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Aircraft Structural Integrity Assessment through Computational Intelligence Techniques

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Abstract: This paper provides an overview of the computational intelligence methods developed for the structural integrity assessment of aging aircraft structures. Computational intelligence techniques reviewed include artificial neural networks, inverse neural network mapping, wavelet based image processing methods, genetic algorithms, spectral element methods, and particle swarm optimization. Multi-site damage, corrosion, and corrosion-fatigue damage in aging aircraft is specifically discussed. Results obtained from selected computational intelligence methods are presented and compared to the existing alternate solutions and experimental data. The results presented illustrate the applicability of computational intelligence methods for assessing the structural integrity of aging aircraft structures and materials.

keyword: Corrosion, Multi-site Damage, Fatigue, Structural Integrity, Computational Intelligence, Particle Swarm Optimization, Wavelets

1 Introduction

The Aloha airlines flight accident on April 28, 1988, was a turning point in aviation history, and created awareness of extensive damage that can be caused by aging aircraft in the public as well as the aviation community. A major portion of the upper fuselage of the aircraft was lost in full flight at 24,000 feet. Multiple fatigue cracks and corrosion damage were detected near the holes of the upper row of rivets in several fuselage skin lap joints (www.airdisaster.com/photos). Although the casualties were not high, the damage done to the aircraft structure was irreversible. Several such accidents have since been reported concerning aging aircraft. Inspection of other similar aircraft revealed corrosion, disbonding, and cracking problems in the lap joints.

The major problems of aging aircraft as described by Lincoln (1995) and Chang (1995) include in-service cracking of the aircraft wing upper surface, widespread fatigue damage of the various structural components, uncertainty in variable amplitude loading, overload effects of aircraft, discrete source damage induced by foreign objects, and repairs of metallic components with composite counterparts to extend the service life. Periodic inspections of critical areas using appropriate NDE (Nondestructive Evaluation) techniques are carried out to ensure safety. The inspection intervals are calculated based on damage tolerance predictions of crack growth or full scale testing (Bates, 1995). A wide variety of NDI (non-destructive inspection) techniques are available for characterizing damage from different sources in materials and structures (Boving, 1989). Several NDI systems (eddy current inspection systems, enhanced visual inspection system or stereographic system, acoustic emission, and others) have been used to detect the cracks/damage in aging structures and materials (Wilson and Hagemaier, 1999; Grandhi, Nkrumah, Sundaresan, Kemerling, Thomas, 2005; Haugse, Leeks, Ikegami, Johnson, Ziola, Dorighi, May, Phelps, 1999; Rong-Sheng, 2004; Finlayson, Friesel, Carlos, Miller, Godinez, 2000). Wilson and Hagemaier (1999) present an overview of various NDI techniques for aging aircraft. Acoustic emission technique has also been used for crack monitoring (Grandhi, Nkrumah, Sundaresan, Kemerling, Thomas, 2005; Haugse, Leeks, Ikegami, Johnson, Ziola, Dorighi, May, Phelps, 1999), corrosion process (Rong-Sheng, 2004), and structural health monitoring (Finlayson, Friesel, Carlos, Miller, Godinez, 2000). Sometimes, it is necessary to use a combination of different NDI methods to detect specific damage (cracks, disbonds, etc.) characteristics.

Aging aircraft structures experience various complex types of damage mechanisms that may include multiple site damage (MSD), corrosion, corrosion-fatigue, and creep-fatigue. The strength and durability characteristics of aging structures/components depend on various parameters like loading spectrum, material geometry, and

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environment and then complex relationships. Wallace and Hoeppner (1985) 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, Jstars) and in transport aircraft fuselage that is subjected to corrosion damage. Corrosion in lap joints has many effects including material loss, pillowing stresses, pillowing cracks, rivet failures and interactions with fatigue, among others. Fatigue may interact with corrosion in the lap joints, and their combined effect is not completely understood. In order to estimate the effect of corrosion damage for structural analysis, the material loss information alone is not sufficient. Advanced structural integrity models require quantitative information in the form of metrics either direct or indirect of corrosion damage. The metrics for corrosion damage structural analysis may include corrosion morphology, crack size and location, and rivet condition (Kinzie and Peeler, 1999).

After damage has been detected and quantified, it may be necessary to prevent further growth and subsequent catastrophic failure. This is accomplished by fracture mechanics analysis and repair considerations for structural integrity. Considerable efforts have also been devoted to studying widespread fatigue damage behavior and its effects on structural integrity (Smith, Hijazi, Haque, and Mysore, 1999). Material degradation as a result of widespread fatigue damage, is quantified in terms of reduction in strength, fracture toughness and fatigue life. There is a vast amount of literature on damage detection using various techniques. However, only a focused review of the literature on multi-site damage problems in aging aircraft is presented here. Several approaches have been used to estimate the residual strength of aircraft panels with multisite damage (Swift, 1993; Wang, Chow, Kawai and Atluri, 1998; Moukawsher, Heinemann, and Grandt Jr., 1996; Smith, Perry, Saville, Adil Mouak, Myose, 2000). Swift (1993) developed an analytical method to determine the residual strength of a panel based on yield stress method. Fracture mechanics techniques also have been used to predict the residual strength of panels with multisite damage (Actis and Szabo, 1992; Atluri and Tong, 1991). Several techniques have also been proposed for establishing widespread fatigue damage (WFD) stress intensity factors, for example, finite element or boundary element methods, super convergent and compounding methods (Actis and Szabo, 1992; Atluri and Tong, 1991; Wang and Atluri, 1996). Several authors (Sivam and Ochoa, 1999; Howard and Mitchell, 1995) have developed methods for identifying and evaluating the effects of corrosion on aircraft. Scheuring and Grandt (1995) have evaluated aging aircraft materials for their mechanical and fatigue behavior. Recently, Horst (2005) developed Monte-Carlo simulations and Wavelet transforms methods to assess multisite damage problems in aging aircraft. A comprehensive review of methodology for structural integrity assessment has been carried out by Atluri (1997).

Assessing the structural integrity of many aerospace engineering structures which are approaching or exceeding their design life becomes increasingly important in determining their load carrying capacity, serviceability and safety. Structural health, or equivalently the state of damage, is directly related to the structural performance and hence has been singled out as a governing parameter with regard to safety of operation (Bartelds, 1998). Structural health of a structure can be established either directly, where one checks for the damage type under consideration such as corrosion, cracks, etc., by applying appropriate inspection techniques, or indirectly, where the effect of certain damage on the structural response characteristic is known. Obviously in both the direct and indirect approaches, the sensitivity and reliability of inspections are important quantitative performance measures. They are determined, on one hand by the laws of physics, but on the other hand, in practice also by the hardware and software quality of the inspection equipment, as well as by the equipment operator/inspector.

