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Cellular Automation Approach to Model Aircraft Corrosion Pit Damage Growth

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The pitting corrosion damage growth in aircraft aluminum is investigated. The main objective is to develop a corrosion pit damage growth process model using the local rules governing the electrochemical reactions and simulate them as a discrete dynamic system using cellular automata approach. The results of corrosion damage growth obtained from simulation are compared qualitatively as well as quantitatively to the experimental data obtained from Center for Materials Diagnostics at the University of Dayton Research Institute, Dayton, Ohio. The effect of various electrochemical parameters on the damage growth are obtained from the simulation are presented and discussed. The results presented illustrate the new approach using cellular automata to model pit damage growth in aircraft aluminum materials. The simulation program is developed in JAVA environment for ease of portability and usability.

I. Introduction

FAILURES may result when aircraft components are operated in a corrosive environment due to nucleation, initiation, and propagation of cracks at the corrosion pits in aircraft materials. Wallace and Hoeppner[1] described many types of corrosion that may occur in aircraft structures. Lap joints are a common structural element in many military aircraft (KC-135, C-130, J-STARS) and in transport aircraft fuselage. These joints are subject to corrosion damage. Corrosion in lap joints results in material loss, pillowing stresses, pillowing cracks, rivet failures, and interactions with fatigue. Corrosion generally attacks the faying surfaces in lap joints and occurs when the adhesive bond/sealant between the layers breaks down, allowing moisture to penetrate. Pitting corrosion usually follows the general attack of corrosion on faying surfaces and may sometimes evolve into exfoliation corrosion.

It is well known that corrosion pitting has a strong effect on fatigue life of aluminum alloys used in aircraft structures.[2–4] Fatigue cracks usually initiate from the corrosion pit sites. Under the interaction of cyclic load and the corrosive environment, cyclic loading facilitates the pitting process, and corrosion pits, acting as geometrical discontinuities, lead to crack initiation, and propagation, and then final failure. Pits almost always initiate at some chemical or physical heterogeneity at the surface, such as inclusions, second-phase particles, flaws, mechanical damage, or dislocations. The aluminum alloys contain numerous constituent particles, which play an important role in corrosion pit formation.[1] To better understand particle-induced pitting corrosion in 2024/T3 and 7075/T6 aluminum alloys, optical microscopy, scanning electron microscopy, and transmission electron microscopy techniques have been used.[2] Because of an aircraft's special service environments, for example, salt water, electrochemical reactions are possible, and corrosion pits are readily formed between the constituent particles and the surrounding matrix in these alloys.

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Prediction of corrosion damage growth is very important for the structural integrity of aircraft materials and structures. The presence of corrosion pits can significantly shorten the fatigue crack initiation life and decrease the threshold stress intensity of an alloy by as much as 50% (Ref. 3). The corrosion mechanisms depend on the material composition, electrolytes, and other environmental conditions.[5] Most of the previous work on corrosion has been focused on chemical process, electric currents and potentials, and limited growth models.[6–10]

Several pitting corrosion models exist in the literature[11–18] and are mostly empirical or phenomenological in nature. Over the years, Macdonald and Macdonald,[19] Macdonald and Urquidi-Macdonald,[20,21] Macdonald,[22] Engelhardt et al.,[23,24] Engelhardt and Macdonald,[25] and Macdonald and Engelhardt[26] have developed deterministic models and algorithms for predicting the accumulation of damage due to localized corrosion pitting, crevice corrosion, and stress corrosion. Their approach is called damage function analysis (DFA). It has a physicochemical basis and incorporates environmental and mechanical parameters.[26] The DFA approach for pitting corrosion includes the nucleation, propagation, and repassivation stages explicitly defined in the prediction and constrained by natural laws (conservation of mass, conservation of charge, and Faraday's law). Even though DFA approach has been applied to many industrial situations and the predictions are reasonable, the approach is very analytical and deterministic.

Artificial neural networks (ANN) have also been applied to pitting corrosion by Lu and Urquidi-Macdonald[27] to map out the relationship between the crack growth rate due to corrosion and the various independent parameters (corrosion potential, pH, temperature, and conductivity). Even though ANN does not contain any empirical or deterministic or physics of the localized corrosion process, it is still may be used to predict future behavior with various parameters. Probabilistic approaches were also used to model localized corrosion.[28–30]

Pitting corrosion is a very complex process and may involve many mechanisms. In general, the corrosion damage function should involve not only physicochemical and environmental factors, but also the various parameters, random in nature. Therefore, a more realistic corrosion damage function should integrate various parameters from solid mechanics, surface- and electrochemistry, materials science, probability and statistics, and fracture mechanics.[31] Also, the corrosion damage quantification should involve not only thickness loss but also morphology and area of corrosion. In addition to various deterministic and empirical methods in the literature, there might be a need to develop computational models that can predict the pit growth morphology, as well as the mechanical parameters for structural integrity analysis for corrosion damage tolerance technology.

