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PREDICTION OF FATIGUE CRACK GROWTH PROCESS VIA ARTIFICIAL NEURAL NETWORK TECHNIQUE

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Abstract: *Failure analysis and prevention are important to all of the engineering disciplines, especially for the aerospace industry. Aircraft accidents are remembered by the public because of the unusually high loss of life and broad extent of damage. In this paper, the artificial neural network (ANN) technique for the data processing of on-line fatigue crack growth monitoring is proposed after analyzing the general technique for fatigue crack growth data. A model for predicting the fatigue crack growth by ANN is presented, which does not need all kinds of materials and environment parameters, and only needs to measure the relation between a (length of crack) and N (cyclic times of loading) in-service. The feasibility of this model was verified by some examples. It makes up the inadequacy of data processing for current technique and on-line monitoring. Hence it has definite realistic meaning for engineering application.*

Keywords: *Artificial neural network; Fatigue crack growth; On-line monitoring.*

1. INTRODUCTION

In spite of decades of investigation, fatigue response of materials is yet to be fully understood. This is partially due to the complexity of loading at which two or more loading axes fluctuate with time. Examples of structures experiencing such complex loadings are automobile, aircraft, off-shores, railways and nuclear plants. Fluctuations of stress and/or strains are difficult to avoid in many practical engineering situations and are very important in design against fatigue failure. There is a worldwide need to rehabilitate civil infrastructure. New materials and methods are being broadly investigated to alleviate current problems and provide better and more reliable future services.

While most industrial failures involve fatigue, the assessment of the fatigue reliability of industrial components being subjected to various dynamic loading situations is one of the most difficult engineering problems. This is because material degradation processes due to fatigue depend upon material characteristics, component geometry, loading history and environmental conditions.

Fatigue is one of the most important problems of aircraft arising from their nature as multiple-component structures, subjected to random dynamic loads. The analysis of fatigue crack growth is one of the most important tasks in the design and life prediction of aircraft fatigue-sensitive structures (for instance, wing, fuselage) and their components (for instance, aileron or balancing flap as part of the wing panel, stringer, etc.).

An example of in-service cracking from B727 aircraft (year of manufacture 1981; flight hours not available; flight cycles 39,523) [1] is given on Fig.1.

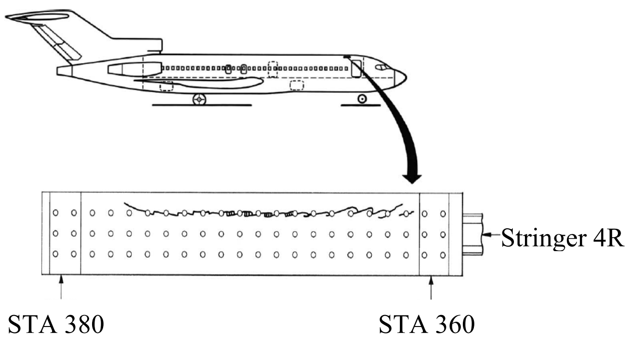


Fig. 1 – Example of in-service cracking from B727 aircraft.

A test program carried out at DSTO in the early 1970s involved the full-scale testing of a Mirage wing. Final failure and collapse of the wing occurred after 32,372 flights (31,230 simulated test flights plus 1142 pre-test equivalent flights) at a blind hole in the AU4SG aluminum alloy lower boom of the main spar. This crack surface was measured using QF [2]. A simple crack prediction was also carried out using a Paris growth law together with a look-up table of da/dN data and cycle-by-cycle addition, although with no retardation or closure allowances. The two curves are presented in Fig. 2. As can be seen the measured growth appears to be exponential, while the handbook solution is not. A picture of the fracture surface is also included. The hole from which the crack initiated was about 10 mm in diameter.

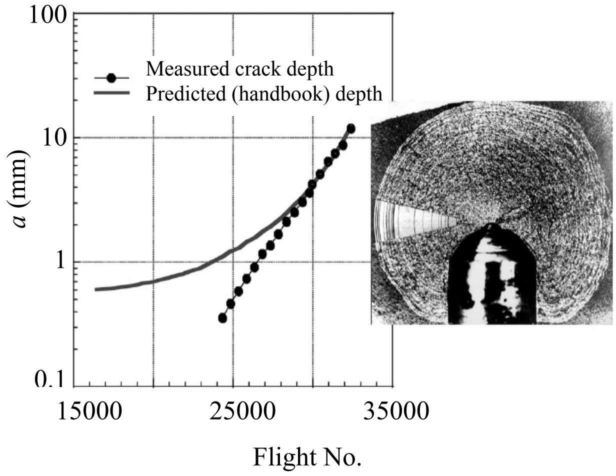


Fig. 2 – Crack growth in Mirage 1110 full-scale fatigue test wing.

Fatigue is a mechanism of crack growth. Fatigue cracks occur by cyclic loading under lower stress condition than the maximum allowable stress. The fatigue lifetime prediction of materials subject to fatigue crack propagation and the calculation of defect tolerance are related with the relationship between the crack's growth rate per cycle (da/dN) and the stress intensity factor range ΔK (Fig. 3).