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 till 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, structural health can be achieved by usage monitoring (Bartelds, 1998). Maintenance and repair of the structure will be easier if maximum allowable values of the damage parameters can be obtained so that the physical health of the structure does not affect the performance

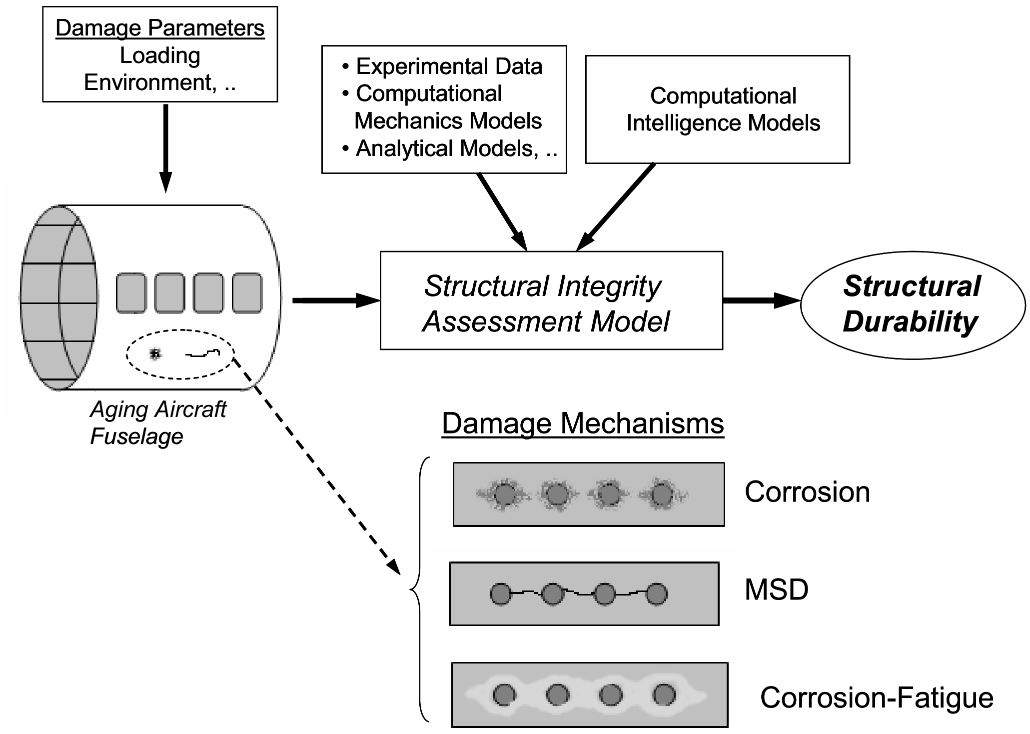


Figure 1 : Schematic of the structural integrity assessment model to estimate structural durability in aging aerospace structures

considerably.

This paper provides an overview of the computational intelligence methods developed for the structural integrity assessment of aging aircraft structures. Computational intelligence techniques studied include artificial neural networks (Russel and Norvig, 1995; Bryson and Ho, 1969), inverse neural network mapping (Pidaparti, Jayanti, Palakal, and Mukhopadhyay, 2003) , wavelet based image processing methods (Umbaugh, 1998), particle swarm optimization (Reynolds, 1994; Eberhart and Kennedy, 1995), genetic algorithms (Mares and Surace, 1996; Friswell, Penny, Garvey, 1998), and spectral element methods (Nag, Mahapatra, and Gopalakrishnan, 2002; Nag, Mahapatra, and Gopalakrishnan, 2002). Estimating the severity of multi-site damage, corrosion damage, and corrosion-fatigue damage in aging aircraft is specifically discussed using these methods. Results obtained from selected computational intelligence methods are compared to the existing alternate solutions and experimental data for corrosion damage, multi-site damage, and corrosion-fatigue damage problems.

2 Structural Integrity Assessment Model

The overall goal of our research is to develop a structural integrity assessment model/system to quantify the damage due to different sources in aging structures, to estimate the severity of the quantified damage, and integrate the developments into an intelligent system so that it can be used to empirically predict fatigue failure and fatigue life of aging materials and structures. Given the different damage parameters for a structure, the goal is to estimate a unique parameter, called a safety index that gives an indication of the safety or reliability of the structure. Figure 1 shows the schematic of a framework for the structural integrity assessment model for predicting the structural durability of an aged structure due to multiple damage mechanisms resulting from corrosion, fatigue, creep and others. A multi-disciplinary approach consisting of materials, damage/fracture mechanics, artificial intelligence, computer vision, pattern recognition techniques, and engineering optimization is being pursued to assess the structural integrity due to damage in aging structures. Figure 2 shows an overview of the damage types in aging aircraft considered and the corresponding computational intelligence techniques used to

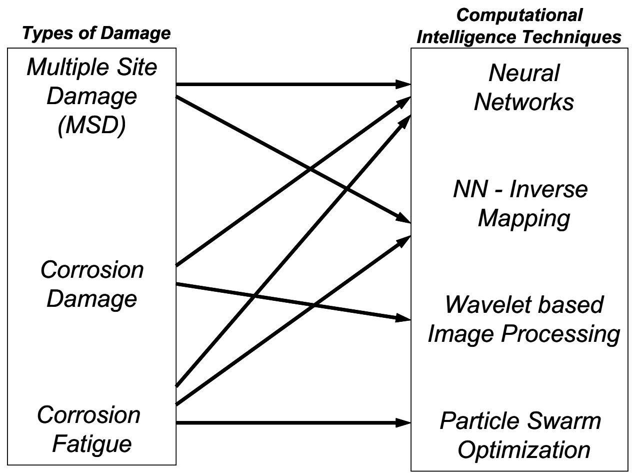


Figure 2 : Overview of the damage types in aging aircraft and the corresponding computational intelligence techniques used to estimate the structural integrity

estimate the structural integrity. Computational intelligence methods based on neural networks, inverse mapping, image processing, and particle swarm optimization are developed to predict the residual strength, material loss due to corrosion, and fatigue life of aging aircraft panels. Thus, the computational intelligence methods can be used to estimate the extent of damage and also its severity. The intelligent system and the associated developments are being validated through a series of carefully selected problems from aging aircraft structures. This paper discusses some of the developments to date and the progress of the proposed intelligent computations to assess the extent of structural damage in aging aircraft structures and materials.

3 Assessment Of Multi-Site Damage (MSD)

Presence of loaded holes in an aircraft structure causes high stress concentration near the edges of the holes, which in turn, facilitates crack formation at the edges. These small cracks slowly grow to coalesce with adjacent cracks and form a continuous crack referred to as the lead (or center) crack spanning a few rivet holes. This sort of crack formation at various sites of the structure is called Multiple Site Damage (MSD) and is very detrimental to structural integrity. Panels with MSD in addition to the lead cracks may exhibit a further loss in strength, especially, in panels made of ductile materials, like 2024-T3 aluminum (Smith, Hijazi, Haque, and Mysore, 1999). Corrosion exacerbates the effects of the stress and fatigue not only when corrosion occurs simultaneously but also as a result of pre-existing corrosion (Koch, 1995). Scheuring and Grandt (1995) have shown that fatigue life and fatigue crack growth rate of aircraft aluminum are adversely affected by pre-existing corrosion. Hence, the presence of MSD along with corrosion needs to be considered for more accurately predicting the structural integrity of the MSD panels as shown in Fig. 3. As these two phenomena act together to cause damage to the structure, the designer has to take into account both the effects together instead of treating them separately. The neural network approach (Russell and Norvig, 1995) is capable of predicting the desired values of residual strength and corrosion parameters, due to two independent effects.