There has been a substantial interest in the morphology of corrosion, but little quantitative work has been done on corrosion damage growth simulation models. Also, there are no models of evolution of corrosion damage growth based on local rules in the literature. Pitting corrosion develops patterns that evolve according to local rules and the corresponding algorithms need to be studied. Quantification of corrosion damage and developing corrosion algorithms are vital for structural integrity analysis to estimate the longevity and safe operation of materials and structures. An improved understanding of the evolution of the corrosion damage growth process would be of practical importance in designing corrosion resistant materials and predicting structural integrity.

To complement empirical, phenomenological, ANN, and DFA approaches in the literature, there should be alternate approaches that account for the morphology and material loss into the prediction of pitting corrosion in a computational model. Prediction of pitting corrosion morphology and its growth is very important for structural integrity analysis, and when coupled with periodic inspections, it might be a valuable approach for avoiding corrosion related failures in general. The current approach of modeling pitting corrosion using cellular automata provides a completely a new way to predict the pitting corrosion growth process.

The main objective of this work is to develop a corrosion pit damage growth process model using the local rules governing the electrochemical reactions and simulate them as a discrete dynamic system using cellular automata approach. The simulation program is developed in JAVA environment. The corrosion damage growth results obtained from simulation are compared qualitatively as well as quantitatively to the experimental data obtained from Center for Materials Diagnostics at the University of Dayton Research Institute, Dayton, Ohio. The effect of various electrochemical parameters on the damage growth are obtained from the simulation are presented and discussed. To appreciate the idea of cellular automata and its generality to model a variety of physical systems, a brief introduction and the model is described.

II. Cellular Automata as a Physical Systems Model

Cellular automata (CA)-based modeling techniques are powerful methods to describe, simulate, and understand the behavior of complex physical systems.[32] The original CA model proposed by Von Neumann (see Ref. 32) is a two-dimensional square lattice in which each square is called a cell. Each of these cells can be in a different state at any given time. The evolution of each cell and the updating of the internal states of each cell occur synchronously and governed by a set of rules. The cellular space thus created is a complete discrete dynamic system. Earlier work by Wolfram[33,34] showed that the CA as discrete dynamic system exhibits many of the properties of a continuous dynamic system, yet CA provides a simpler framework.

Work by Toffoli and Margolus[35] showed the use of cellular automata as a powerful tool to model physical and biological systems. Pioneer works lead to the development of several CA-based modeling applications in diverse areas. The lattice gas model developed by Hardy et al. (see Ref. 32) consisted of a simple and fully discrete dynamics of particles moving and colliding in a two-dimensional cellular space by conserving momentum and particle space. The success of the HPP model proved that the CA method for modeling complex situation is superior to other traditional computing methods. Today, CA models have been successfully applied in modeling of flows in porous media,[36] spreading of a liquid droplet and wetting phenomena,[37] microemulsion,[38] erosion and transport problems,[39] modeling catalytic surfaces,[40] and modeling forest fires.[41] Another important aspect of CA-based modeling is that it can be effectively used to model various levels of reality that exist on any physical system. For example, one can easily model and observe the macroscopic and microscopic scales of phenomena that exist on a physical system. At the microlevel, interactions at the atomic or molecular scale can be modeled, whereas, at the macrolevel, properties of the system due to an aggregate effect at the microlevel can modeled and observed. This particular feature of CA makes it an ideal computational approach to model corrosion damage growth.

III. Corrosion Pit Damage Growth Model

Corrosion begins with small imperfections in the given material referred to as pits. Usually, once a pit is initiated in certain near-neutral aqueous solution, the pit will continue to propagate because the solution within the pit becomes acid, and the alumina is no longer able to form a protective film close to the metal. Further pitting of metal results when the aluminum ions migrate away from the areas of low pH, and alumina precipitates as a membrane by isolating and intensifying local acidity.[5–7] Pits usually have no crystallographic shape, although structurally indicative etch pits can be produced on aluminum. Statistical analysis may be applied to the distribution and depth of pits.

The proposed model captures the pit damage growth based on chemical and electrolyte conditions in the corrosion process. A discrete dynamic model based on cellular automata is developed to simulate the corrosion pit damage growth process. The details of the proposed model are described next.

