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Corrosion Fatigue Through Particle Swarm Optimization

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A particle swarm optimization method was used to investigate the corrosion fatigue problem. The optimization procedure is used in redesigning the operating environment to achieve desired corrosion-fatigue properties for an aircraft panel/material. The operating parameters that would cause a structure to have maximum fatigue properties were obtained from the optimization simulation. The results of operating parameters obtained through the optimization procedure are reasonable and demonstrate the feasibility of the approach for estimating the corrosion fatigue of aging structures.

Nomenclature

a_{ci}	=	critical crack size, mm
a_f	=	final crack size, mm
a_0	=	initial pit size, mm
C_1, C_2	=	positive constants
D_{exp}	=	duration of exposure to the environment, h
f	=	frequency of loading, Hz
k	=	penalty function weight
N_i	=	fatigue crack initiation life, cycles
N_p	=	fatigue propagation life, cycles
p	=	penalty function
R	=	stress ratio
V_I	=	velocity of ith particle
v_i	=	velocity of ith input variable
w	=	inertia weight
X_I	=	position of ith particle
x_i	=	ith input variable
α_1, α_2	=	weight factors for initiation and propagation lives
$\Delta\sigma$	=	stress amplitude, MPa

I. Introduction

CORROSION fatigue has been identified as one of the leading causes of failure among the various damage mechanisms that affect the structural integrity of aircraft structures. Operation of aging aircraft under a corrosive environment may cause failure of the various parts due to initiation and propagation of corrosion fatigue cracks. Scheduled maintenance and inspection of aircraft components in advance may prevent such failures. Establishment of models for predicting corrosion fatigue will be helpful in designing a maintenance program based on the residual life to avoid failure.

Over the past few years, considerable research effort has been focused on the characterization and quantification of damage due to corrosion fatigue. Although many studies are reported in the literature, the mechanism of corrosion fatigue has not been fully understood due to the various uncertainties involved in the process, including the microstructure of the materials. Hence, it is difficult to model accurately all of the uncertainties in the process and thereby predict the reliability of the structures. Generally, the desired estimates often involve extrapolations in time by factors of 10 or more. Several analytical and probabilistic methods have been used to characterize the corrosion fatigue process.[1–5] Bacause mechanistically based analytical models cannot take into account the scatter in the fatigue life data, probabilistic approaches have been used for predicting the reliability of components with corrosion fatigue.[6–10]

For the past few years, the investigators have been studying the structural integrity and durability issues related to aging aircraft structures and materials. Wang et al.[11] presented simple analytical and probabilistic models for predicting the corrosion fatigue life of aircraft materials by considering all stages of the corrosion-fatigue process. The results indicated that crack initiation life varies approximately 10–40% as compared to crack propagation life. Recently, Pidaparti et al.[12] investigated the pitting corrosion classification, distribution, and prediction of corrosion-fatigue life of aircraft panels using neural network models. The predictions from the neural networks compared well with the existing experimental data and analytical methods.

The need for integrating structural design with damage prediction has to be explored for the redesign and stipulation of operating requirements for aging structures. Changes in the structural integrity of structures/components may affect the performance to such an extent that remedial measures may become necessary. To reduce the repair and maintenance costs, one might perform early repair on the structures before the damage grows to a dangerous size. Alternatively, the repair may even be postponed until the aircraft is taken out of service for scheduled maintenance. In the latter case, it may become important to adapt operational usage to limit or even stop the damage growth. If sufficient knowledge exists to relate damage rates to mission types, this can be achieved by monitoring usage.[13] Maintenance and repair of the structure will be easier if it is possible to obtain the maximum allowable values of the damage parameters so that the physical health of the structure does not adversely affect its performance.

A review of the literature indicates that optimization methods are currently not being used to investigate corrosion fatigue of aircraft materials and structures. Therefore, it will be interesting to explore the benefits of using optimization methods to estimate corrosion fatigue and predict optimal operating environments for aging aircraft structures for a specified durability. In the present study, we propose to investigate corrosion fatigue as an optimization problem where we predict a combination of operating parameters that will achieve the extreme values of the fatigue characteristics in terms of crack initiation and propagation lives. For this purpose, particle swarm optimization approach is used.

