a sizable data set for training. Whereas most would require a very sizeable data set for training purposed. Specifically, data is needed regarding crack growth by corrosion-fatigue damage. However, information discussing the health of air fleets is often highly proprietary. As a result, data for training the neural network will need to be artificially fabricated through a fleet simulation that considers the effects of corrosion using environmental factors.

3.2 Fleet Simulation

In simulating the effects of corrosion-fatigue damage, several factors need to be considered, including air pollution, distance of the airport from the coast, and weather patterns. Information on air pollution and distance will be used in the PACER LIME Model (Figure 5) developed by the Air Force Logistic Command (AFLC) to devise a progressive corrosion index.

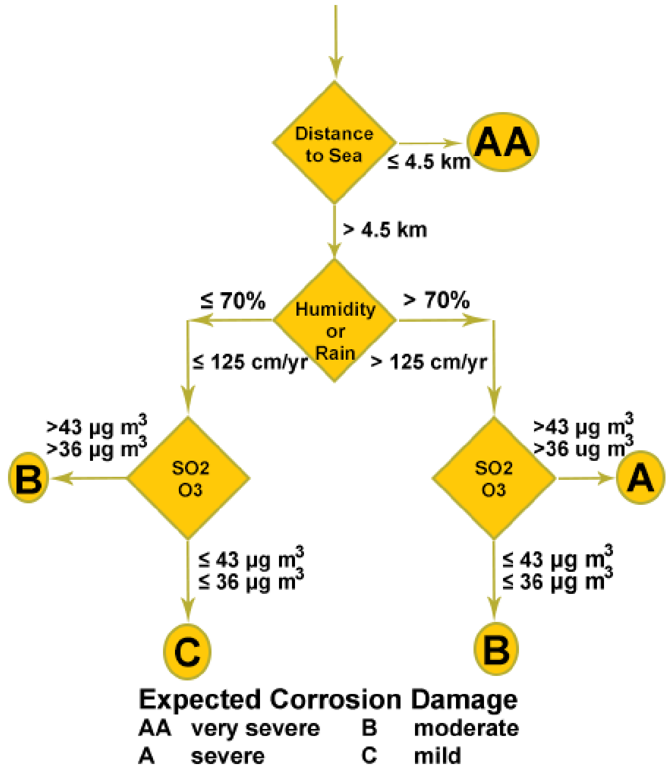

Figure 4. Pacer Lime Model. Modified [13].

In previous research by Dourado and Viana [12], they simulated the effects of CF damage by using an arbitrarily selected index representing corrosion, a table of load magnitudes and load frequencies adapted from De Jonge et al., and a flight probability matrix used to assign flight types per mission (Table 2).

The values represented in Table 2 are the probabilities of a ‘flight type’ to be selected with each row adding up to 1 for 100%. Each flight type has a different load frequency for the same load set magnitude as shown in Table 1. For instance, flight type X has the highest probability of any of the 6 missions with only 3 cycles (takeoff, flight, and landing). In contrast, flight type I is the least likely flight type to occur with a total of 55 load cycles, indicating a severe and rare weather pattern.

The research aims to make the simulation as realistic as possible by developing a route system with different levels of difficulty for each route. This makes the flight simulation for crack length data more realistic than a random draw for each destination.

Table 1. Flight type load matrix distribution and related normalized minimum and maximum stresses. The stresses are given in MPa.

Load Magnitude						
	A	B	C	D	E	F
S_{min}	0.10	4.25	8.25	12.25	16.25	20.25
S_{max}	52.15	48.10	44.0	40	36	32
Load Frequency						
Flight Type	A	B	C	D	E	F
I	2	2	3	5	13	30
II	2	2	2	2	12	29
III	1	2	2	2	12	29
IV	1	1	2	2	12	29
V	1	1	1	2	12	29
VI	0	1	1	2	12	29
VII	0	0	1	2	12	29
VIII	0	0	0	2	12	29
IX	0	0	0	0	1	7
X	0	0	0	0	0	3

Table 2. Flight Type Probability (Modified for 6 designations)

Flight type					
Mission	I	II	III	IV	V
1	$5.\,10^{-5}$	$7.5\ 10^{-5}$	$1.0\ 10^{-5}$	$2.4\ 10^{-3}$	$1.1\ 10^{-2}$
2	$2.5\ 10^{-5}$	$2.5\ 10^{-5}$	$1.2\ 10^{-3}$	$1.5\ 10^{-3}$	$6.75\ 10^{-}$
3	0	0	$1.3\ 10^{-3}$	$2.4\ 10^{-3}$	$1.6\ 10^{-2}$
4	0	$5.\,10^{-5}$	$9.5\ 10^{-4}$	$2.5\ 10^{-3}$	$8.5\ 10^{-3}$
5	0	0	$1.2\ 10^{-3}$	$2.3\ 10^{-3}$	$6.\,10^{-3}$
6	$1.\,10^{-4}$	$2.5\ 10^{-5}$	$7.5\ 10^{-4}$	$2.3\ 10^{-3}$	$6.13\ 10^{-}$
Flight Types					
Mission	VI	VII	VII	IX	X
1	0.01	0.095	0.15	0.248	0.4824
2	0.025	0.035	0.155	0.273	0.5025
3	0.025	0.025	0.105	0.273	0.5530
4	0.013	0.095	0.055	0.323	0.5030
5	0.015	0.045	0.105	0.2975	0.5278
6	0.015	0.045	0.08	0.3975	0.4528