Let $S(t, \boldsymbol{x})$ be the corrosion state function of cell $\boldsymbol{x}$ at time t. The variable $\boldsymbol{x}$ is the two-dimensional position vector defines a region of interest for a particular material. The range of $S(t, \boldsymbol{x})$ is a predefined interval: At the lower end, it indicates uncorroded, and the upper end, it indicates fully corroded. Both the position parameter and the time parameter in the state function take discrete values. By the local cellular automata rules, the corrosion state of cell $\boldsymbol{x}$ at the next instant in time is determined by the current corrosion state at $\boldsymbol{x}$ and the current corrosion states of its eight Moore neighbor cells (Fig. 1). Because the pitting process is not reversible, the state function is an increasing function with respect to time. The increment for next time step is the sum of all of the influences from its neighbors and the cell itself. Besides these deterministic effects, a nondeterministic factor Δ is also included in the increment. This is due to nondeterministic characteristic of the corrosion process, that is, corrosion pits and their depth distributions vary probabilistically, and hence, we need to have a nondeterministic term $(k_4\Delta)$ in the pit damage growth equation to describe the stochastic behavior of the model. The way the cells affect each other is represented through some effectiveness functions. The effectiveness functions $f(.)$ are not uniform but should be the same for symmetric neighbors. The effectiveness functions take a parabola shape, as the cell changes from uncorroded to partially corroded and finally to fully corroded, similar to the activity of the chemical reaction increases from zero up to some point then falls back to zero. The environmental chemical parameters that affect the pitting growth rate are also incorporated into the model through the effectiveness functions. The equation for the overall corrosion pit growth model is given by

$$S(t+1, \boldsymbol{x}) = S(t, \boldsymbol{x}) + k_1 f[S(t, \boldsymbol{x})] + k_2 \sum_i f[S(t, \boldsymbol{x} + c_i)] + k_3 \sum_j f[S(t, \boldsymbol{x} + d_j)] + k_4 \Delta \tag{1}$$

where the terms c, d, and function f are given by

$$c_i = (0,-1), (1,0), (0,1), (-1,0), \qquad i = 1,2,3,4$$

$$d_j = (1,1), (1,-1), (-1,-1), (-1,1), \qquad j = 1,2,3,4$$

$$f(y) = 128^2 - (y - 128)^2$$

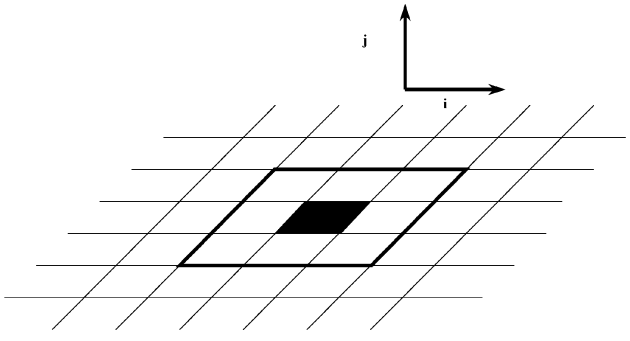


Fig. 1 Moore neighborhood window for the simulation model.

The function $f(.)$, is the effectiveness function used to describe the corrosion growth process effectively. The term Δ is a standard random variable with mean 1 and variance 1.

Continuous mathematical models are used to find out which parameters affect the pitting process and how they affect the growth rate as given in Eq. (2). Based on the review of the literature, we can express the k in terms of the chemical parameters that affect the corrosion growth[21]:

$$k_1 = \lambda \times (\mathrm{pH}-7)^2 \times \mathrm{step}(4, 8.5) \times e^{\phi_M - \phi_S} \times (1/T) \times C \times D \times z \quad (2)$$

where

λ	=	discount factor that ranges from 1 to 3
pH	=	pH value of the solution
step(4,8.5)	=	function with value 0 between 4 and 8.5, and 1 otherwise
ϕ_M	=	potential of the metal
ϕ_S	=	potential of the solution
T	=	absolute temperature
C	=	concentration of the reaction species
D	=	diffusivity of the reaction species
z	=	charge of the reaction species

The parameters k_2, and k_3 are in similar forms as k_1 but with different discount factors. This is because the farther from cell $\boldsymbol{x}$, the less effective role the neighbors take in the corrosion of cell $\boldsymbol{x}$. The simulation program is developed in JAVA environment for ease of portability and usability. The program is run with various parameters to simulate correctly the corrosion pit growth process. The most important parameters affecting the corrosion pit damage growth process are the pH, the concentration, and the potential of the solution. After obtaining a simulated corrosion pit damage growth image corresponding to a certain parameter, a comparison is made qualitatively to the experimental data to see how the various parameters affect the corrosion pit damage growth process.

IV. Feature Analysis

To validate our CA model with the experimental data, we extract certain features from both the corrosion simulation images and experiment images and then perform a feature analysis to compare the results quantitatively. This type of comparison is similar to any of the image processing techniques[42] for comparing two images. We utilize histogram features and wavelet features for this analysis.

Histogram Features

The histogram features that we extract from an image are statistically based, where the histogram of the image is considered as the probability distribution of the pixel values. These features provide us the characteristic information of the pixel value distribution for the corrosion damage process. Five histogram features, mean, standard deviation, skew, energy, and entropy, are obtained through the image feature analysis process.[42] The histogram features are briefly given next.

