Cellular Automata Approach to Aircraft Corrosion Pit Growth

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Abstract

Corrosion is one of the degrading mechanisms that greatly affect the structural integrity of aerospace components. Corrosion begins with small imperfections in the given material referred to as "pits". Over time, and with exposure to the environment and loading stresses, these pits grow into structural cracks. These cracks, under further exposure to elements and stress, will eventually lead to material failure. To better understand how corrosion growth process takes place in materials, research is being conducted to simulate corrosion pit growth process using computational intelligence methods. The objective of this study is to develop a discrete dynamic model using cellular automata to simulate the pitting corrosion growth process in aircraft materials, and see how it affects the structural integrity.

Introduction

The strength and integrity of a structural component deteriorates mainly due to corrosion and fatigue, and other mechanisms. Corrosion is caused by the environmental conditions under which the structure is operated and maintained.

Among various aspects of corrosion, pitting corrosion is a complex process, and is a major problem in many aerospace structural components. Corrosion begins with small imperfections in the given material referred to as "pits". Over time, and with exposure to the environment and loading stresses, these pits grow into structural cracks. The corrosion mechanisms depend on the material composition, electrolyte and other environmental conditions [1]. Currently, we do not have a precise understanding of the nature of the corrosion growth characteristics and their relationships to material loss and structural integrity. Also, the mechanical characteristics and their relationships at multiple levels due to pitting corrosion are not known. Pitting corrosion develops patterns that evolve according to local rules and the corresponding algorithms need to be studied. An improved understanding of the evolution of the corrosion process would be of practical importance in designing corrosion resistant materials and predicting structural integrity.

Most of the previous work on corrosion has been focused on chemical process and electric currents and potentials, and limited growth models [2-6]. There has been a substantial interest in the morphology of corrosion but little quantitative work has been done on three-dimensional growth simulation models. There have been 1D and 2D models of pitting corrosion. But there are no models of evolution of pitting corrosion based on local rules in the literature.

The cellular automata (CA) approach is adopted to simulate the aircraft corrosion growth process by modeling as a discrete dynamical system. The model captures the pitting growth based on chemical parameters and a continuous mathematical model is used to find out which parameters affect the pitting process and how they affect the growth rate. All the important factors are considered into the cellular automata rules. The model is very general and can apply to different materials. Some simulation results are presented in this paper.

CA as a Physical System Model

Work by Toffoli et. al [7] showed the use of cellular automata as a powerful tool to model physical and biological systems. This pioneering work lead to the development of several CA-based modeling applications in diverse areas. The lattice gas model, called the HPP model, developed by Hardy et. al [8] 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 HPP model proved that the cellular automata 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 [9], spreading of a liquid droplet and wetting phenomena [10], microemulsion [11], erosion and transport problems [12], modeling catalytic surfaces [13], and modeling forest fires [14].

The original CA model proposed by Von Neumann [8] is a two-dimensional square lattice in which each square is called a *cell* (see Fig. 1). 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 dynamical system. Earlier work by Wolfram [15, 16] showed that the CA as discrete dynamical system exhibits many of the properties of a continuous dynamical system, yet CA provides a simpler framework. This particular feature of CA makes it an ideal computational approach to model corrosion growth.

Corrosion Pit Growth Model

A discrete dynamical model based on cellular automata is developed to simulate the corrosion damage growth process. The local cellular automata rules of this proposed model is as follows:

Let $S(t,x)$ be the corrosion state function of cell x at time t, here x is the 2D position vector, the range of $S(t,x)$ is a predefined interval. $S(t,x)$ at the lower end indicates uncorroded, and the upper end indicates fully corroded. Both the position parameter and the time parameter in the state function take discrete values. By the local cellular automata rule, the corrosion state of cell x at the next moment is determined by the current corrosion state at x and the current corrosion states of its eight Moore neighbor cells. Because the pitting process is not reversible, the state function is an increasing function with respect to time. The increment is the sum of all the influences from the cell itself and its neighbors. Besides these deterministic effects, a non-deterministic factor is also included in the increment. That is because of the non-deterministic characteristic of the corrosion process, corrosion pits and their depth distributions vary probabilistically and hence we need a non-deterministic item in the rule equation to describe the stochastic behavior the model. The way the cells affect each other is represented through some effectiveness functions. The effectiveness functions are not uniform, but should be the same for symmetric neighbors. It takes a parabola shape, as the cell changes from uncorroded to partially corroded and finally to fully corroded, the activity of the chemical reaction increases from zero up to some point then falls back down to zero. The environmental chemical parameters that affect the pitting growth rate also need to be incorporated into the model. They produce the effect through the coefficients of the effectiveness functions with their corresponding ratio. The equation for the overall corrosion growth model is given in equation (1):

$$S(t+1,x) = S(t,x) + k_1 f(S(t,x)) + k_2 \sum_i f(S(t,x+c_i)) + k_3 \sum_j f(S(t,x+d_j)) + k_4 \Delta \quad (1)$$

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

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

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

The function $f(.)$ is to transform the corrosion to the effectiveness. Δ is a standard random variable with mean 0 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 equation (2). Based on the collected information, we can express the k's in terms of the chemical parameters that affect the corrosion growth [18].

$$k_1 = \lambda * (PH-7)^2 * step(4,8.5) * e^{Pot} * \frac{1}{T} * C * D * z \quad (2)$$

where,

- λ is a discount factor;
- PH is the ph value of the solution;
- step(4,8.5) is a function with value 0 between 4 and 8.5, and 1 otherwise;
- Pot is the potential difference between the metal and solution;
- T is the absolute temperature;
- C is the concentration of the reaction species;
- D is the diffusivity of the reaction species;
- z is the charge of the reaction species.

k_2, k_3 and k_4 are in similar forms as k_1, but with different discount factors. This is because the farther from cell x, the less effective role the neighbors take in the corrosion of cell x.

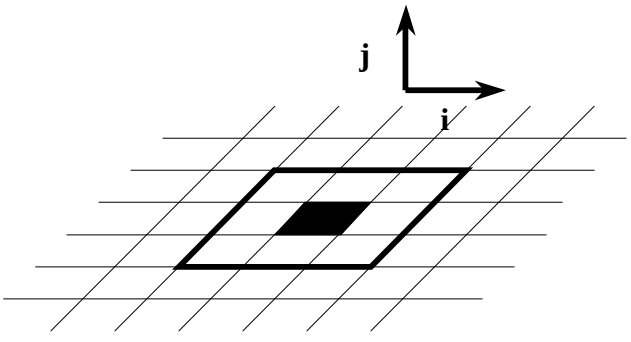

Figure 1. The Moore neighborhood window for the model

Image Features Extraction

In order to quantify the corrosion growth after CA simulation, important features were extracted from

simulated images of corrosion growth. The features considered include *area*, *energy*, and *spectral* values which are obtained through the image analysis process [19]. The area of a corroded region is given by,

$$A = \sum_{r=0}^{N-1} \sum_{c=0}^{N-1} I_i(r,c) \tag{3}$$

where, the *area A* is measured in pixels and indicates the relative size of the corroded region, *I* is the corroded region of size *NxN*. The *energy* feature indicates something about how the pixel intensities are distributed in the region under consideration. In the case of corrosion image, this feature indicates the degree of corrosion at the pit level. The energy feature is extracted using equation (4) as [19],

$$energy = \sum_{g=0}^{L-1} [P(g)]^2 \tag{4}$$

where, $P(g)$ is the histogram probability, L is the range of gray levels depicting the corrosion strength (0-255 in this case). The *power* feature indicates the texture property in an image and in this case, the level of corrosion itself. The higher the power value, the texture change will be higher. The power feature is computed using equation (5) given by [19],

$$power = |T(u,v)|^2 \tag{5}$$

where, *T* is the Discrete Fourier Transform of image *I* from equation (3).