II. Corrosion-Fatigue Problem

Corrosion fatigue is a process that is an outcome of synergistic interactions among the environment, material microstructure, and cyclic loads. The most important factors that determine the corrosion fatigue life of aircraft panels are fatigue loading and corrosion

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environment. Fatigue loading is characterized by maximum stress amplitude $\Delta\sigma$, stress ratio R, and the frequency of loading f. Corrosion is considered by taking into account the duration of exposure $D_{\exp}$ of the material to the environment. The corrosion fatigue process, represented as the total number of cycles, comprises the cycles needed to form a critical pit-crack transition size (pit nucleation due to fatigue and pit growth due to environment) and the cycles needed to propagate the crack to failure. When combined knowledge of pitting growth, fatigue crack nucleation, and fatigue crack growth is used, it is possible to estimate the total corrosion fatigue life.

Fatigue crack initiation life, N_i, is considered to be the number of cycles consumed in the nucleation and growth of small crack to a length where it becomes a dominant fatigue crack. Fatigue propagation life N_p is considered to be the remaining number of cycles required to grow the initiated fatigue crack to final fracture.[14] To account for both portions of the failure life, local strain[15] and linear elastic fracture mechanics (LEFM) approaches[15] have been extensively used in fatigue-life analysis. For crack initiation life estimates, local strain is the most widely employed technique, whereas the LEFM approach has found wide acceptance for crack propagation life estimates. The difficulty in estimation of fatigue life in a corrosive environment becomes evident when considering the numerous mechanical, metallurgical, and environmental variables that contribute to the process. However, from an engineering point of view, it is often assumed that the adverse effects of the environment can be included in fatigue life estimation procedures by determining the material fatigue properties in the environment of interest.

In the normal design of aerospace structures, only the structural failure mechanisms such as yielding, buckling, fracture, etc., are considered. However, with aging aerospace structures, the redesign of the structure should also take into account other damage mechanisms such as multiple-site damage, corrosion fatigue, and creep fatigue that will affect the reliability of the structure/material. In this study, we consider the redesign of the operating environment to achieve specific corrosion fatigue properties through an optimization procedure.

The corrosion-fatigue problem (redesign) involves finding a set of operating parameters that correspond approximately to desired corrosion fatigue properties in terms of crack initiation and propagation lives. This might help in better understanding the interaction between the operating parameters and the fatigue properties. We have developed a neural network model to capture the corrosion-fatigue mechanism and predicted the properties.[12] The results obtained from the neural network model agree very well with existing experimental data and other solutions. Of the various types of optimization algorithms used with the neural network approach, evolutionary algorithms are the most popular. Particle swarm optimization (PSO) is an algorithm that falls into this category and is explored in this study. We pose the corrosion fatigue problem as an optimization problem where we predict a combination of damage parameters that will achieve the desired extreme corrosion fatigue characteristics.

Note that, due to the large number of parameters and uncertainty in estimating the corrosion-fatigue mechanism, the optimization algorithm is likely to converge to local minima at times. The objective of the present study is to obtain the different damage parameters that will give relatively high durability in terms of the fatigue life. Because it is difficult to control the external environment and loading, obtaining the global maximum value of strength may not be of practical use. Instead, if we obtain different combinations of the damage parameters that give relatively higher strength values (local maxima), it will be helpful to tabulate the results and to use the data for evaluating the maintenance needs of the structure. When the current damage (as reflected in the damage parameters such as pit size) in the structure is examined, performance criteria can be formulated for the safety of the structure.

III. PSO

Several optimization algorithms have been used in the past to solve various engineering problems. The optimization approaches that are most frequently used with neural networks fall into the category of evolutionary methods, where the algorithm searches through the solution space so as to maximize a so-called fitness function. Evolutionary algorithms imitate genetic changes in living organisms. As compared to traditional search algorithms, evolutionary computation techniques work on a population of potential solutions (points) of the search space. The different iterations of the algorithm are called generations, where the algorithm changes the positions of the points to find a better solution. Eberhart and Kennedy[16] and Kennedy and Eberhart[17] developed a new evolutionary computation technique, PSO, inspired by social behavior simulation. A brief description of the PSO procedure is given now.