The mean is the average value, which is defined as

$$\bar{g} = \sum_r \sum_c \frac{I(r,c)}{M} \quad (3)$$

where I is the pixel value on the corroded region and M is the number of pixels in the region. The standard deviation describes the spread in the data, which is related to the contrast. The standard deviation is defined as

$$\sigma_g = \sqrt{\sum_{g=0}^{L-1} (g-\bar{g})^2 P(g)} \quad (4)$$

where $P(g)$ is the histogram probability of pixel value g and L is the range of pixel values depicting the corrosion strength (0–255 in our case). The skew feature measures the asymmetry about the mean value in the distribution. It can be calculated by

$$\mathrm{skew} = (\bar{g} - \mathrm{md})/\sigma_g \quad (5)$$

where md is the mode, which is defined as the peak pixel value. The energy feature tells something about how the pixel values are distributed in the region under consideration. In the case of corrosion damage image, this feature indicates the degree of corrosion at the pit level. The energy feature is extracted using the following:

$$\mathrm{energy} = \sum_{g=0}^{L-1} [P(g)]^2 \quad (6)$$

The entropy is an important measure of digital information. It indicates the number of bits we need to code the image data and is given by

$$\mathrm{entropy} = -\sum_{g=0}^{L-1} P(g) \log_2 [P(g)] \quad (7)$$

Wavelet Features

For the wavelet features, a two-dimensional discrete wavelet transform is applied on the images before the feature extraction. The wavelet transform performs very well in separating the local information from the global information of the images. It can be described as a transform that has basis functions that are shifted and expanded versions of them. Therefore, the wavelet transform contains not only the frequency information but spatial information as well. The two-dimensional discrete wavelet transform is implemented in the spatial domain by using separable one-dimensional convolution filters, including both high-pass filter and low-pass filter, along the vertical and horizontal directions. There are numerous filters. Among them we use Daubechies filters to implement the two-dimensional discrete wavelet transform (see Refs. 43 and 44).

We extract the wavelet features through the processes of singular values decomposition (SVD) and principal components analysis (PCA) on the wavelet coefficients of the image, which are calculated during the wavelet transform. The SVD features of the wavelet coefficient matrix A are extracted as the scalar values σ with the corresponding singular vectors $\boldsymbol{u}$ using the following relations:

$$Av = \sigma \boldsymbol{u}, \qquad A^T \boldsymbol{u} = \sigma v \quad (8)$$

The PCA features of the wavelet coefficient matrix X are calculated as the components from the eigenvector of the covariance matrix $V = X^T X$. The singular value features give a good indication of the corrosion rate. The principal component features show the categorizer characteristic. They are close to each other and form a cluster. These features give good indications of the corrosion state, and so they can be used in the comparison of the experimental data and simulated data to show whether the simulation of our model is in accordance with the real data.

Both histogram and wavelet feature analysis is carried out on simulated corrosion pit damage images, as well as with the experimental data to validate the CA approach of corrosion pit growth model.

V. Results and Discussion

On the basis of the CA pit growth model, we have developed a computer program to simulate the corrosion pitting growth process and carried out the feature-based validation with experimental data. Given an initial pitting site on any material panel, the simulation program predicts the pit growth with time. The simulation model is implemented in object-oriented programming with JAVA environment by taking each data set as individual object. This way the future extension and modification of the simulation model functionality will be handled conveniently. The flowchart of the simulation model validation process with experimental data is shown in Fig. 2.

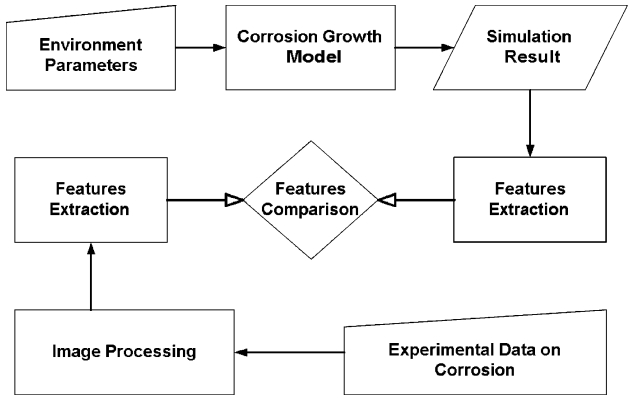
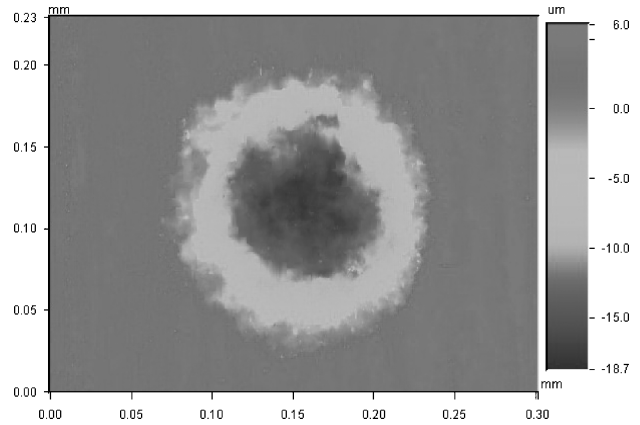
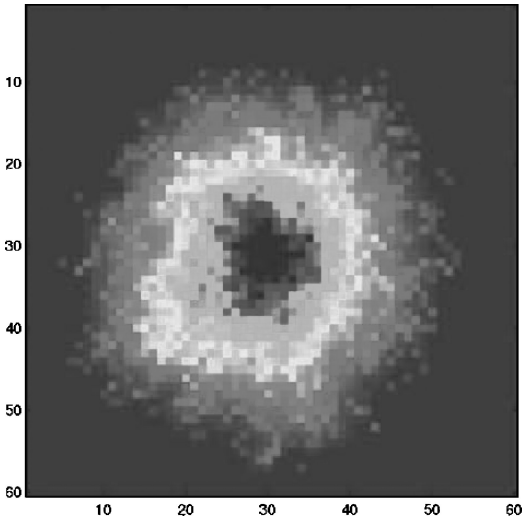


