JOURNAL OF AIRCRAFT
Vol. 39, No. 1, January–February 2002

Residual Strength and Corrosion Rate Predictions of Aging Aircraft Panels: Neural Network Study

R. M. Pidaparti,* S. Jayanti,† and M. J. Palakal‡
Indiana University–Purdue University at Indianapolis, Indianapolis, Indiana 46202

The strength of an aging aircraft component deteriorates mainly as a result of corrosion and fatigue damage, among other failure mechanisms. Corrosion causes loss of material thickness, and the fatigue reduces the strength as a result of damage at multiple sites in aging aircraft. This paper presents a neural network study of both residual strength and corrosion of aging aircraft panels. The results obtained from the neural network model are compared to the analytical and experimental data available in the literature. The results obtained indicate that the neural network model predictions are in good agreement with the experimental data. To demonstrate the utility of neural network, several simulations are carried out to predict the trends with varying input parameters.

Nomenclature

a_1	=	MSD crack length measured from center of hole
a_2	=	half-crack length of lead crack
b	=	ligament length
d	=	average diameter of the hole
L	=	average MSD crack length measured from hole edge
n	=	number of holes with MSD cracks
P_c	=	critical load
R	=	hole radius $= d/2$
t	=	specimen thickness
W	=	specimen width
δ	=	hole spacing

I. Introduction

THE strength of an aging aircraft component deteriorates mainly as a result of corrosion and fatigue damage, among other failure mechanisms. Corrosion is caused by the environmental conditions under which the aircraft is operated and maintained. However, fatigue damage is caused by the physical operating conditions of the aircraft. These two phenomena can act individually, sequentially, or simultaneously. Corrosion causes loss of material, thereby reducing the net load carrying section (net thickness), and fatigue damage accumulates in the form of small-scale cracking at various places of high stress concentrations, such as rivet holes or notches. This type of damage is commonly referred to as multiple site damage (MSD). 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 (see Fig. 1).

Panels with MSD in addition to lead cracks may exhibit a further loss in strength, especially panels of ductile materials such as 2024-T3 aluminum.[1] Corrosion exacerbates the effects of the stress and fatigue, not only when corrosion occurs simultaneously, but also as a result of preexisting corrosion.[2] Scheuring and Grandt[3] have shown that fatigue life and fatigue crack growth rate of aircraft aluminum are adversely affected by preexisting corrosion. Hence, the presence of MSD along with corrosion needs to be considered to more accurately predict the structural integrity of the MSD panels.

Traditionally, various methods have been used for predicting the residual strength of MSD panels. One method is through experiments on test panels under uncorroded[4–6] and precorroded[4,5,7] conditions. The other method is by using the analytical methods incorporating the elastic and elastic-plastic fracture mechanics approaches.[1,5,6] The finite element method is the third type of method commonly used to predict the residual strength of MSD panels.[4,8–10]

Until recently, the additional loss in strength caused by MSD was often ignored in analytical methods. The net section yield method does not take this aspect into consideration. To explain this phenomenon, Swift[11] described an analytical model commonly known as the linkup model (also known as plastic-zone-touch model). This model takes into account the plastic zone formed in front of the crack tip due to strong stress riser effects of the cracks (Fig. 1). Failure (or linkup) load is the load at which the plastic zones from adjacent cracks touch each other. The linkup model clearly shows an additional loss in strength from MSD. However, it does not accurately predict the magnitude of the loss for many geometric configurations.[1] A few modifications to the linkup model have since been proposed, through empirical analysis, by Smith et al.[1,6] and have been shown to work well for a variety of geometric configurations.

Most of the analytical methods developed to predict the residual strength of corroded MSD panels do not include the material loss/rate information. Instead, they modify the thickness to predict the residual strength of MSD panels. Because various factors affect the residual strength and corrosion rates, the neural network approach is used in this study to complement the existing methods. Neural networks have been shown to accurately model various types of physical phenomena.[12–15] A single neural network model that will predict residual strength and corrosion rate of corroded MSD panels is developed in this study. The results obtained from the neural network are compared with other analytical models in relation to the experimental data as described in the following sections.

II. Residual Strength Methods Used for Comparison

The residual strength is the maximum load an MSD panel can handle before failure occurs. This failure may be in terms of crack linkup or complete failure. Three analytical methods were used for comparison: The net section yield method, Swift's linkup load method, and the modified linkup models.[6] The analytical equations are presented in Secs. II.A to II.C for completeness.