PSO is similar, in some ways, to evolutionary programming and is also related to cultural algorithms.[18] Each particle is treated as a point in an N-dimensional (input) space. The ith particle (individual) is represented as $X_I = (x_{i1}, x_{i2}, \ldots, x_{iN})$, where $x_{i1}, x_{i2}, \ldots, x_{iN}$ are the N input variables for the problem considered. The function to be optimized is called the fitness function. In the present study, the fitness function is the reliability characteristic that is measured in terms of the fatigue lives predicted by the neural network models. Hence, the positions of the particles in the input space are the input vectors for the neural network models, whereas the outputs from the neural networks form the fitness function. The best previous position (the position giving the maximum fitness value) of the ith particle is stored in memory and represented as $P_I = (p_{i1}, p_{i2}, \ldots, p_{iN})$. The index of the best particle among all of the particles in the population is represented by g. The rate of change of position (velocity) for particle i is represented as $V_I = (v_{i1}, v_{i2}, \ldots, v_{iN})$. The new positions and velocities of the particles are obtained according to the following equations[19]:

$$V_{in} = w \times v_{in} + C_1 \times \text{rand}(\,) \times (p_{in} - x_{in}) + C_2 \times \text{Rand}(\,) \times (p_{gn} - x_{in}) \tag{1a}$$

$$x_{in} = x_{in} + v_{in} \tag{1b}$$

where c_1 and c_2 are two positive constants and rand ( ) and Rand ( ) are two random functions in the range [0, 1]. Equation (1a) is used to calculate the particles new velocity according to its previous velocity and the distance of its current position from its own best experience (previous best position) and the group's best experience. Then the particle flies toward a new position according to Eq. (1b). This process of updating the positions of the particles to get the optimum position is carried out until a specified number of iterations. At the end of the final iteration, it is assumed that all of the particles have converged or are close to a single position in the input space where the fitness function has a global optimum. The imposition of velocity to the particle from its current position is similar to mutation in genetic algorithms. Instead of creating a whole new set of individuals from the previous population, PSO simply moves the particles through the search space, based on the personal and social flying experience of the particles.

Parameters for PSO

Performance of the PSO in obtaining the global optimum depends on the parameters used for the PSO algorithm, such as the inertia weight, the maximum velocity, the number of iterations, etc. The performance of each particle is measured according to a predefined fitness function. As discussed earlier, the fitness function is problem dependent and must be determined accurately for a reasonable solution. The inertia weight w is employed to control the impact of the previous history of velocities on the current velocity, thereby influencing the tradeoff between the global (wide-ranging) and local (nearby) exploration abilities of the flying points. A larger inertia weight w facilitates global exploration (searching new areas), whereas a smaller inertia weight tends to facilitate local exploration to fine tune the current search area.[19] One important parameter in PSO is the maximum velocity of the particles. The maximum velocity allowed to a particle acts as a constraint that controls the maximum global exploration ability that the PSO can have. A large value of the maximum allowed velocity will cause the PSO to have a large range for global exploration, whereas a small value would limit the global exploration ability, thereby favoring a local search.

Shi and Eberhart[19] have also shown that by setting the maximum allowable velocity to two, better performance was achieved by using an inertia weight w in the range (0.9, 1.2). This means that the algorithm has greater chances of obtaining the global optimum within a reasonable number of iterations with a smaller inertia weight. Hence, the controlling parameters for the PSO should be chosen appropriately, to achieve meaningful solutions within a reasonable amount of time.

Physical Constraints

In most physical problems, the input space is generally constrained, and the input parameters cannot fall out of a certain range called the feasible space. Hence, such problems are posed as constrained optimization problems. The physical constraints can be imposed externally by not allowing the optimization algorithm to predict inputs outside the feasible range. However, this will need numerous IF statements in the code. Another simple way of imposing the constraints is by penalizing the algorithm through the fitness function, for predictions outside the feasible space. Because evolutionary algorithms use a number of individuals (particles) for obtaining the optimum, one can afford to incorporate the penalty due to the constraints, in the individual's fitness functions. This will reduce the fitness value of the individual (particle) for use in the next generation/population. Hence, those individuals (particles) that have input values outside the feasible space will have low fitness value and, hence, will be discarded from the future generations.

The PSO algorithm discussed here was implemented in MATLAB® software, due to the simplicity of developing neural network models in MATLAB. Furthermore, because there was no need to change the neural network algorithm as such, only the outputs were used for optimization.

IV. Optimization for Corrosion Fatigue

The previously developed neural network model for corrosion fatigue[12] was used in the PSO algorithm to provide the initiation and propagation lives, which constitute the fitness function.