Fig. 2 Flowchart of corrosion pit damage growth simulation and validation process.



a) Experiment

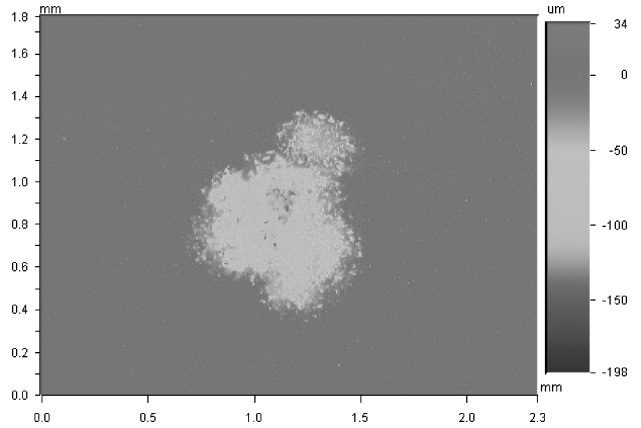


b) Simulation

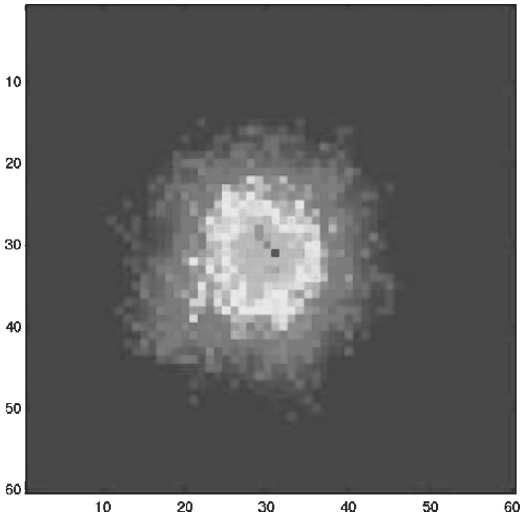
Fig. 3 Comparison of simulated data with the experimental data obtained from the Center for Material Diagnostics, Dayton, Ohio; blue indicates corrosion (courtesy of C. Kacmar).

Validation

Figures 3 and 4 show the qualitative comparison of typical corrosion pit damage growth from simulation model with the experimental data obtained from Center for Materials Diagnostics at the University of Dayton Research Institute. The pH value of the solution is set at 1.5, and the absolute temperature set at 300°F. The concentration of the solution is set at 0.2 (moles $\cdot$ dm^{-3}). In Fig. 3, the potential is set at 0.57 V and the growth time is 3600 s, whereas in Fig. 4, the potential is 0.72 V and the growth time is 600 s. It can be seen from Fig. 3 and 4 that simulated pitting growth of corroded images compare qualitatively well when the complex process



a) Experiment



b) Simulation

Fig. 4 Comparison of simulated data with the experimental data obtained from the Center for Material Diagnostics, Dayton, Ohio; blue indicates corrosion (courtesy of C. Kacmar).

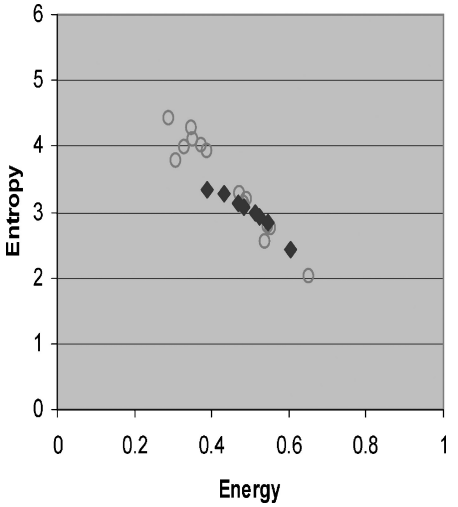


Fig. 5 Entropy vs energy comparison: ♦, present simulation and ○, experimental data.

of corrosion and various factors affecting it are kept in mind. The image of the corroded region was first segmented into four separate regions based on color and intensity. The first segment corresponds to most corroded innermost region, whereas the fourth segment corresponds to the uncorroded, outermost region. The energy feature is extracted from these segments correctly depicts the degree of corrosion in the region. For example, region 1 has high energy value (the most corroded region), whereas region 4 has least energy value