A. Net Section Yield Method

To determine the residual strength of the panel, this method uses the net section stress that will cause failure. The residual strength is calculated as

Received 22 August 2000; revision received 5 February 2001; accepted for publication 9 February 2001.

*Professor, Department of Mechanical Engineering, Purdue School of Engineering and Technology. Associate Fellow AIAA.

†Graduate Student, Department of Mechanical Engineering, Purdue School of Engineering and Technology. Member AIAA.

‡Professor and Chair, Department of Computer and Information Science, Purdue School of Science.

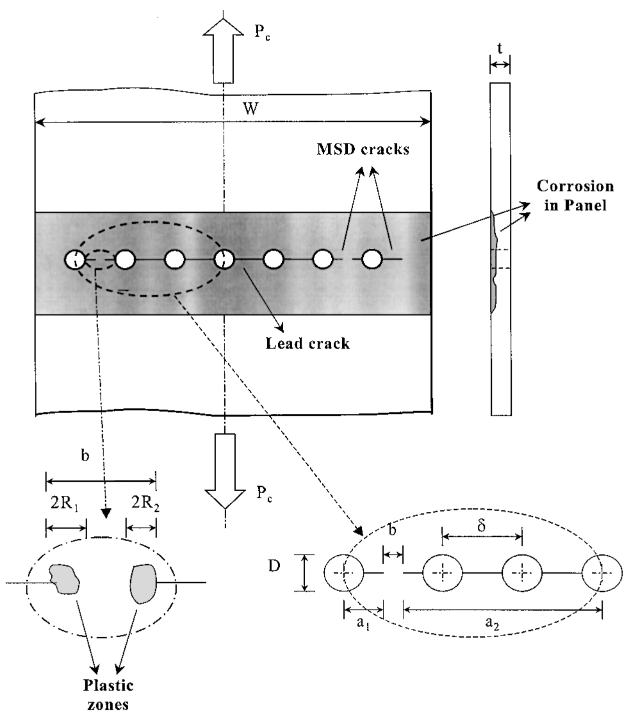


Fig. 1 Typical precorroded MSD panel configuration.

$$P_{c_{\text{net}}} = \sigma_{ys} t (W - 2a_2 - nd - 2nL) \tag{1}$$

B. Swift's Linkup Load Method

The residual strength in the Swift's method is determined from the following equation as

$$P_{c_{\text{swift}}} = \sigma_{ys} * t * W_{\text{net}} * \left[b \big/ \left\{ a_1 * \beta_h^2 * \beta_{I_1}^2 + a_2 * \beta_{I_2}^2 \right\} \right]^{\frac{1}{2}} \tag{2}$$

where σ_{ys} is the panel yield stress, r is the hole radius, and β_{I_1} and β_{I_2} are the crack correction factors[11]:

$$b = (n+1)/2 * \delta - (a_1 + d/2) - a_2 \tag{2a}$$

$$W_{\text{net}} = W - n * d - 2n * L \tag{2b}$$

$$\beta_h = [F_1/(F_2 + a_1/r) + F_3] \text{ with}$$

$$F_1 = 0.6865, \qquad F_2 = 0.2772, \qquad F_3 = 0.9439$$

C. Smith et al.[6] (WSU3) Method

Residual strength from the WSU3 formula developed by Smith et al.[6] is determined from the following equation as

$$\sigma_C = \sigma_{ys} / [C_3 \ln(a_2/b) + (C_4 + 1)] \tag{3}$$

where the empirically determined constants are $C_3 = -0.1806$ and $C_4 = 0.4791$.

III. Neural Network Approach

Neural networks are computational models that can obtain knowledge of a process by training with sample input and known output data. Back-propagation neural networks are very popular for approximating nonlinear relationships. These networks are one of several different kinds of neural networks and have been used successfully to model the behavior of engineering problems.

The characterization of corrosion behavior in aircraft materials is very complex. It is also very difficult to quantitatively evaluate the extent or nature of corrosion damage. In addition to these problems, aircraft materials are intended to be corrosion resistant. Although that is good for the aircraft, it creates difficulty because tests that are done in even the harshest aircraft environments can take several years to produce a specimen with significant corrosion. Correlation between accelerated corrosion tests and the actual environments experienced by aircraft are almost completely qualitative. These problems, along with residual strength prediction of MSD panels under corrosion environment, can be effectively addressed with a neural network approach.