Results and Discussion

Based on the cellular automata model, we have developed a computer program to simulate the corrosion growth process and carried out the feature-based validation with the experimental data. The computer program is mainly implemented in an object-oriented environment with Java by taking each data set as an individual object. Therefore, future extension and modification of the program functionality will be handled conveniently. Several simulation runs were carried out to understand the corrosion growth process and the results are presented in the following sections.

Figure 2 shows the CA simulated pitting growth of corroded images (first row) starting from a given initial pitting point for an aircraft aluminum material. The results in Fig. 2 are obtained by using a PH value of the solution as 1.5, and the absolute temperature as 300. In the simulation, the potential difference between the metal surface and the solution is set at 0.5v and the concentration of the solution is set at 0.2 (moles dm^{-3}). There are 30 iterations between every two images during one-step of pitting growth simulation. The color mapping of these simulation images is given in the last row of Fig. 2. Red indicates fully corroded and the blue indicates fully uncorroded.

We varied the values of different parameters and carried out the simulations to see the effects of corrosion growth when certain parameters are changed. The second row in Fig. 2 shows the simulated growth images when the potential difference between the metal and the solution is increased to 0.7v, and other parameters are unchanged. The corrosion growth rate becomes faster as the potential difference increases. On the third row in Fig. 2, the solution concentration is changed to 0.3 (moles dm^{-3}) from 0.2 and other parameters are kept same as the first simulation (first row of Fig. 2).

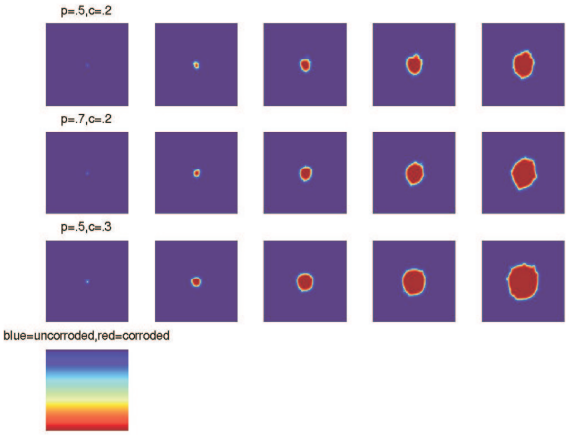

Figure 2. corrosion pit growth images for changes in various parameters in the model

In order to systematically study the effect of various parameters, each parameter is varied in the model, and the results of simulation are obtained and presented.

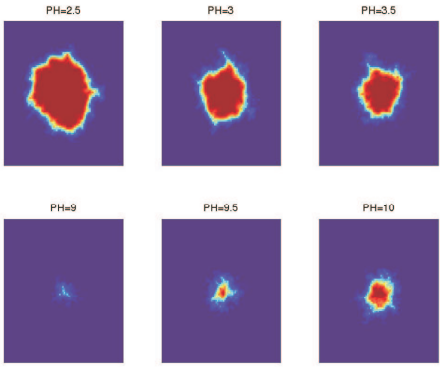

Figure 3. Effect of PH values on corrosion pit growth simulations

The features extracted from the simulated images (Fig. 3) are shown in Fig. 4.

Effect of PH

The CA simulated corrosion growth images for various PH values are shown in Fig. 3. Because the pitting corrosion does not occur with PH between 4 and 8.5, six values out of that interval are chosen to set the PH values.