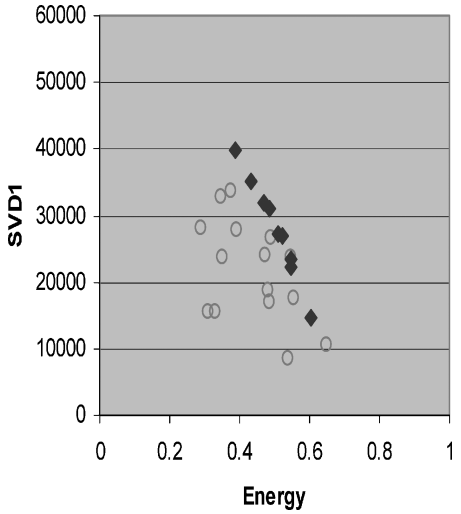


Fig. 6 SVD value-1 vs energy comparison: ♦, present simulation and ○, experimental data.

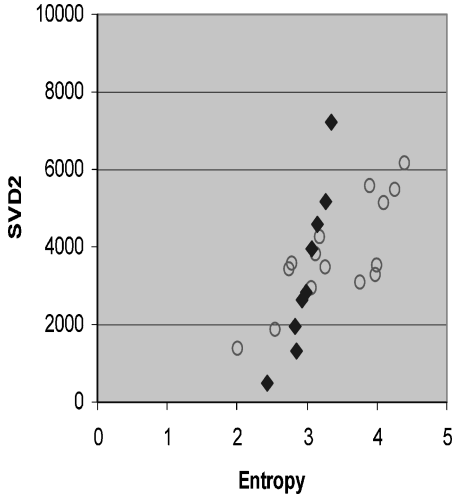


Fig. 7 SVD value-2 vs energy comparison: ♦, present simulation and ○, experimental data.

(the uncorroded region). This feature is used to compare quantitatively the simulated results with the experimental data.

To compare quantitatively the simulation model results, both histogram and wavelet features are extracted for all of the experimental images and simulated corroded images. Of various features considered, we have found that energy, entropy, SVD1, and SVD2 showed significance with various parameters in the corrosion pit damage growth process. The result of these features comparison is shown in Figs. 5–7. It can be seen from Fig. 5 that the histogram features such as entropy and energy from the simulation results compare well with the experimental data. Similarly, the wavelet features SVD1 and SVD2 vs energy feature shown in Figs. 6 and 7 are used to compare the range of experimental data with simulation results. It can be also seen from Figs. 6 and 7 that the scatter in the experimental data is also very large, and this is due to various parameters affecting the corrosion pit damage growth process and not knowing all of the values of parameters in experiments. From the comparisons in Figs. 5–7, we can see the areas bounded by the changing chemical parameters are in high agreement with the Dayton experimental data. This shows that given the proper chemical parameters as inputs our model can approximate the corrosion pit growth process very accurately. Also, the features extracted from the simulation are very close to the features from the experiment and, therefore, can be used as indications of the corrosion material loss if combined with a prediction model. Overall, the simulation results presented in Figs. 3–7 validate the pit damage corrosion damage growth process.

Effect of Parameters

To see how the different chemical parameters actually affect the corrosion pit growth process, we change the parameters in the model, redo the simulation, and extract features from the simulated pitting image. The effects of pH, potential, and solution concentration are varied because those parameters most affect the corrosion pit growth. Because pitting corrosion does not occur when the pH value is between 4 and 8.5, six values out of that interval are chosen for the pH parameter. Figure 8 shows the effect of varying pH values on the corrosion pit growth. It can be seen that lower values of pH have a greater effect on the corrosion pit growth compared to higher values. The features extracted from Fig. 8 also indicate that as the pH value gets lower (when smaller than 4), or higher (when larger than 8.5), the corrosion rate increases. This aspect of prediction by the model is in agreement with the experimental data available[7] in the literature. The morphology of the simulated pit growth is reasonable.