Fitness Function

The initial fitness function for corrosion fatigue problem is as follows:

$$f = \alpha_1(\text{initiation life}) + \alpha_2(\text{propagation life}) \tag{2}$$

If the factors α_1 and α_2 are chosen such that their sum is 1, then the fitness function can be thought of as the total fatigue failure life.

After the penalty is incorporated, the new fitness function is given by

$$f_n = 1/f + \kappa p \tag{3}$$

The penalty function p is defined as the distance by which a particle exceeds the input domain. For a given particle, penalty for individual inputs is determined, and the maximum of the individual penalties is set as the penalty for the particle.

The objective of the PSO is to minimize the new fitness function f_n so that the original fitness function f is maximized and the penalty p is minimized for the particles. Note that the individual penalties of the particles in the different input directions should have the same order of magnitude (tens or hundreds) so that all of the inputs have a similar effect in determining the penalty. This is very important because we are considering the maximum individual penalty as the particle's penalty. For example, the typical values for the critical pit size are in the range of 0.01–0.96 mm, whereas those for stress amplitude and duration of exposure are in the hundreds. The penalty for a particle lying far outside the input space for a critical crack size will still be a small value as compared to the penalty for a particle that has the duration of exposure value lying a little outside the feasible space. Hence, all of the individual penalties are amplified by suitable factors to have the same order of magnitude as the others. The factor κ in Eq. (3) ensures that the values of both terms on the right-hand side are of the same order. This will ensure that the optimization is not governed by the penalty function, but by the original fitness function.

Constraints

Several constraints on corrosion fatigue parameters are selected for the optimization algorithm to work within a feasible space to have meaningful results. The constraints are chosen based on the data and other solutions for similar problem in the literature.[9–11]

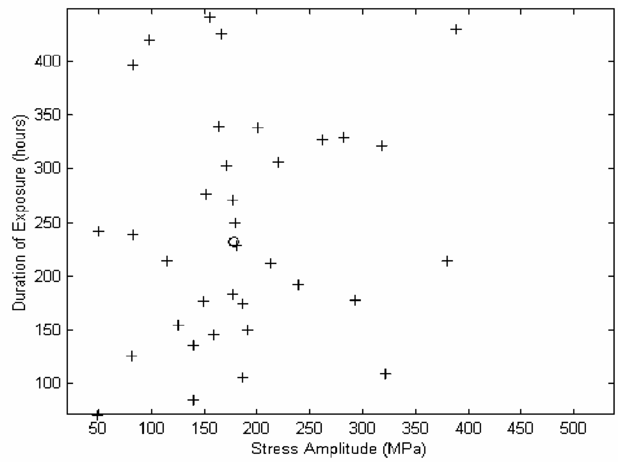

Fig. 1 Position of particles in the input space after two iterations.

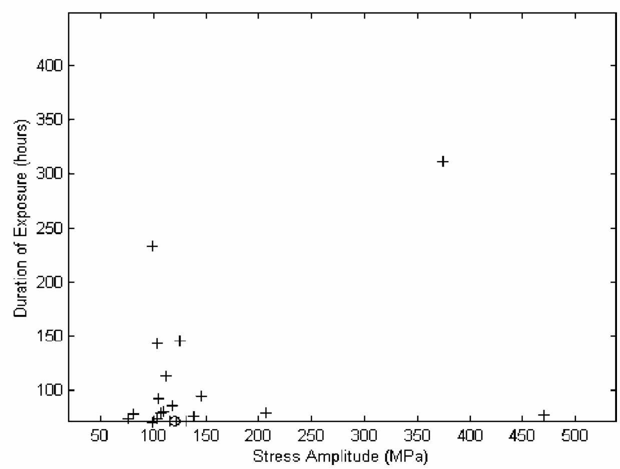

Fig. 2 Position of particles in the input space after 10 iterations.