Table 1 Input values corresponding to various corrosive environments

Environment type	Input value
Saturated hydrogen sulfide	1
Saturated carbon dioxide	2
Saturated sulfur dioxide	3
Aircraft carrier deck exposure	4
Modified ASTM B386 acetic acid salt fog test with pH = 2.5	5

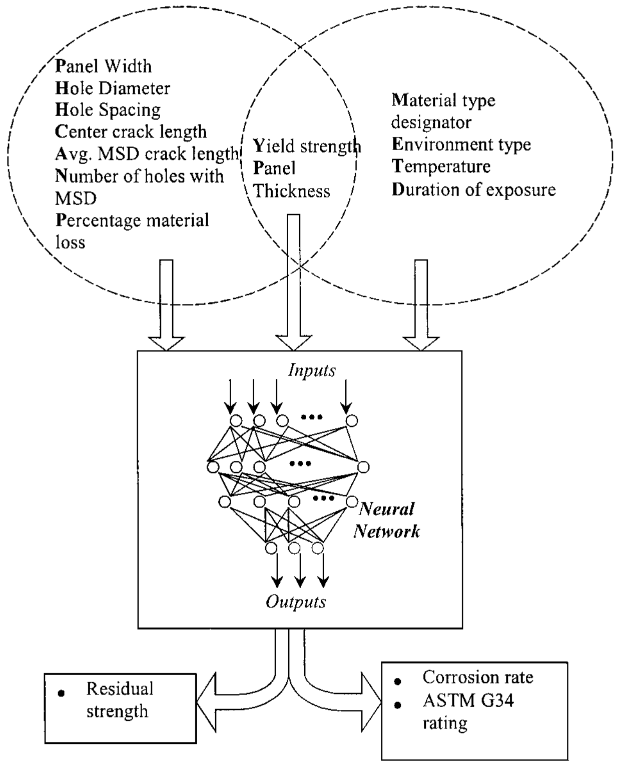


Fig. 2 Input/output parameters affecting strength and corrosion behavior of MSD panels in the neural network study.

A neural network model is developed for predicting the residual strength and corrosion parameters of MSD panels of aging aircraft. A multilayer, feed-forward neural network with a back-propagation learning algorithm was used in this study. Figure 2 shows the parameters affecting the corrosion behavior and residual strength of MSD panels. A total of 13 parameters as used to model both the phenomena. All the parameters except material type designator and corrosion environment are continuous variables. Material type designator can take integer values from one to four, 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 one to five, depending on the type of environment, as shown in Table 1.

The three output variables are the residual strength, the American Society for Testing and Materials (ASTM) G34 corrosion rating, and the material loss rate (expressed in cm/cm^2-days). It is important to note that the material loss rate is the thickness lost per unit area per elapsed days of exposure. The ASTM G34 ratings have been fuzzified to numeric values according to Table 2. The geometry of all the panels used for developing and testing the neural network model is presented in Table 3.

The data used for developing the neural network model were obtained from experiments reported in the literature. The data were

Table 2 Numerical conversion of ASTM G34 rating

Rating	Environment type	Input value
N	No appreciable attack	0
P	Pitting	0–0.2
EA	Superficial exfoliation	0.2–0.4
EB	Moderate exfoliation	0.4–0.6
EC	Severe exfoliation	0.6–0.8
ED	Very severe exfoliation	0.8–1.0

Table 3 Geometry of MSD panels used as training set

Reference/panel ID	Width (cm)	Thickness (cm)	Yield strength (MPa)	Hole spacing (cm)
(2024-T3)[a]	60.96	0.1575	275.82	2.54
(7075-T6)[a]	60.96	0.1575	441.28	2.54
[5] (all)	22.86	0.2286	374.39	1.905
WSU (10–12, 24–26)[b]	60.96	0.1600	310.27	2.54
WSU (13–23, 27–30)[b]	60.96	0.1600	275.80	2.54
[7] (all)	7.62	0.1600	310.04	7.62

[a]See Ref. 4. [b]See Ref. 6.