The objective of the neural network approach is to predict the residual strength and corrosion properties of aircraft aluminum panels with MSD. A multi-layer, feed-forward neural network, with back-propagation learning algorithm (Bryson and Ho, 1969), is developed (Pidaparti, Jayanti and Palakal, 2002). The input parameters used for network can be divided into three categories as shown in Figure 4. The parameters affecting only the residual strength of the MSD panel are panel width, number of holes, hole diameter, center crack length, average MSD crack length and material loss, while those affecting the corrosion rate and corrosion rating of the panel include the material type, corrosion environment type, yield strength, temperature and the duration of exposure. Yield strength and panel thickness are the two inputs that are common to both these phenomena. Figure 4 shows all the input parameters (total of 13) affecting the corro-

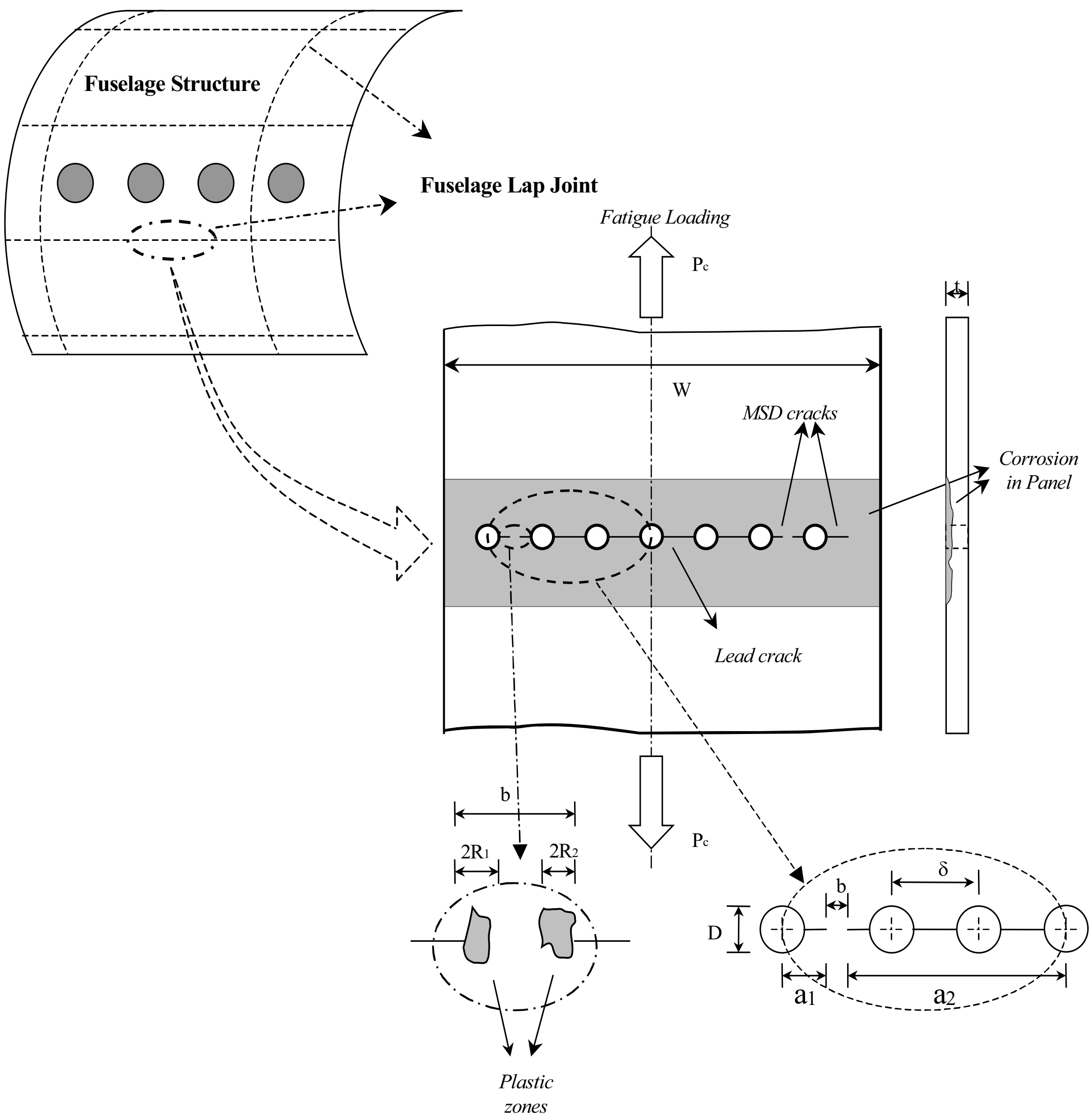


Figure 3 : Schematic showing the various damage parameters for aircraft fuselage panels with Multiple Site Damage (MSD) and corrosion

sion behavior and residual strength of MSD panels. All the parameters except material type designator and corrosion environment are continuous variables. Material type designator can take integer values from 1 to 4 depending on whether the material belongs to the 2xxx, 3xxx, 6xxx or 7xxx series of Aircraft Aluminum, respectively. Similarly, the corrosion environment can take integer values from 1 to 5, depending on the type of environment.

The data for training the NN was obtained from various sources in the literature (Smith, Hijazi, Haque, and Myose, 1999; Wang, Chow, Kawai, and Atluri, 1998; Moukawsher, Heinemann, and Grandt Jr., 1996; Smith, Perry, Saville, Mouak, and Myose, 2000; Sivam and Ochoa, 1999; Sheuring and Grandt Jr., 1995). Figure 5 shows the correlation between the neural network predictions and the experimental values of residual strength for the training set. A set of nine panels were set aside for testing the generality of the network and were therefore not included in the training data set for the neural network. The residual strength predictions for these panels using various methods are presented in Fig. 6. The NN predictions are compared with different analytical mod-