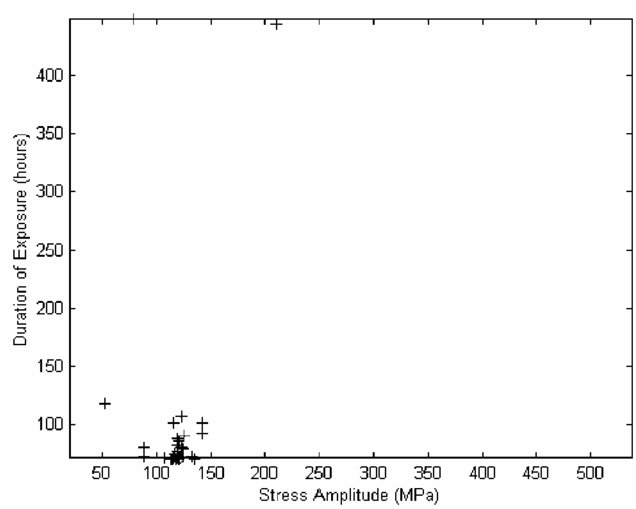

Fig. 3 Position of particles in the input space after 25 iterations.

Corrosion, which is accounted for as duration of exposure the environment, is in the range of 72–448 h is based on the accelerated tests. The constraints were incorporated into the penalty function such that they reduce the value of the fitness function of the particle for cases where the particle's position lies outside the feasible space. The constraints for the corrosion fatigue problem can be summarized as follows: stress amplitude $\Delta\sigma$, $120 < \Delta\sigma < 438$ MPa; duration of exposure $D_{\exp}$, $72 < D_{\exp} < 448$ h; stress ratio R, $-1 < R < 1$; frequency f, $5 < f < 15$ Hz; initial pit size a_0, $0.015 < a_0 < 0.03$ mm; final crack size a_f, $0 < a_f < 20$ mm; and critical crack size a_{ci}, $0.01 < a_{ci} < 0.96$ mm.

Simulations

We predicted the various damage parameters for an aircraft panel under corrosion-fatigue environment using the PSO approach discussed. After the necessary adjustments in the constraints and fitness functions are made, the PSO is used to obtain the damage parameters for the desired reliability. The PSO algorithm was run for 50 iterations with the following parameters: maximum velocity $= 1.3$, $C_1 = C_2 = 1$, number of particles (agents) $= 100$, and inertia weight $w = 0.329$.

These parameters were chosen based on the performance results by PSO as obtained by Shi and Eberhart.[19] The factor for the penalty function, k, was set to 0.001, so that both the terms in Eq. (3) for the corrosion-fatigue problem are in the range of 10^{-1}–10^{0}. Results of simulation obtained from the optimization procedure are presented in the next section.

V. Results and Discussion

Figures 1–3 show the particles flying in the input space of two of the seven input variables in this optimization study. Although not shown, the particles move in the input space for the rest of the inputs also, in a similar fashion. The cross marks are the particles of the population, whereas the best particle is represented by the circular mark. As the PSO was reaching the designated number of iterations (50), it was observed that all of the particles had flocked near a single (best) particle and were flying toward this position for several iterations. This indicates that the search for optimum has converged to a solution in the input space. However, it is not necessary that the optimum reached is the global optimum. In this study, the primary goal for using the PSO technique is not to obtain the global optimum, but to explore the possible failure conditions and the interaction of the damage parameters, to control the damage or repair it at the earliest. It is difficult to control all of the damage parameters for an existing structure, for example, temperature, yield strength of the material, etc., but this method can give an insight into other parameters that can be controlled (diameter of rivet holes, pitch, etc.), so as achieve desired reliability characteristics.

Three sets of simulations were performed for the corrosion fatigue problem by changing the controlling factors [α_1 and α_2 in Eq. (2)] in the fitness function. Each of the simulations is described.

Simulation 1

The first set of simulations were performed on the operating parameters to achieve maximum of both initiation and propagation lives. The fitness function for this simulation is $f = 0.5N_i + 0.5N_p$. The results for this simulation for two cases 1 and 2 are summarized in Table 1. Note from Table 1 that the critical pit size is larger and the final crack size smaller for case 2 as compared to case 1. However, the faitigue lives are comparable for both cases 1 and 2. From a common sense point of view, it may be easily inferred that this condition should lead to a smaller propagation life, if other factors are ignored in calculating the fatigue lives. However, in principle, a smaller stress ratio, a smaller stress amplitude, and a shorter duration of exposure, coupled with high-frequency loading, may increase the fatigue life of the structure.[20] These two cases (1 and 2) clearly show this phenomena, thereby further reinforcing the possibility that the predictions from the optimization procedure are reasonable and that the neural network model has correctly captured the inherent physical process of the corrosion-fatigue damage mechanism.