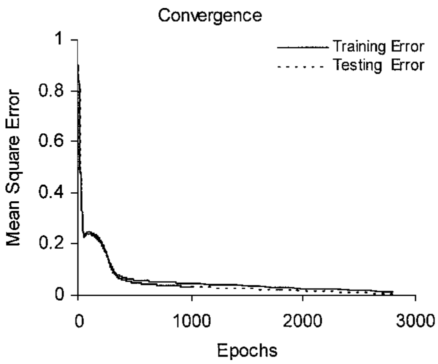


Fig. 3 Convergence of mean square error for the neural network.

taken from several sources, including Luzar,[4] Moukawsher et al.,[5] Smith et al.,[6] Sivam and Carl,[7] Tankins et al.,[16] and De Renzo.[17] A set of the data was set aside for testing the network for generality. To avoid a situation in which the network might memorize the training set instead of generalizing, a large set of data was generated from the original training dataset, using a random data generator.

The network chosen for this study consisted of two hidden layers of 25 and 10 neurons, respectively. The learning rate for the network was 0.01, and the momentum term was 0.9. The network converged to a targeted mean square error of 0.01 after 2805 epochs. The mean square error of the network while training as well as testing for the training set data is shown in Fig. 3. Although the testing error was initially lesser than the training error, it starts approaching the training error and may exceed the training error after a few epochs, thereby causing overtraining. Hence, training needs to be stopped once this situation arises. However, the target error of 0.01 was achieved before such a situation arose, thereby automatically stopping further training. After the neural network is trained, testing is carried out to see how the network performs under unknown conditions.

IV. Results and Discussion

The results of residual strength and material loss/rate obtained from the neural network model are compared to the existing analytical models and experimental data available in the literature. After the trained results were validated, sensitivity analysis of the neural network architecture and simulations were carried out to demonstrate the utility of the neural network model.

Table 4 Percent error in residual strength on the neural network training set from different methods

Reference	Number of panels	Net section yield method, Eq. (1)	Swift's linkup load, Eq. (2)	Modified linkup load,[a] Eq. (3)	Neural network
4	8	133.45	45.63	31.11	4.89
5	12	32.57	36.44	45.63	2.68
6	18	52.95	8.56	7.81	10.51
7	19	8.30	——	——	4.57

[a]See Ref. 6.

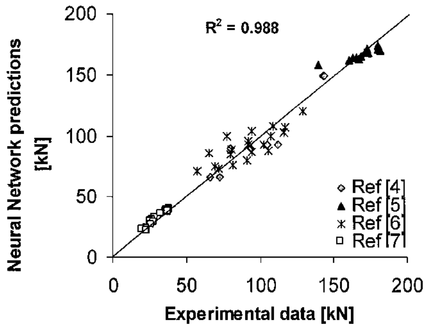


Fig. 4 Correlation of neural network predictions of residual strength compared to the experimental data.

A. Validation

The correlation coefficient for the neural network predictions of residual strength was high for both the training set (0.988) and the testing set (0.97). Table 4 presents the maximum error for different panels using various analytical methods and the neural network method as compared to the experimental data. It can be seen from Table 4 that the net section yield method does not predict the residual strength very well. The linkup model developed by Swift[11] predicts better than the net section method. The modified linkup models proposed by Smith et al.[6] further improve these predictions. The neural network model, developed in the present study, was able to train well and predicts the residual strength better than the analytical models for the training set. Figure 4 compares the predictions from the neural network with the experimental data for all the panels in the training set.

Table 5 presents the predictions from the different analytical models and the neural network models, along with the experimental data, for the testing set. Although the analytical methods predict better than the neural network model for a few panels, overall, the predictions from the 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. Figures 5a and 5b compare the corrosion rate and the ASTM rating predicted for the panels in the training set with the experimental data. As observed from these figures, the network model captures the corrosion phenomena fairly accurately.

B. Sensitivity Analysis

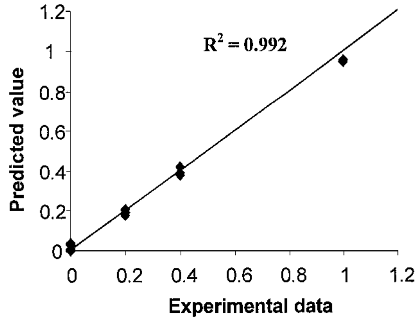
Different neural network models were considered for the sensitivity analysis in this study. In the first model, the total number of holes in the MSD panel was used as one of the inputs. However, this was redundant because it also includes the holes within the lead crack. Hence, only those holes with MSD were used for developing the final model.