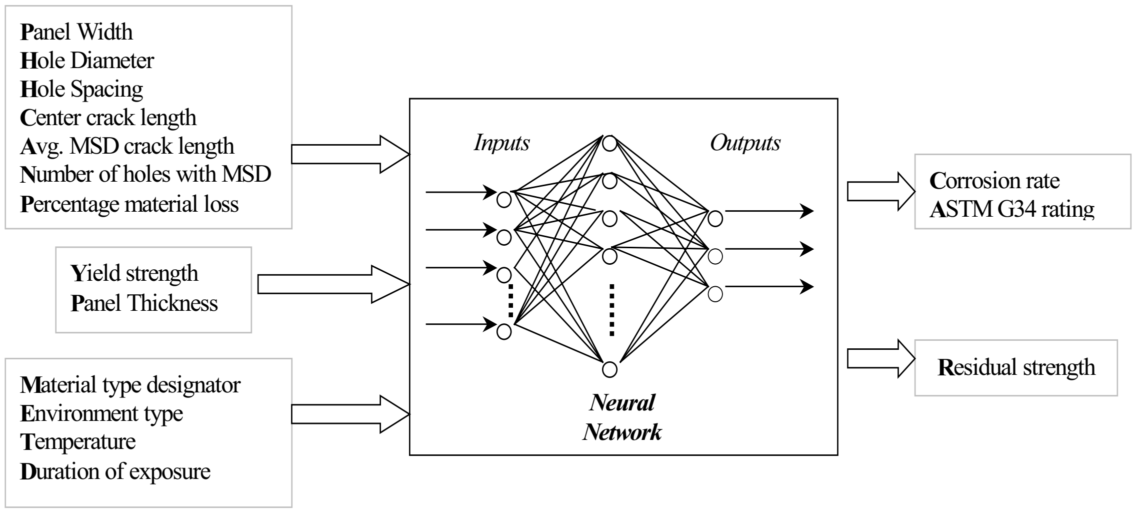


Figure 4 : A neural network model for predicting the residual strength and corrosion rating for a MSD panel in aging aircraft

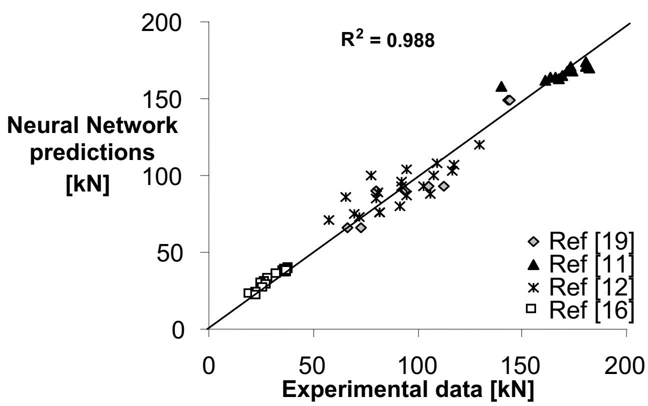


Figure 5 : Correlation of neural network predictions with experimental residual strength data during training

els along with the existing experimental data (Moukawsher, Heinemann, and Grandt Jr., 1996; Smith, Perry, Saville, Mouak, and Myose, 2000; and Sheuring and Grandt Jr., 1995). The average absolute error of prediction by the neural network method was less than 12% for all the test panels. However, the mean absolute error in the residual strength predicted by other analytical methods was as high as 50% for some panels. Overall predictions from neural network are consistently close to the experimental data. The neural network is able to predict fairly well the corrosion rate and the ASTM rating for the panels. In this study, the network model captures the corrosion phenomena fairly accurately as presented in Fig 6. Overall, the neural network predictions are reasonably close to the experimental values of residual strength and corrosion. Pidaparti and Palakal (1998 and 1995) developed an optimization NN to predict the fatigue crack growth in MSD panels in aging aircraft.

3.1 Sensitivity Analysis

A sensitivity analysis is carried out to observe which of the geometry, material and environmental parameters are important in affecting residual strength and corrosion rate. After the knowledge is captured through neural networks, an inverse mapping approach (Pidaparti, Jayanti, Palakal, and Mukhopadhyay, 2003) is used to obtain the sensitivity of various parameters. Table 1 ranks the importance of various parameters for residual strength and corrosion rate. It can be seen from Table 1 that lead crack-length and post-corrosion material are most important for residual strength where as the duration of exposure and yield strength of the material is important for corrosion rate. Based on the ranking results, it is obvious that it is very important to control/monitor the lead crack-length in MSD panels for structural integrity purposes. Also, if MSD panels are operating in a corrosive environment, post corrosion material existing in the panel is very important for the residual strength of MSD panels.

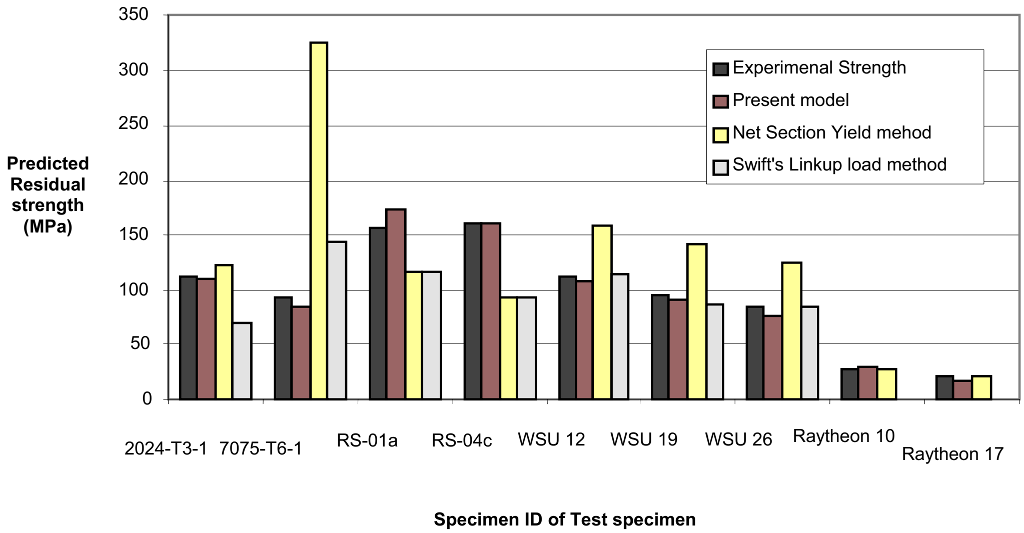


Figure 6 : Comparison of neural network predictions of residual strength for an aging aircraft MSD panel with other analytical methods and experimental data [11, 12, 18]

Table 1 : Ranking of various input parameters from sensitivity studies for MSD problem

Rank	*Residual Strength*	*Corrosion Rate*
1	Lead crack length	Duration of exposure
2	Post-corrosion material	Yield Strength
3	Average MSD crack length	Environment type
4	Yield strength	Center crack length
5	Hole spacing	Average MSD crack length

4 Assessment of Corrosion Damage

An approach for automatic corrosion identification and quantification based on NDI images is discussed in this paper. Also, a neural network method is developed to predict the residual strength and fatigue life of corroded panels based on the amount of material loss. The proposed methodology of corrosion identification and quantification gives an indication of the extent of damage, in terms of material loss, based on the images that are obtained using various NDI techniques such as eddy current, ultrasound, x-ray and others. Since visual inspection of the structure or the NDI images is a tedious and an unreliable task, an automatic method of detection and quantification would be of immense help to the material inspection personnel and would also raise safety standards. In this section, we discuss how to quantify the corrosion damage due to different NDI sources in aging structures/components and estimate the severity of the quantified damage using intelligent computational methods. Image analysis-based techniques are being developed for the identification and quantification of corrosion damage based on NDI techniques (acoustic imaging, infrared imaging, eddy current imaging, impedance imaging and X-ray radiography). The overall process of identification and quantification of corroded regions