Simulation 2

The second set of simulations were performed on the operating parameters to achieve maximum fatigue crack propagation life. The original fitness function in this case is $f = 0.1N_i + 0.9N_p$. The results of this simulation for cases 1 and 2 are summarized in Table 2. Note from Table 2 that the pit and crack sizes are approximately the same for both the simulations; however, the initiation lives are different, possibly due to the effects of other parameters. For case 1, higher initiation life (3.08×10^5) is predicted with smaller stress ratio and frequency and larger values of stress amplitude and duration

Table 1 PSO simulation results for fitness function $f = 0.5N_i + 0.5N_p$

Corrosion-fatigue parameter	Cases 1	Cases 2
Stress amplitude $\Delta\sigma$, MPa	175.6	125.2
Duration of exposure $D_{\exp}$, h	201.6	169.6
Stress ratio R	0.800	0.011
Frequency, cycles/day	4.982	7.075
Initial pit size a_0, mm	0.00291	0.00258
Critical crack pit depth a_{ci}, mm	0.108	0.380
Final crack size a_f, mm	15.548	12.289
Initiation life N_i, cycles	$4.24E+11$	$4.25E+11$
Propagation life N_p, cycles	$4.24E+11$	$4.25E+11$

Table 2 PSO simulation results for fitness function $f = 0.1N_i + 0.9N_p$

Corrosion-fatigue parameter	Cases 1	Cases 2
Stress amplitude $\Delta\sigma$, MPa	218.0	200.0
Duration of exposure $D_{\exp}$, h	395.0	333.0
Stress ratio R	0.152	−0.807
Frequency, cycles/day	8.374	12.510
Initial pit size a_0, mm	0.013	0.011
Critical crack pit depth a_{ci}, mm	0.042	0.042
Final crack size a_f, mm	4.062	4.062
Initiation life N_i, cycles	$3.08E+05$	$4.71E+02$
Propagation life N_p, cycles	$4.99E+10$	$4.99E+10$

Table 3 PSO simulation results for fitness function $f = 0.9N_i + 0.1N_p$

Corrosion-fatigue parameter	Cases 1	2	3	4	5
Stress amplitude $\Delta\sigma$, MPa	226.3	200.0	233.0	216.0	196.0
Duration of exposure $D_{\exp}$, h	110.0	139.0	285.0	429.0	273.6
Stress ratio R	0.921	−0.172	−0.780	0.052	0.737
Frequency, cycles/day	5.500	8.240	5.226	5.939	6.377
Initial pit size a_0, mm	0.015	0.023	0.014	0.021	0.020
Critical crack pit depth a_{ci}, mm	0.666	0.026	0.017	0.077	0.020
Final crack size a_f, mm	9.149	16.292	17.644	8.269	12.837
Initiation life N_i, cycles	$4.99E+10$	$4.99E+10$	$4.99E+10$	$4.99E+10$	$4.99E+10$
Propagation life N_p, cycles	$5.47E+01$	$1.41E+02$	$6.26E+03$	$2.95E+05$	$6.30E+06$

of exposure, as compared to case 2, where the initiation life was predicted as 471 cycles.

Simulation 3

The last set of simulations were performed on the operating parameters to achieve maximum initiation life and minimum propagation life. The original fitness function for this case is given by $f = 0.9N_i + 0.1N_p$. A total of five simulations were conducted, and the predicted parameters are given in Table 3. Each of the five simulations predicts an initiation life of 4.99×10^9 cycles, which is high compared to the propagation life. The propagation life for each of these cases is different depending on the combination of the damage parameters. The results presented in Tables 1–3 illustrate the impact of various combination of operating parameters used to achieve extreme fatigue properties for an aging aircraft panels. The results also support the applicability of the PSO procedure for investigating the corrosion-fatigue problem.

VI. Conclusions

A PSO approach was utilized to obtain the operating parameters that would enable an aircraft structure to have maximum corrosion fatigue characteristics. The simulation cases predicted the operating parameters reasonably well, thereby demonstrating the validity of the approach for investigating the corrosion-fatigue problem. The results presented also point to the fact that PSO can successfully predict the optimal fitness function and the parameters. The present approach may be extended to achieve the operating parameters for multiple-site damage and creep fatigue problems as well.

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