3.3 Corrosion Index

This research aims to improve previous work by Dourado and Viana by implementing a progressive corrosion index using real life data on environmental factors. The factors are sulfur dioxide (SO2), ozone (O3), relative humidity (RH), and airport distance from the coast. These factors are used by the Pacer Model shown in figure 5 to rank the corrosivity of an airport. These ranking are valued from 0 to 1 and are as follow:

- AA – Very Severe = 1
- A – Severe = 0.844
- B – Moderate = 0.608
- C – mild = 0.361
- D – No Corrosion = 0

These values were adapted from Dourado and Viana, 2019.

The data on SO2, O3, and RH is collected and consolidated from the United States Environmental Protection Agency (US EPA) and FrontierWeather. The EPA is an organization that makes sure federal laws regarding human health and environment are enforced as intended by Congress and performs and publishes environmental research. An example is the Air Quality System (AQS) which contains information on "meteorological data, and descriptive information about each monitoring station (including its geographic location and its operator), and data quality assurance/quality control information" [15].

Data used for this research is separated into categories in this online database with various locations for the collection of pollutants and readings. As a result, the location of airports was chosen by matching data sets. To further elaborate, data on SO2 and O3 were found in Broward Country, Florida, but RH was not found in the same county. Thus, RH from the Miami-Dade region would have been used due to its relative closeness. Large and popular airports were chosen in the regions with matching data sets which resulted in the following airports being selected:

- Fort Lauderdale – Hollywood International Airport
- Jacksonville International Airport
- Boston Logan International Airport
- Kansas City International Airport
- John Glenn Columbus International Airport
- Norfolk International Airport

Airports that lie within a 4.5 km range to the coast will always have a corrosion index of 1 because of the ocean's salinity. Other airports will either have a ranking of A, B, or C depending on their environmental factors. However, an airport will never be assigned a ranking of D as it implies a relative humidity of 0% which would be a more pressing issue than crack growth.

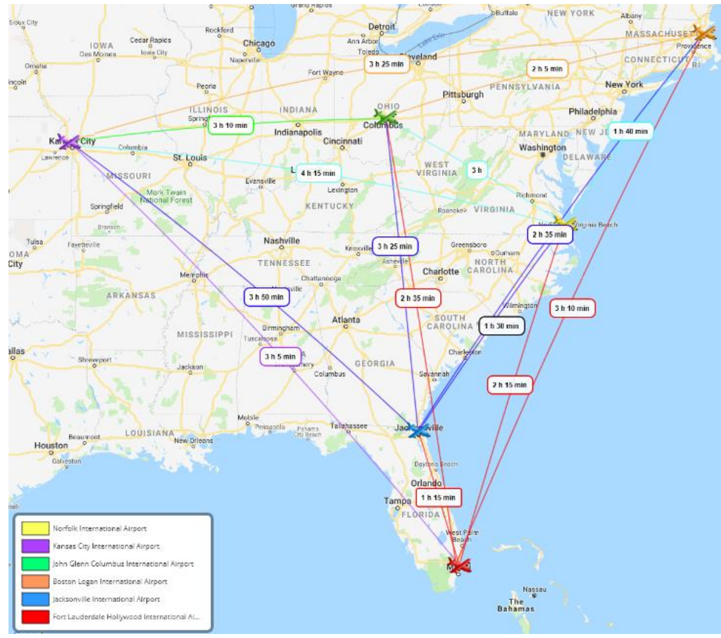

Figure 5. Mapped Airports for Flight Simulation

3.4 Physics Informed Neural Network

The PINN network is a multilayer perceptron that utilizes both a physics-informed layer and a data-driven layer. Though a multi-layer perceptron with an activation function can be used, it would not be ideal as the necessary data for this research is limited and proprietary. Also, if such data was available, the results would not be comparably trustworthy as weights would need to be initially established. Depending on initialization, it could lead the network down the correct path or astray. The PINN network minimizes the amount of uncertainties by using well-known physics related to the problem to help guide the network and using a multilayer perceptron for what the engineers do not know.

The hybrid model is ideal to use in this case as the fatigue model known as Paris Law (3) can accurately describe the effects of mechanical loads in crack propagation. The data-driven layers can then be used to describe the effects of corrosion using a minimal amount of data in comparison to just using a multi-layer perceptron.

$$\frac{da}{dN} = C\,(\Delta \mathrm{K})^{\mathrm{m}} \tag{3}$$

The PINN network would use the data from the fleet simulation for training.