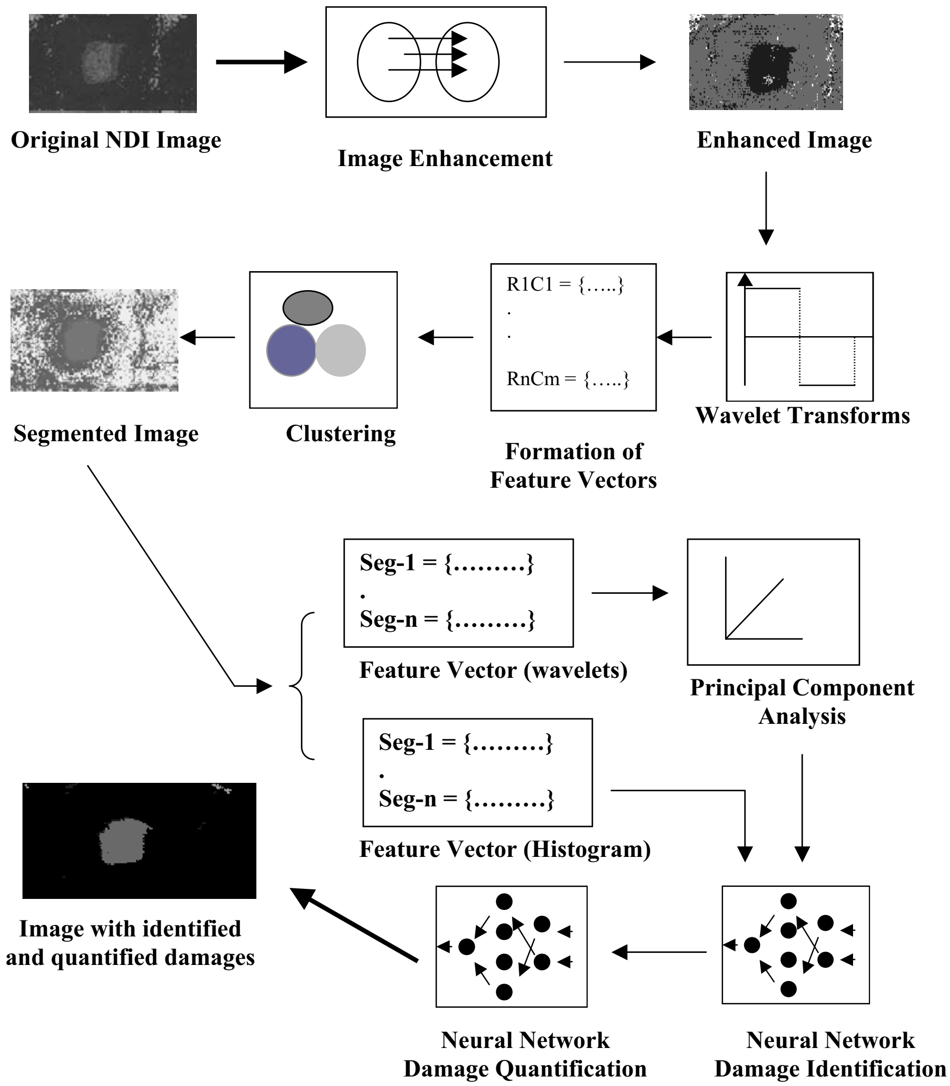


Figure 7 : Schematic representation of the process of identification and quantification of corrosion on a NDI images

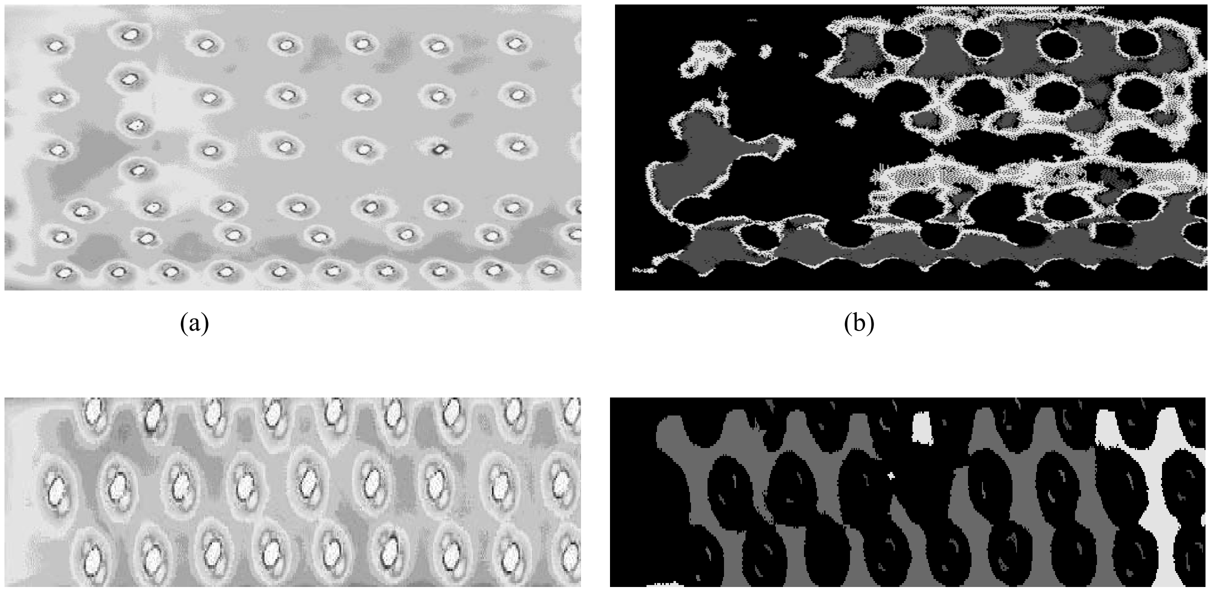
from NDI images is shown in Figure 7 (Palakal, Pidaparti, Rebbapragada, and Jones, 2001).

4.1 Corrosion Damage Identification

The images that are obtained through conventional NDI methods are not suitable for automatic identification of damaged regions. Therefore, the damage identification process involves three major steps: feature extraction, segmentation, and classification. Wavelet analysis techniques are used for feature extraction, a Clustering technique is used for segmentation, and a K-means distance-based method is used for damage classification. The classification process involves segmenting the image into various regions. Multi-resolution wavelet analysis is performed on the NDI images to obtain a set of wavelet coefficients as feature vectors. These features were used for the identification of the damaged regions on the NDI images using clustering techniques and neural networks. Each of the segments on the segmented image would correspond to a damaged region or an undamaged region (see Fig. 7).