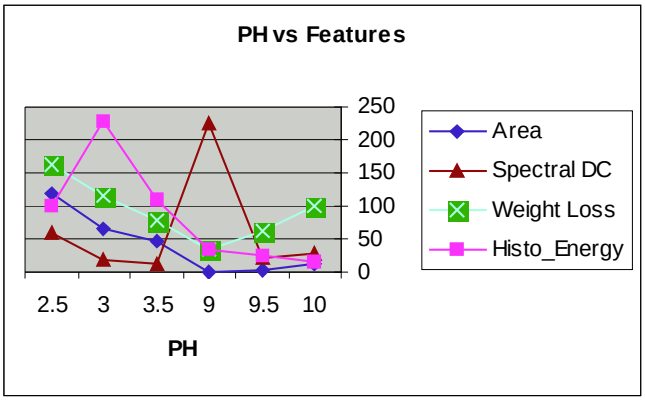

Figure 4. Effects on image features from corrosion growth simulation on PH

It can be seen from Fig. 3 that as the PH value gets lower (when smaller than 4), or higher (when larger than 8.5), the corrosion rate increases. This prediction by the model is in agreement with the experimental data available in the literature [19]. The weight (material) loss data shown in Fig. 4 compares well qualitatively and matches well with the corrosion area data. Both weight loss and corrosion area give a good indication of corrosion. The power data also suggest this phenomena where the power value is maximum (when PH=9)indicating that the corrosion is at its highest level when weight loss is maximum.

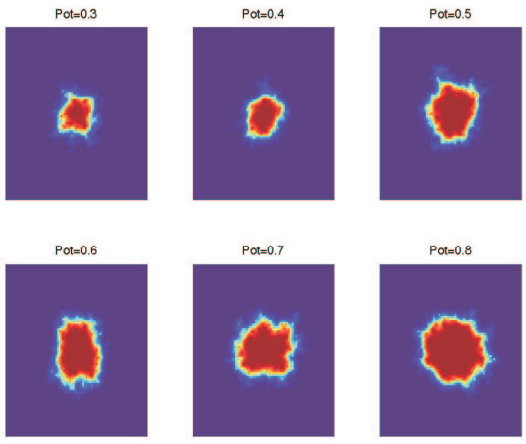

Figure 5. Corrosion images resulting when the potential difference values are changed in the simulation

Effect of Potential Difference

A second set of simulation was carried out by changing the potential difference between the metal surface and the solution. Higher potential difference increases both the chemical reaction rate and the mass transport rate, so it increases the corrosion rate. The effect of this parameter on corrosion growth predicted by the simulation model is shown in Fig. 5. In this simulation, the PH value was kept at 3.5 and the solution concentration was set at 0.2.

Figure 6 shows the features obtained from Fig. 5 as a function of the potential difference in the simulation. It can be seen from Fig. 6 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 [20].

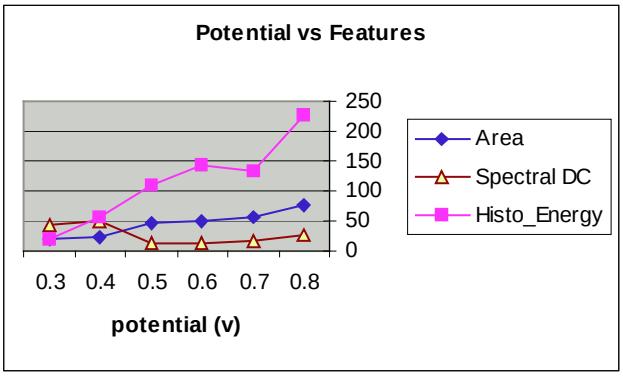

Figure 6. Effects on image features from corrosion growth simulation on potential difference

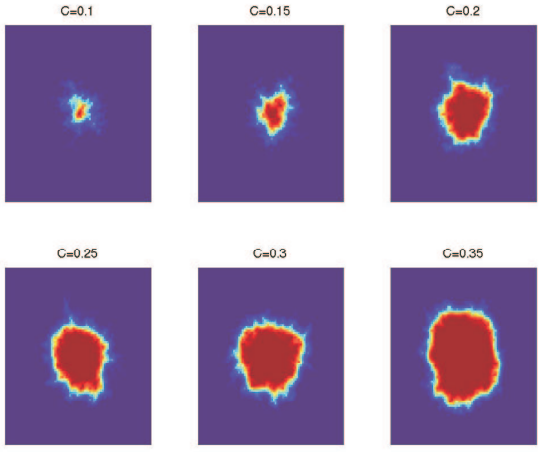

Figure 7. Corrosion images resulting by changing the solution concentration in the simulation

Effect of Solution Concentration

The third set of simulation involved changing the solution concentration level. 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. 7. In this simulation, the PH value was kept at 3.5 and the potential difference was set at 0.5. The feature analysis on the images in Fig. 7 shows that both area and corrosion levels increase as the solution concentration is increased. The feature analysis of the corrosion images (Fig. 7) is presented in Fig. 8. Again, both the *area* and *power* features of the image match well with the corrosion rate.