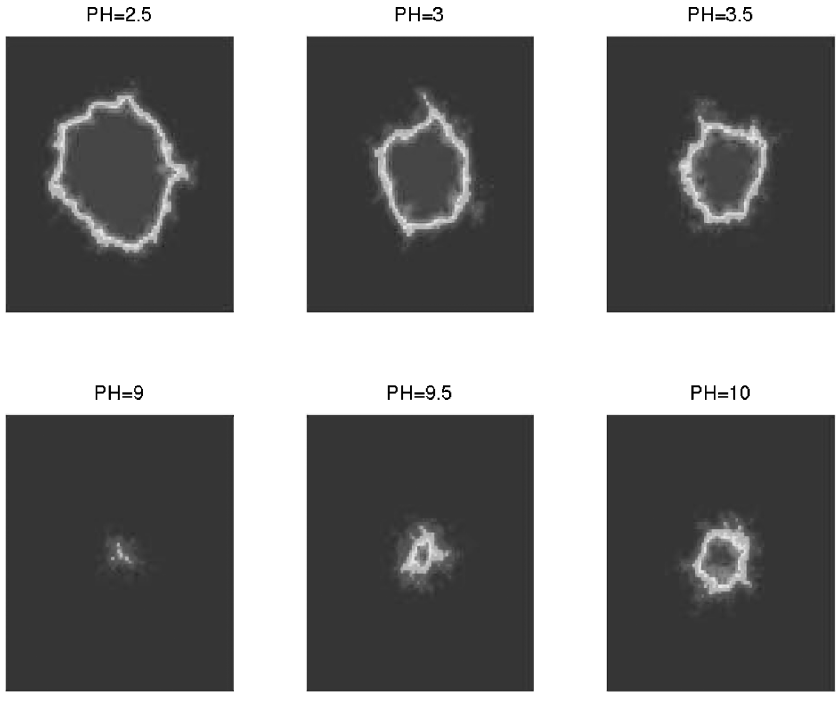


Fig. 8 Effect of pH value on the corrosion pit damage growth through simulation.

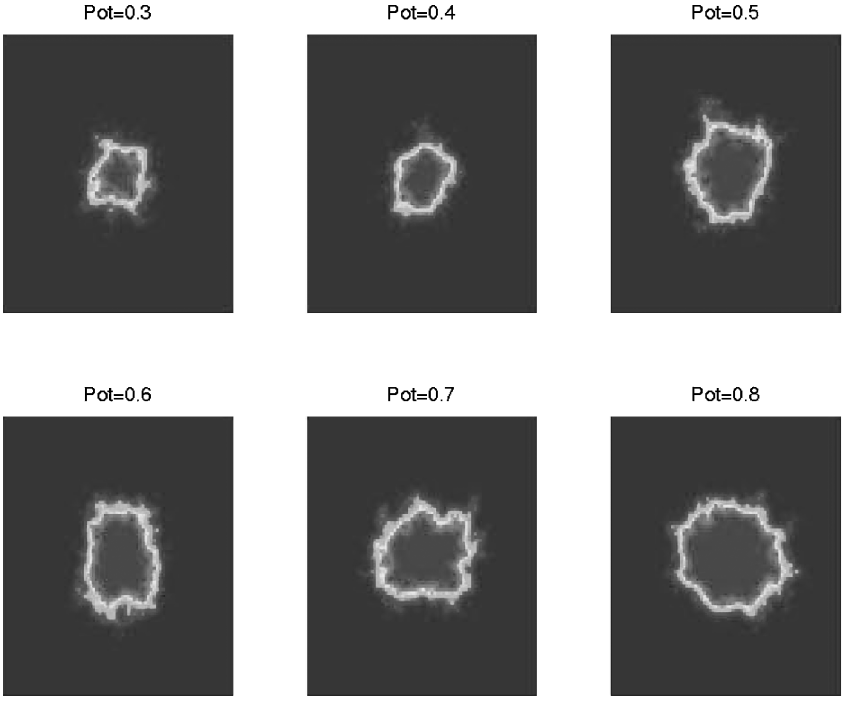


Fig. 9 Effect of potential difference values on the corrosion pit damage growth through simulation.

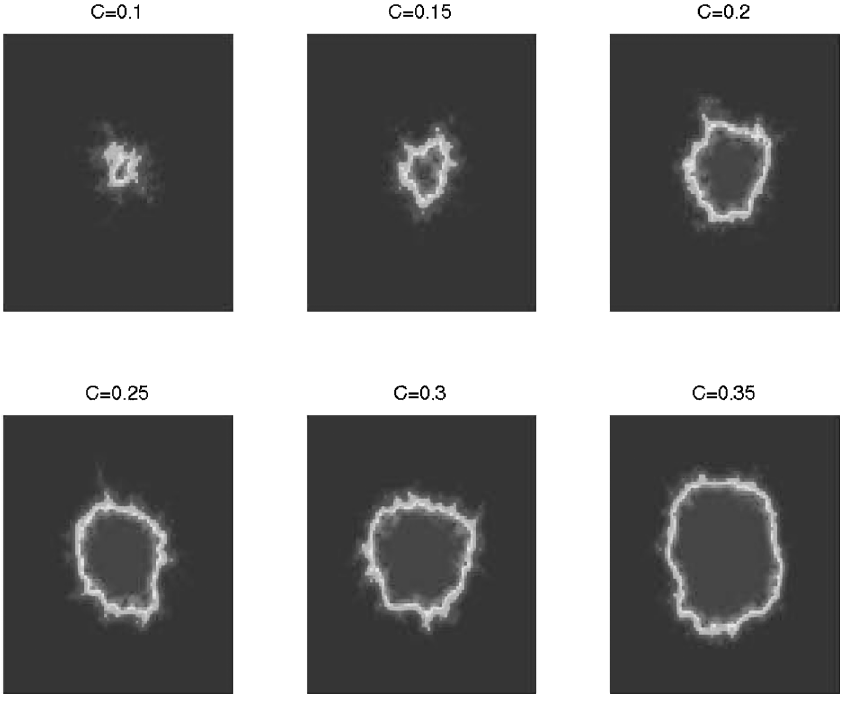


Fig. 10 Effect of solution concentration on the corrosion pit damage growth through simulation.