The third output was originally chosen to be the cm/cm^2 of material lost. This was later factored by the duration of exposure because the range of the values for the material lost was several orders of magnitude in size, which caused problems while training.

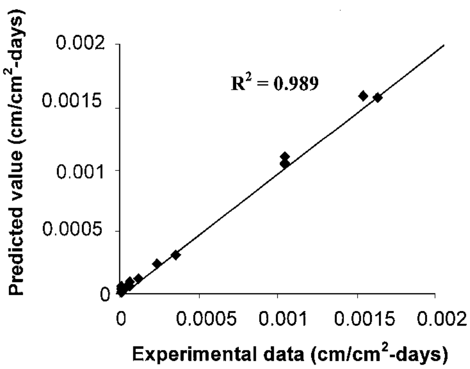
The network architecture is a very important factor in achieving the best model. Hence, different network architectures were tested, and the one with the higher correlation coefficient for the testing set,

Table 5 Prediction of residual strength for the testing set from various methods

Reference	Specimen ID	Experimental strength (kN)	Neural network model (kN)	Net section yield method (kN)	Swift's linkup load (kN)
4	2024-T3	112.23	109.11	123.52	69.78
4	7075-T6	92.73	86.22	325.74	143.96
3	RS-01a	156.72	173.29	115.99	116.05
3	RS-04c	160.94	159.58	93.76	93.12
6	WSU 12	112.18	107.65	158.62	114.04
6	WSU 19	94.94	92.54	141.80	87.15
6	WSU 26	83.70	76.37	124.99	85.42
2	10	27.59	30.00	28.83	——
2	17	20.06	16.77	21.80	——



a) ASTM G34 rating



b) Corrosion rate

Fig. 5 Comparison of neural network results of corrosion rate and rating against experimental data for the training set.

as well as the training set, was used. Initially, a large network was chosen for training. After the network was tested for proper training, the number of nodes was systematically reduced to achieve the right combination of hidden layers that can predict the outputs within an acceptable range of error. The initial architecture consisted of 32 neurons in the first hidden layer and 16 in the next layer. The final network has 25 nodes in the first hidden layer and 10 nodes in the next layer.

C. Simulations

To examine the generalization ability of the network in predicting the outputs for different conditions, two sets of simulations were done. The first set consisted of six simulations for ascertaining the effect of the geometric parameters affecting the residual strength. Each simulation tested the effect of a particular input parameter on the predictions for a particular panel. Specifically, the effect of material loss on the residual strength of Boeing 2024-T3-1[4] and RS-01b[5] panels, and the effect of varying hole diameter and MSD crack lengths on the residual strength of RS-01b[5] and Boeing 7075-T6-1[4] panels, were investigated. The results for all these simulations are presented in Figs. 6a–6f along with the values predicted by the three analytical methods. In these figures, $P_{c\text{net}}$ represents the critical load (in kN) predicted by the net section yield method, which is given by Eq. (1). Similarly, $P_{c\text{Swift}}$ and WSU3 represent the critical loads predicted by the Swift linkup method in Eq. (2) and the modified linkup load methods in Eq. (3), respectively. The critical loads predicted by the neural network are in fair agreement with the predictions of the linkup models for these simulations, and are also closed to the experimental data.

1. *Effect of Material Loss*

The effect of increasing corrosion on residual strength of the MSD panels is shown in Figs. 6a and 6b, which compare the analysis methods with test results from Moukawsher et al.[5] and Luzar,[4] respectively. As expected, the residual strength decreases as the material remaining after corrosion decreases. Luzar has shown that the strength in precorroded MSD panels can be predicted by simple accounting of corroded material loss for 2024-T3-clad materials. It can be seen from Figs. 6a and 6b that the analytical models, as well as the neural network model, are able to predict the strength quite close to the experimental data.

2. *Effect of Hole Diameter*

The effect of hole diameter on the residual strength of RS-01b[5] and Boeing 7075-T6-1[4] panels is shown in Figs. 6c and 6d, respectively. Other geometric parameters being constant, it can be seen from Figs. 6c and 6d that the increase in the hole diameter causes a decrease in the residual strength of the panel. The neural network model is able to capture this effect well and also predicts the strength close to the experimental data. The two linkup models are also close to the experimental data.

3. *Effect of MSD Crack Length*

The effect of MSD crack length on the residual strength of RS-01b[5] and Boeing 7075-T6-1[4] panels is presented in Figs. 6e and 6f. Although the neural model captures the trend properly for both the materials, the results using the WSU3 modified linkup model are close to the experimental values.