4.2 Corrosion Damage Quantification

Once the damage regions are identified on the image, the next task is to quantify the damage. The extent of material loss is used to quantify the damage on the panels. Various features that are obtained on the corroded region based on histogram and/or wavelet analysis dur-



(a) (b) (c) (d)

Figure 8 : Corrosion damage assessment – experimental data obtained from the National Research Council of Canada (courtesy of Dr. Peeler of AFRL and Dr. Forsyth of NRC). The original damage panels (a) & (c) were obtained using Eddy Current at 12kHz. Images on right (b) & (d) are identified and quantified corroded regions obtained using the proposed techniques. The color index shows the material loss as, Black: 0%; Blue: 0% - 5%; Green: 5% - 10%; Yellow: 10% - 15%; Magenta: 15% - 20%; and Red: 20% - 25%.

ing the segmentation stage will be used to estimate the material loss. Once the damaged segments are identified, first-order and second-order features are extracted from each identified segment (Umbaugh, 1998). First order statistical features are computed using the histogram of the NDI images. These include *mean*, *standard deviation*, *skew*, *energy*, and *entropy*. The second order features such as *angular second moment*, *inverse second moment*, *entropy*, and *contrast* are calculated using a co-occurance matrix. The co-occurance matrix is an estimate of the second order joint probability density. A back-propagation NN is then used to quantify the damage.

To demonstrate the corrosion damage assessment approach, an aircraft corroded panel imaged using Eddy current NDI technique was used for corrosion damage identification and quantification. Figure 8 shows the original panel along with the quantified results of corroded panel using the approach presented earlier. The quantification of damage is based on the extent of material loss. For further results on material loss prediction, see (Palakal, Pidaparti, Rebbapragada, and Jones, 2001). Quantified information about the damage can be used for further analysis such as severity evaluation, prediction, repair guidance, and so on.

4.3 Correlation of Material Loss to Residual Strength and Fatigue Life

In order to estimate the effect of corrosion damage on structural integrity, the material loss information alone is not sufficient. We need to know the residual strength and fatigue life characteristics when an aircraft panel is corroded. Advanced structural integrity models require quantitative damage information for structural analysis. A neural network is developed to predict the residual strength and fatigue life of a corroded panel. Figure 9 shows the neural network predicted values of residual strength corresponding to a given material loss due to corrosion. The results of neural network model are compared to the experimental data obtained by Sivam and Ochoa (1999). It can be seen from Fig. 9 that a good agreement is found.

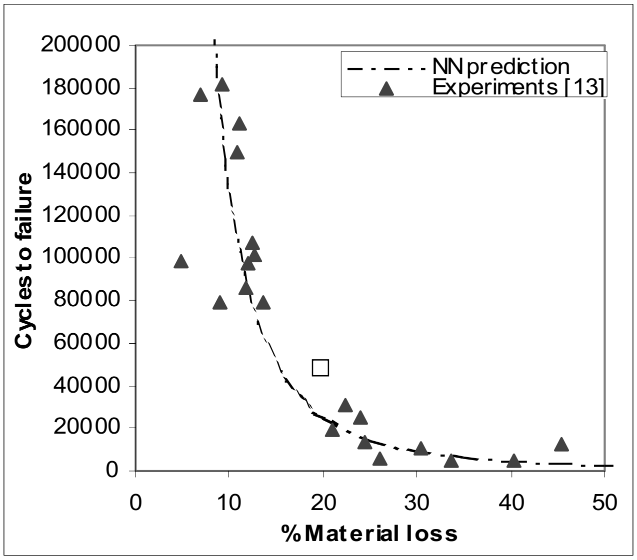


Figure 9 : Comparison of neural network predictions of fatigue life of corroded panels with experimental data [16]

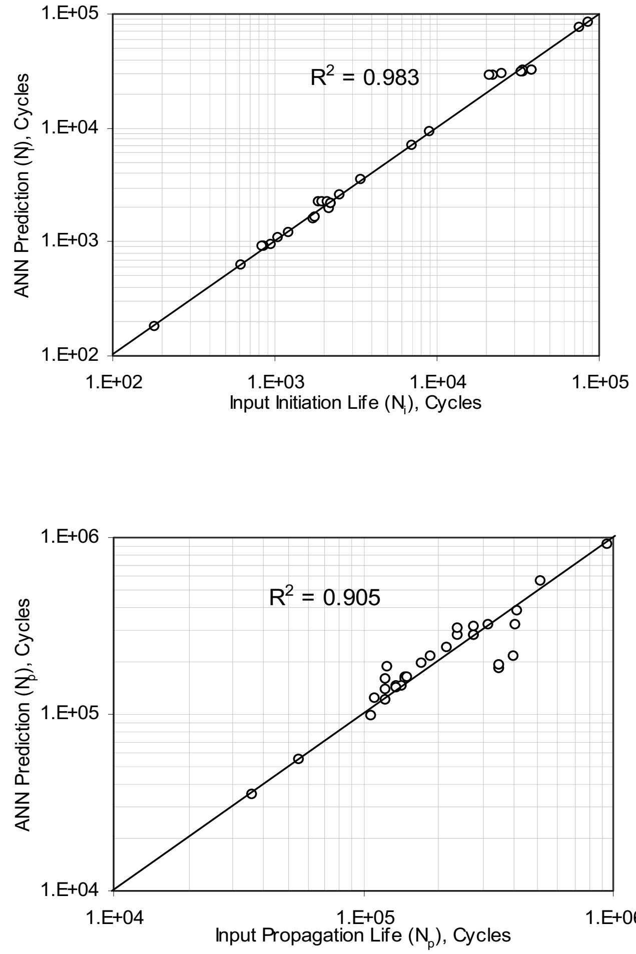


Figure 10 : (a) Comparison of initiation life for training set between NN prediction and the network input for initiation life; (b) Comparison of propagation life for training set between NN prediction and the network input for propagation life

5 Assessment of Corrosion – Fatigue Damage

To assess the structural integrity of aircraft panels subjected to corrosion-fatigue damage, a neural network (NN) methodology is developed to predict the initiation and propagation life. Since it is important to characterize both the initiation and propagation life separately, these two parameters were used as the outputs for the neural network (Pidaparti, Jayanti, Sowers, and Palakal, 2002). The most important factors that determine the life of the panels are the fatigue loading and corrosion properties. Fatigue loading is characterized by maximum stress amplitude ($\Delta\sigma$), stress ratio (R) and the frequency of loading (f). Apart from these parameters, environment plays a major role in the corrosion fatigue mechanism. Duration of exposure (D_{exp}) of the material to corrosive environment is considered in developing the neural model, for incorporating the effect of environmental conditions. Hence, these factors are chosen as part of the input parameters for neural networks developed in this study. In addition to the external parameters, geometry of the crack is also a very important factor for accurately modeling the corrosion fatigue mechanism. Corrosion-fatigue crack growth rates are strongly influenced not only by the specific combinations of cyclic loads, material and environment, but also by the crack size. Hence, the present model uses the critical pit size (a_{ci}), which is the pit size when a crack grows from a corrosion pit. The initial pit size (a_0) represents the material and manufacturing quality. The final crack size (a_f), before failure, (as defined by the user or the inspection criteria) is also used as one of the inputs. The final crack size is associated with the failure condition, the experimental termination condition, or the replacement or repair condition of the panel. However, in this study it represents the detectable crack size, which will help in the maintenance planning of the aging aircraft components.