In addition, the area loss data matches with the corrosion area data quite well.

The second set of simulations is carried out by changing the value of potential difference between the metal surface and the solution to see how the corrosion pit grows. A higher potential difference increases both the chemical reaction rate and the mass transport rate, so that it increases the corrosion pit growth rate. Figure 9 shows the effect of increasing the potential difference on corrosion pit growth predicted by the simulation model. In this simulation, the pH value was kept at 3.5 and the solution concentration was set at 0.2. It can be seen from Fig. 9 that the corrosion pit growth increases as the potential difference increased from 0.3 to 0.8. The morphology/area is also increases. Once again, the morphology of the simulated pit growth is reasonable. The feature analysis indicated that all of the key features, area, energy, and power increase as the value of the potential increases. This prediction of the model is again in agreement with the experimental data found in the literature.

The third set of simulations is carried out by changing the value of the solution concentration level to see how the corrosion pit grows. If the concentration is changed, both the mass transport rate and the chemical reaction rate will be affected. The result of this simulation is shown in Fig. 10. In this simulation, the pH value was kept at 3.5 and the potential difference was set at 0.5. It can be seen from Fig. 10 that the corrosion pit growth increases as the potential

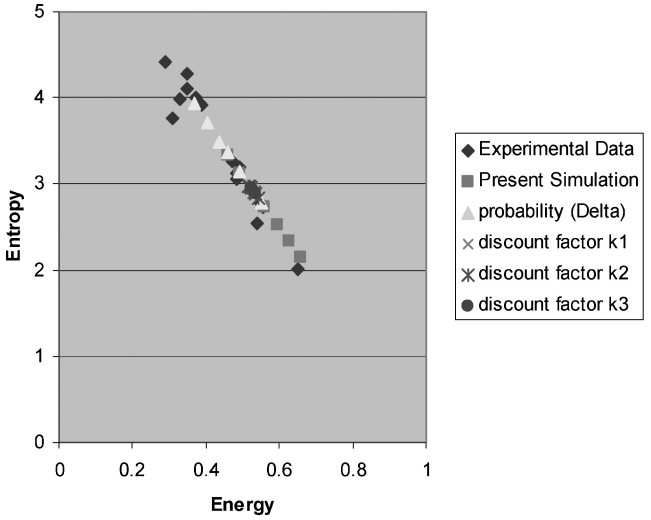


Fig. 11 Sensitivity analysis of the extracted features for various parameters in the corrosion pit damage growth model and comparison to experimental data.

difference increased from 0.1 to 0.35. The morphology/area is also increased. Once again, the morphology of the simulated pit growth is reasonable. The feature analysis on the images in Fig. 10 shows that both area and corrosion levels increase as the solution concentration is increased. Again, both the area and power features of the image match with the corrosion rate very well.

There are several numerical parameters in our corrosion pit damage growth model [Eqs. (1) and (2)], such as the probability of the nondeterministic term and the discount factors. Setting them to a proper value could affect the performance of our whole model. To refine them, sensitivity analysis of these different parameters with regard to the extracted features is carried out to help find the suitable values. The result corresponding to the energy and entropy is shown in Fig. 11. To see how the discount factors affect the corrosion pit growth in the simulation model, a sensitivity analysis is carried out for all of the experimental data obtained from the Center for Materials Diagnostics. Figure 11 shows the results of sensitivity analysis of the extracted histogram features of entropy vs energy. It can be seen that the discount factors selected are in good agreement with the experimental data.

VI. Conclusions

A corrosion pit damage growth process model for aircraft aluminum materials is developed using CA approach. The local rules in CA are based on the governing electrochemical reactions and simulating them as a discrete dynamic system. The simulation program is developed in JAVA environment for ease of portability and usability. The resulting corrosion pit damage growth obtained from simulations are compared qualitatively as well as quantitatively to the experimental data obtained from Center for Materials Diagnostics at the University of Dayton Research Institute, Dayton, Ohio. The results of comparison indicate that the present model can capture the corrosion pit damage growth process. The effects of various electrochemical parameters on the damage growth obtained from the simulation are presented and discussed. The results presented illustrate the new approach using CA to model pit damage growth in aircraft aluminum materials. The present model includes only the pit growth. For a realistic localized corrosion prediction, the model should include pit nucleation and repassivation stages of pit formation, similar to the DFA model. The proposed model is a general solution to structural corrosion in materials so that it can be scaled up to other structural materials such as steel alloys, etc. Our future plans are to seek fundamental understanding of the macro- and microlevel corrosion growth from various physical phenomena and to model them based on local rules that can provide valuable information and tools for designing corrosion resistant materials for a variety of applications.

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