The second set of simulations was conducted to observe the effect of duration of exposure, material type, and corrosion environment on the corrosion behavior. Eight corroded panels were simulated in this set. The effect of the duration of exposure (about 800 days) to two environments (aircraft carrier and ASTM B386) on the corrosion behavior of 7XXX and 2XXX aluminum materials was predicted.

4. *Effect of Duration of Exposure*

The results of the corrosion rate for both 7XXX and 2XXX aircraft materials under the two corroded environments are shown in Figs. 7a–7d. It can be seen from Fig. 7a that the corrosion rate of 7XXX material decreases by 20.5%, compared with 36.6% in 2XXX material, after exposure to an aircraft carrier environment for 800 days. Similarly, in Fig. 7b, the ASTM rating value increases by 18.6% for 7XXX material, and it increases by 23.0% for 2XXX material. Similar trends are observed for these materials under the ASTM B386 environment in Figs. 7c and 7d. Although the corrosion rate of 7XXX material decreases by 2.7% after exposure for 800 days, it decreases by 12.4% in 2XXX material. After an

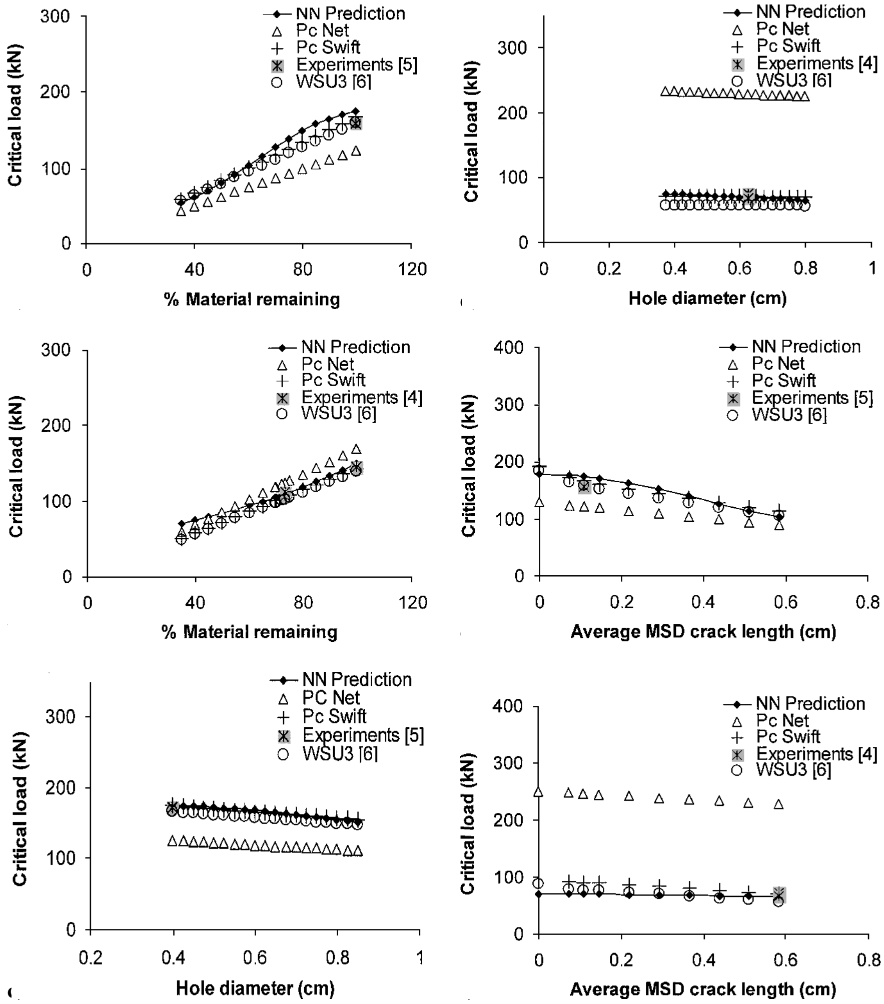


Fig. 6 Effect of various neural network simulations on residual strength prediction and comparisons: a) comparison of the critical load with experiments [5] for Rs-01b, b) comparison of the critical load with experiments [4] for 2024-T3-1, c) comparison of the critical load with experiments [5] for RS-01b, d) comparison of the critical load with experiments [4] for 7075-T6-1, e) comparison of the critical load with experiments [5] for Rs-01b, and f) comparison of the critical load with experiments [4] for 7075-T6-1.