The data for training the neural network was obtained from various studies published in the literature (Harlow and Wei, 1999; Rokhlin, Kim, Nagy, and Zoofan, 1999;

Table 2 : Comparison of fatigue life predictions from present NN model with experimental data

Case	*NN Prediction*	*Experimental Data*
Stress Amplitude, $\Delta\sigma$ = 180 MPa Duration of Exposure, D_{exp} = 192 Hrs Frequency, f = 10 Cycles/day Initial Pit Size, a_o = 0.125 mm Final Crack Size, a_f = 3 mm	184,237 cycles	198,659 cycles Ref. [34]
Stress Amplitude, $\Delta\sigma$ = 198 MPa Duration of Exposure, D_{exp} = 144 Hrs Frequency, f = 10 Cycles/day Initial Pit Size, a_o = 0.024 mm Final Crack Size, a_f = 3 mm	306,255 cycles	306,086 cycles Ref. [34]
Stress Amplitude, $\Delta\sigma$ = 206 MPa Duration of Exposure, D_{exp} = 72 Hrs Frequency, f = 15 Cycles/day Initial Pit Size, a_o = 0.0897 mm Final Crack Size, a_f = 3 mm	426,682 cycles	422,076 cycles Ref. [33]

Zamber and Hillberry, 1999). Since there was a lack of sufficient data quantifying the initiation and propagation lives separately, the analytical equations suggested by Wang, Pidaparti, and Palakal (2001) were used to complement the missing life data (either initiation or propagation life) for training. The rationale for using these equations is the fact, that these equations take into account the nucleation of the pit, while other analytical method do not consider the pit nucleation in the initiation life. Hence the neural network was trained with a total failure life same as the experimental values, but with an initial life as predicted by Wang, Pidaparti, and Palakal (2001).

The network converged to a target mean square error of 0.001 after 9660 epochs. The correlation of the predicted lives after training versus the lives predicted by the analytical equations as well as experiments is presented in Figure 10. Figures 10 (a) and (b) presents the comparisons for the NN predicted initiation and propagation lives respectively. Figures 10 (a) and (b) show the NN predicted results for the training set. In order to see how the trained NN can predict general cases, separate data sets were created for validation. The predictions of fatigue life from NN model for three representative cases are compared to the experimental data in Table 2. It can be seen from Table 2 that a good agreement is found between the neural network model and the experimental data from multiple sources for various changes in input conditions. A more detailed comparison of results can be found in Pidaparti, Jayanti, Sowers, and Palakal (2002). To show the generality of NN predictions, the effects of critical pit size and frequency of fatigue loading are presented next.

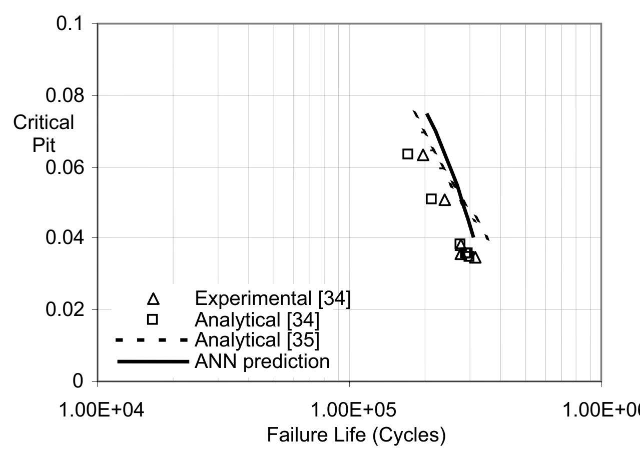


Figure 11 : Effect of critical pit size on the total failure life predicted by NN in comparison to analytical and experimental data

The critical pit size greatly affects the fatigue life. In

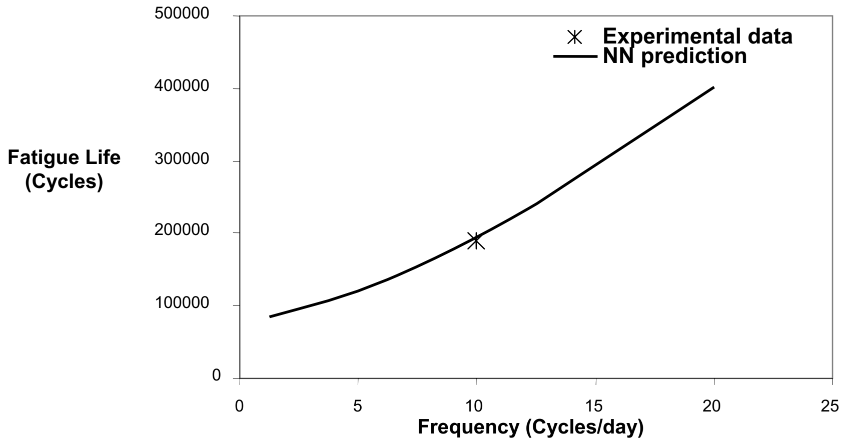


Figure 12 : Comparison of neural network predictions of fatigue life for an aging aircraft panel with experimental data

order to predict the fatigue life of an aircraft panel with given a pit size and a critical pit size, the predictions with varying critical pit size were obtained after training the network. Figure11 shows the NN predictions as a function of critical pit size. The simulations obtained from NN are also compared to those obtained by experimental data (Zamber and Hillberry, 1999) as well as analytical solutions (Wang, Pidaparti, and Palakal, 2001). It can be seen that a reasonably good agreement is found between NN predictions and the other data from the literature.

In order to predict the effect of varying frequency of fatigue loading on the fatigue life, a simulation was carried out where the frequency of loading varies from 1.25 to 20 cycles/day. Figure 12 presents the fatigue life as a function of the loading frequency. The other parameters for the specimen are $\Delta\sigma$g= 180MPa, R = 0.1,a_{ci} = 0.112mm, a_f = 3mm, a_0 = .001mm, while the duration of exposure (D_{exp}) is 144hrs. The cross mark in Fig. 12 indicates the experimental result for the case with the similar specimen but with a stress amplitude of 198MPa. It can be seen that NN predictions are again close to the experimental data.

5.1 Optimization of Fatigue Life

In the corrosion-fatigue damage optimization problem, we are trying to predict the damage parameters for maximum fatigue life, so that the damaged panel has maximum durability. It must however, be noted that due to the large number of parameters and uncertainty in corrosion-fatigue damage mechanism, the optimization algorithm is likely to converge to local minima at times. The objective of our approach is to obtain the different damage parameters that will give relatively high durability in terms of the fatigue life. Since it is difficult to control the external environment and loading, obtaining the global maximum value of fatigue life may not be of practical use. Obtaining different combinations of the damage parameters giving relatively higher fatigue lives (local maxima), might be of interest for aiding the maintenance of the structure. In this study, the primary goal for using the Particle Swarm Optimization (PSO) technique is not to obtain the global optimum, but to explore the possible failure conditions and the interaction of the damage parameters, so as to control the damage or repair it at the earliest. Since it is difficult to control all the damage parameters for an existing structure (e.g. temperature, yield strength of the material, etc.), this method can give an insight into other parameters that can be controlled (diameter of rivet holes, pitch, etc.), so as to have predetermined reliability characteristics.