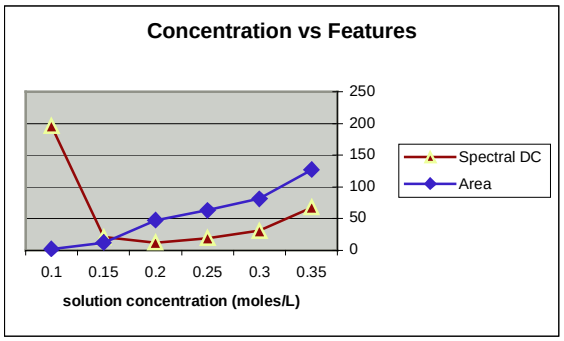

Figure 8. Effects on image features from corrosion growth simulation on solution concentration

Experimental Validation

In order to validate our model, feature extraction was conducted on the experimental data obtained from the Center for Materials Diagnostics (courtesy of Mr. Chris Kacmar), Dayton. Ohio. The validation results are presented in Fig 9. Because of different color maps in the experimental data, the blue indicates corroded and red indicates uncorroded regions. Only a couple of parameters from the experimental data are known for the simulation. Even with that the simulation results shows right behavior and the parameter sensitivity follows the right trend. Overall the comparison in Fig. 9 indicates that the present model can qualitatively predict the corrosion pit growth, even though several parameters affect the process.

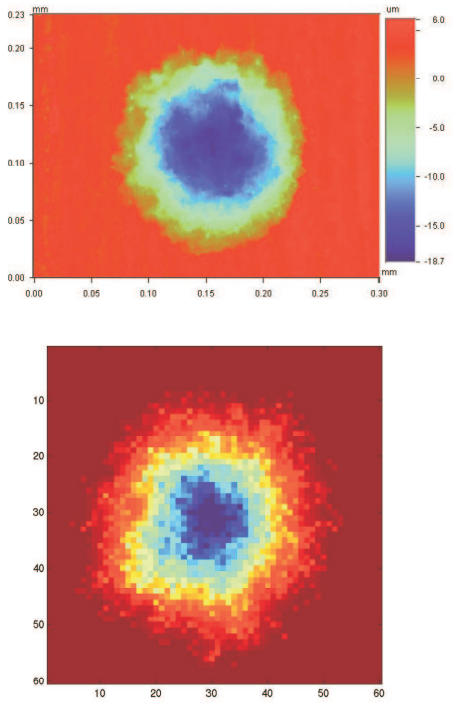

Figure. 9 A typical pit corrosion in aircraft aluminum from electro-chemical experiments (top) and present simulation (bottom)

Summary and Future Work

The problem of corrosion pit growth in aircraft materials is approached through a cellular automata model. A discrete dynamical model based on cellular automata is developed to simulate the corrosion damage growth process based on local rules involving electro-chemical reactions. A continuous mathematical model is used to find out which parameters affect the pitting process and how they affect the growth rate. Both the rates of mass transport and chemical reaction are formulated. Preliminary results were obtained and validated qualitatively with the experimental data. The results presented correctly capture the corrosion pit growth process to in response to changes in various parameters. Currently, corrosion growth experiments are being conducted to systematically obtain the data so that a better validation with the simulation model can be carried out. Our future plans are to seek fundamental understanding of the macro- and micro-level corrosion growth and to model this process based on local rules provide valuable information and tools for designing corrosion resistant materials for a variety of applications.

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