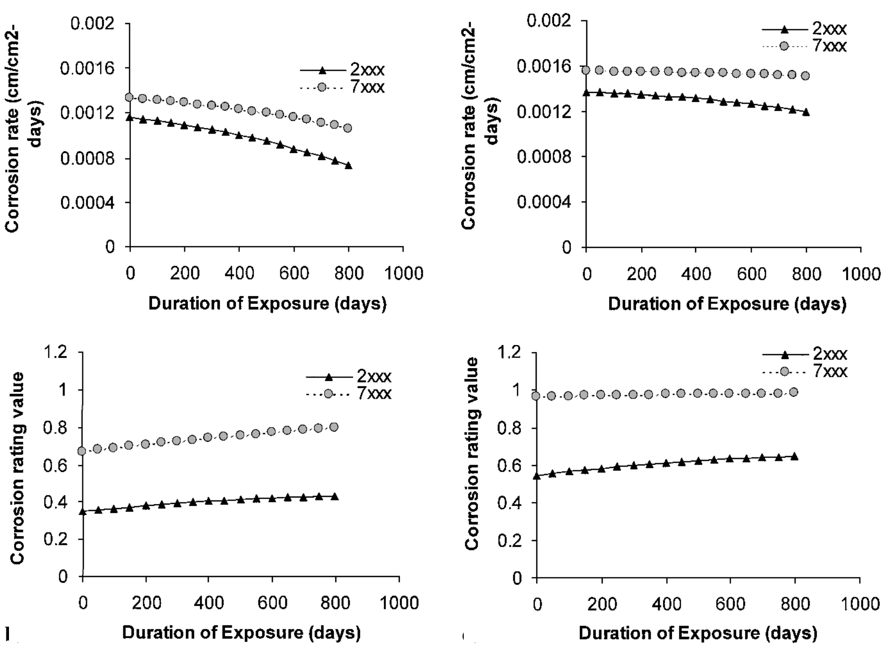


Fig. 7 Effect of various neural network simulations on corrosion behavior prediction: a) effect of aircraft carrier environment on the corrosion rate, b) effect of aircraft carrier environment on corrosion rating value, c) effect of ASTM B386 environment on the corrosion rate, and d) effect of ASTM B386 environment on the corrosion rating value.

exposure of 800 days, the ASTM rating value for 7XXX aluminum increases by 1.6%, and that for the 2XXX aluminum increases by 18.0%.

The results obtained from the neural network studies indicate that 7XXX aluminum deteriorates more than the 2XXX aluminum under both kinds of corrosive environments considered. However, in general, 2XXX aluminum has lower corrosion resistance capacity because of the presence of copper in the alloy.[18] Other factors, which need further investigation, may affect the corrosion resistance. Based on the results presented in Figs. 7c and 7d the ASTM B386 environment causes more deterioration than the aircraft carrier environment of the aluminum materials considered in this study.

V. Conclusions

A neural network study was carried out to investigate the residual strength and corrosion behavior of aging aircraft panels. The results obtained from the neural network are compared with the various analytical models and experimental data. The results obtained indicate that the modified linkup model[6] (WSU3) and the neural network are both effective models for predicting the residual strength of the MSD panels for a wide variety of configurations. Also, the neural network model developed in this study is able to predict the corrosion behavior of the MSD panels in addition to predicting the residual strength. Currently, the neural network model is being integrated with corrosion fatigue and crack-growth models to estimate the structural integrity of aging aircraft panels.

Acknowledgments

This research was sponsored by the National Science Foundation through Grant CMS-9812723. The authors also thank B. L. Smith of Wichita State University, Alten F. Grandt of Purdue University, Joseph Luzar of The Boeing Company, and T. P. Sivam of Raytheon Systems Company for the data and helpful discussions.

References

[1]Smith, B. L., Hijazi, A. L., Haque, A. K. M., and Myose, R. Y., "Modified Linkup Models for Determining the Strength of Stiffened Panels With Multiple Site Damage," *Proceedings of the FAA/NASA Symposium on the Continued Airworthiness of Aircraft Structures*, 1999, pp. 555–566.