The previously developed neural network model for corrosion fatigue (Pidaparti, Jayanti, Sowers, and Palakal, 2002) was used in the PSO algorithm to provide the initiation and propagation lives (Dowling, 1993), which constitute the fitness function. The initial fitness function for corrosion fatigue problem is as follows:

$$f = \alpha_1(\text{Initiation Life}) + \alpha_2(\text{Propagation Life}) \qquad (1)$$

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 incorporating the penalty, the new fitness function is given by,

$$f_n = \frac{1}{f} + \kappa p \tag{2}$$

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. It is worth noting here, 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 the inputs have a similar effect in determining the penalty. This is very important since 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, while those for stress amplitude and duration of exposure are in 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 the individual penalties are amplified by suitable factors so as to have the same order of magnitude as the others. The factor κ, in Equation (2) 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. 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 found in Ref. (Pidaparti and Jayanti, 2003).

PSO Algorithm

Particle Swarm Optimization (PSO), is related to cultural algorithms (Reynolds, 1994), and is similar to evolutionary programming (Eberhart and Kennedy, 1995). Each particle in PSO is treated as a point in an N-dimensional (input) space. The ith particle (individual) is represented as $X_I = (x_{i1}, x_{i2}, x_{iN})$, where x_{i1}, x_{i2}, …etc., 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 characteristics which are 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, while 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 the particles in the population is represented by the symbol 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 (Eberhart and Kennedy, 1995):

$$\begin{aligned} V_{in} &= w * v_{in} + c_1 * rand() * (p_{in} - x_{in}) \\ &\quad + c_2 * Rand() * (p_{gn} - x_{in}) \end{aligned} \tag{3}$$

$$x_{in} = x_{in} + v_{in}$$

where c_1 and c_2 are two positive constants, rand () and Rand () are two random functions in the range [0,1], and w is the inertia weight. The above equation is used to calculate the particles new velocity according to its previous velocity and the distances of its current position from its own best experience (previous best position) and the group's best experience. This process of updating the positions of the particles to get the optimum position is done until a specified number of iterations. At the end of the final iteration, it is assumed that all the particles have converged or are close to a single position in the input space where the fitness function has a global optimum.

Simulations

We predicted the various damage parameters for an aircraft panel under corrosion-fatigue environment using the particle swarm optimization approach discussed above. After making the necessary adjustments in the constraints and fitness functions, 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

Inertia Weight, w = 0.329

Table 3 : Prediction of input conditions for a given corrosion fatigue life (initiation and propagation lives) through particle swarm optimization

Fitness Function (f)	*Predicted input parameters*
$f = 0.9N_i + 0.1N_p$	Stress Amplitude, $\Delta\sigma$ = 233 MPa Duration of Exposure, D_{exp} = 285 Hrs Stress Ratio, R = -0.780 Frequency, f = 5.226 Hz Initial Pit Size, a_o = 0.014 mm Final Crack Size, a_f = 17.644 mm
$f = 0.5N_i + 0.5N_p$	Stress Amplitude, $\Delta\sigma$ = 176 MPa Duration of Exposure, D_{exp} = 202 Hrs Stress Ratio, R = 0.800 Frequency, f = 4.982 Hz Initial Pit Size, a_o = 0.00291 mm Final Crack Size, a_f = 15.548 mm
$f = 0.1N_i + 0.9N_p$	Stress Amplitude, $\Delta\sigma$ = 218 MPa Duration of Exposure, D_{exp} = 395 Hrs Stress Ratio, R = 0.152 Frequency, f = 8.374 Hz Initial Pit Size, a_o = 0.013 mm Final Crack Size, a_f = 4.062 mm

The factor for the penalty function, k was set to 0.001, so that both the terms on Equation (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.

Three sets of simulations were performed with different fitness functions for the problem of corrosion-fatigue damage. The results of input parameters obtained from the particle swarm optimization are summarized in Table 3. The first simulation corresponds to a function given by: f = *0.9* $N_i + 0.1N_p$ which represents maximum fatigue initiation life. This simulation yielded a maximum initiation life of 4.99 x 10^{10} cycles. It can be seen from Table 3 that in order to have a maximum initiation life, the final crack size is around 17.644 mm. The second set of simulation corresponds to a fitness function given by: $f = 0.5N_i + 0.5N_p$. This case corresponds to having equal importance in initiation life and propagation life. This simulation yielded both initiation and propagations lifes to be of the order of 4.25 x 10^{11} cycles. It can be seen from Table 4 that the predicted parameters can be easily inferred which leads to a smaller propagation life, if other factors were ignored in calculating the fatigue lives. However, in principle, a smaller stress ratio, a smaller stress amplitude and shorter duration of exposure, coupled with high frequency loading, may increase the fatigue life of the structure (Dowling, 1993). Cases 1 and 2 presented in Table 3 clearly show this phenomena, thereby further reinforcing the proposition that the neural network model has correctly captured the inherent physical process of the corrosion-fatigue damage mechanism. The third simulation corresponds to a case for maximum propagation life. The fitness function in this case is given by: f = *0.1* $N_i + 0.9N_p$. This simulation yielded a maximum propagation life of 4.99 x 10 ^{10} cycles. It can be seen from Table 4 that the final crack size is around 4.062 mm, and they are larger values of stress amplitude and duration of exposure. It can be seen from Table 3 that PSO may provide a set of parameters for a given fitness function, thus illustrating that a proper combination may be useful for controlling the structural integrity of an aging aircraft. More examples related to corrosion-fatigue optimization can be found in Pidaparti and Jayanti (2003).

6 Summary

The computational intelligence methods developed for the structural integrity assessment of aging aircraft structures are summarized in this paper. The computational intelligence techniques include artificial neural networks, inverse neural network mapping, wavelet based image processing methods, particle swarm optimization, genetic algorithms, and spectral element methods. The specific damage types considered include multi-site damage, corrosion, and corrosion-fatigue damage. The results obtained from the computational intelligence methods compared reasonably well to the existing alternate solutions and experimental data. From a practical point of view, the developed framework for estimating the structural integrity using computational intelligence methodology has advantages and limitations. For example, trained neural networks from various data sources (experimental data, analytical and computational methods) can generalize various damage phenomena and can predict reasonably well the structural integrity for some general cases. However, it should be kept in mind that the neural network training data should include some extreme or unprobable cases so that the knowledge about the phenomena is captured for general predictions. Shyur, Luxhoj, and Williams (1996) used neural networks to predict component inspection requirements for aging aircraft and compared to multiple regression models and concluded that neural networks offer a promising technology.

The computational intelligence methods discussed are part of an intelligent structural damage assessment system (ISDAS) being developed for the purpose of estimating the structural integrity of aging aircraft panels with multiple damage mechanisms. The ISDAS program uses analytical/neural network solutions to predict the residual strength, fatigue crack-initiation, fatigue crack-growth, and fatigue life based on several user-defined failure criteria. Currently, this system is being extended to include an optimization method to determine the safety index of an aged structure.

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