The PINN is also a type of recurrent neural network where the same cell is repeated for many iterations as shown in figure 7. The cell makes use of equation 4 for graphical analyses but can also determine the change in crack length by setting the results as a power to a value of 10.

$$\log_{10} \Delta a_t = \log_{10} C + m * \log_{10} \Delta K_t \tag{4}$$

$$\Delta a_t = \mathrm{C}\Delta \mathrm{K}_{\mathrm{t}}^{m} \tag{5}$$

Since this change is calculated for each cycle, dN as seen in Equation 3 becomes 1 which makes the integration of crack length a simple addition problem by just adding the previous step (6).

$$a_t = a_{t-1} + da_t \tag{6}$$

The two multilayer perceptrons can be seen below in calculating the slope value ‘m’ and the intercept ‘C.’ These are the variables that will adjust the outcome for calculating CF damage.

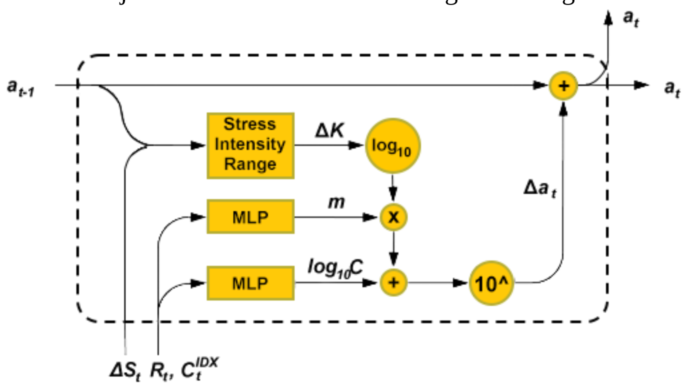

Figure 6. Physics-informed neural network cell. Adopted from [12].

4. PRELIMINARY FINDINGS

From previous research done by Dourado and Viana, the PINN network was found to be quite accurate.

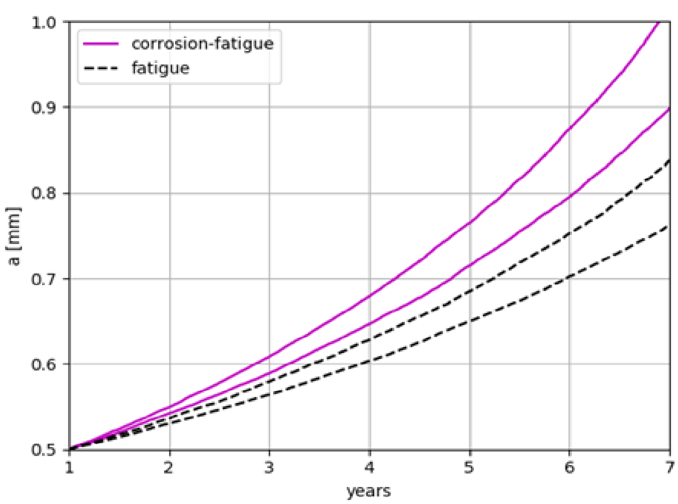

Figure 7. Effect of corrosion and fatigue on crack length over time

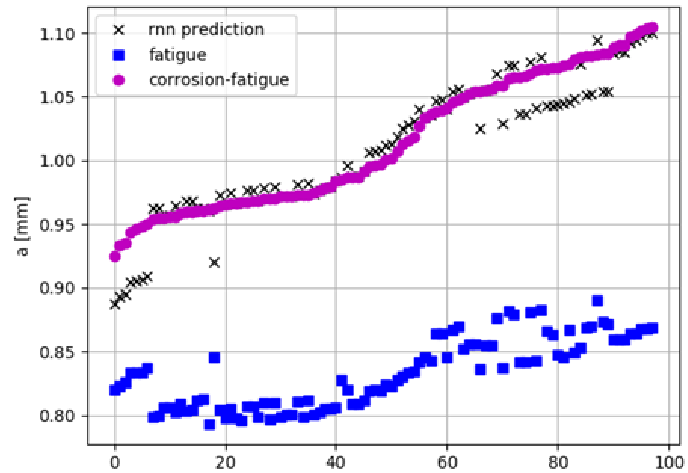

Figure 8. physics-informed neural network predictions. Adopted from [12].

As shown in Figure 8, the percent error of the predicted CF damage to the actual was minimal, making the prediction fairly accurate. Figure 8 also portrays the disparity in crack length if only fatigue crack calculations are performed.

5. Planned Research

Currently, a method is being sought to fill in missing data non-linearly rather than using an average mean and to complete the programming that provides fleet simulation crack data for neural network training.

Programs such as Python, Spyder, and Tensor Flow are being used to code the functions and to program a neural network. Further training is needed in the use of these programs to continue with the research.

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