[2]Koch, G. H., "On the Mechanisms of Interaction Between Corrosion and Fatigue Cracking in Aircraft Aluminum Alloys," *Structural Integrity of Aging Aircraft*, edited by C. I. Chang and C. T. Sun, AD-Vol. 47, American Society of Mechanical Engineers, 1995, pp. 159–169.

[3]Sheuring, J. N., and Grandt, A. F., Jr., "An Evaluation of Aging Aircraft Material Properties," *Structural Integrity of Aging Aircraft*, edited by C. I. Chang and C. T. Sun, AD-Vol. 47, American Society of Mechanical Engineers, 1995, pp. 99–110.

[4]Luzar, J., "Pre-corroded Fastener Hole Multiple Site Damage Testing," EA 96-135 TH-041, KC-135 Fleet Support Contract, F34601-96-C-0111, The Boeing Company, St. Louis, Missouri, Sept. 1998.

[5]Moukawsher, E. J., Heinemann M. B., and Grandt A. F., Jr., "Residual Strength of Panels with Multiple Site Damage," *Journal of Aircraft*, Vol. 33, No. 5, 1996, pp. 1014–1021.

[6]Smith, B. L., Saville, P. A., Mouak, A., and Myose, R. M., "Strength of 2024-T3 Aluminum Panels with Multiple Site Damage," *Journal of Aircraft*, Vol. 37, No. 2, 2000, pp. 325–331.

[7]Sivam, T. P., and Carl, M. O., "Aircraft Corrosion Inspection and Evaluation Technique Using Ultrasonic Scanning Methods," *2nd Joint DoD/NASA/FAA Aging Aircraft Conference*, Williamsburg, VA, Aug. 31–Sept. 3, 1999.

[8]Dawicke, D. S., "Residual Strength Prediction Using Crack Tip Opening Angle Criterion," *Proceedings of the FAA–NASA Symposium on the Continued Airworthiness of Aircraft Structures*, 1997, pp. 555–566.

[9]Wang, L., and Atluri, S. N., "Predictions of Stable Growth of Lead Crack and Multiple Site Damage Using Elastic-Plastic Finite Element Method (EPFEM) and Elastic-Plastic Finite Element Alternating Method (EPFEAM)," *Proceedings of the FAA–NASA Symposium on the Continued Airworthiness of Aircraft Structures*, Atlanta, GA, 1996, pp. 505–518.

[10]Wang, L., Chow, W. T., Kawai, H., and Atluri, S. N., "Residual Strength of Aging Aircraft with Multiple Site Damage/Multiple Element Damage," *AIAA Journal*, Vol. 36, No. 5, 1998, pp. 840–847.

[11]Swift, T., "Widespread Fatigue Damage Monitoring Issues and Concerns," *5th International Conference on Structural Airworthiness of New and Aging Aircraft*, 1993.

[12]Bailey, R. A., Pidaparti, R. M., and Palakal, M. J., "Corrosion Prediction in Aging Aircraft Materials," *Damage and Fracture Mechanics VI—Computer Aided Assessment and Control*, edited by A. P. S. Selvadurai and C. A. Brebbia, WIT Press, Southampton, 2000, pp. 587–600.

[13]Pidaparti, R. M. V., and Palakal, M. J., "Neural Network Approach to Fatigue-Crack-Growth Prediction Under Aircraft Spectrum Loading," *Journal of Aircraft*, Vol. 32, No. 4, 1995, pp. 825–831.

[14]Pidaparti, R. M. V., and Palakal, M. J., "Fatigue-Crack-Growth Predictions in Aging Aircraft Panels Using Optimization Neural Network," *AIAA Journal*, Vol. 36, No. 7, 1998, pp. 1300–1304.

[15]Seibi, A., and Al-Alawi, S. M., "Prediction of Fracture Toughness Using Artificial Neural Networks," *Engineering Fracture Mechanics*, Vol. 56, No. 3, 1997, pp. 311–319.

[16]Tankins, E., Koxol, J., and Lee, E. W., "The Shipboard Exposure Testing of Aircraft Materials," *Journal of Materials*, Vol. 47, No. 9, 1995, pp. 40–44.

[17]DeRenzo, D. J., *Corrosion Resistant Materials handbook*, 4th ed., Noyes Data Corporation, Park Ridge, N.J., 1985, p. 609.

[18]Philip, A. S., *Corrosion and Corrosion Protection Handbook*, Marcel Dekker, New York, 1989.