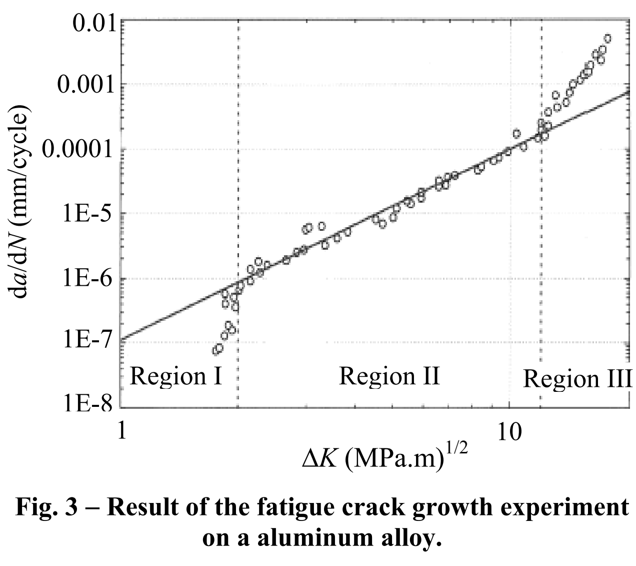


Fig. 3 – Result of the fatigue crack growth experiment on a aluminum alloy.

The fatigue crack growing process is classified in three regions according to the change of fatigue crack growth rate, da/dN (Fig. 3, where the result of the fatigue crack growth experiment on a aluminum alloy obtained by [3] is presented).

Region I is a state of crack initiation. The value of the stress intensity factor (K) is as low as the fatigue threshold (K_{th}), and the crack growth rate is very slow.

In region II, the crack growth rate increases according to the crack length. The crack growth condition in region II is the so-called stable crack growth.

In region III, the crack-growth rate quickly increases and failure of the material occurs. It is called unstable crack growth.

The boundary between regions II and III is the transition point (K_{Tr}) [4], and the stress intensity factor at failure is known as the fracture toughness (K_c).

The stress intensity factor defines the amplitude of the crack tip singularity and is a function of the applied nominal stress (σ), the crack length (a), and a geometric function (F) [5]:

$$K = F\sigma\sqrt{\pi a}. \quad (1)$$

In region I, in order to characterize the time-to-crack initiation (TTCI), X, it may be used the following probability density functions (PDF) [6]:

- Gaussian PDF:

$$g(x) = \frac{1}{\sigma\sqrt{2\pi}}\exp\left[-\frac{(x-\mu)^2}{2\sigma^2}\right],$$

$$x \in (-\infty,\infty),\ \mu \in (-\infty,\infty),\ \sigma > 0, \quad (2)$$

where μ and σ are the location and scale parameters, respectively;

- 2 parameters lognormal PDF:

$$l_2(x) = \frac{1}{x\sigma\sqrt{2\pi}}\exp\left[-\frac{(\ln x - \ln\vartheta)^2}{2\sigma^2}\right],$$

$$x > 0,\ \vartheta > 0,\ \sigma > 0, \quad (3)$$

where σ and ϑ are the shape and scale parameters, respectively.

- 3 parameters lognormal PDF:

$$l_3(x) = \frac{1}{\sigma\sqrt{2\pi}}\frac{1}{x-\gamma}\exp\left[-\frac{(\ln(x-\gamma) - \ln\vartheta)^2}{2\sigma^2}\right],$$

$$x > \gamma,\ \vartheta > 0,\ \sigma > 0,\ \gamma \in (-\infty,\infty), \quad (4)$$

where σ, ϑ and γ are the shape, scale and threshold parameters, respectively;

• 2 parameters Weibull PDF:

$$w_2(x) = \frac{\delta}{\beta}\left(\frac{x}{\beta}\right)^{\delta-1} \exp\left[-\left(\frac{x}{\beta}\right)^{\delta}\right],$$

$$x \geq 0, \beta > 0, \delta > 0, \quad (5)$$

where β and δ are the scale and shape parameters, respectively;

• 3 parameters Weibull PDF:

$$w_3(x) = \frac{\delta}{\beta}\left(\frac{x-\gamma}{\beta}\right)^{\delta-1} \exp\left[-\left(\frac{x-\gamma}{\beta}\right)^{\delta}\right],$$

$$x \geq \gamma, \beta > 0, \delta > 0, \gamma \in (-\infty, \infty), \quad (6)$$

where β, δ and γ are the scale, shape and threshold parameters, respectively.

From an engineering standpoint, crack initiation is considered to be one of the two major periods (I and II) in the fatigue life of a component or structure. The period of crack initiation or the time-to-crack initiation (TTCI) is defined as the time in cycles or flights or flight hours it takes for a non-detectable crack from the beginning of fatigue loading to grow to a reference crack size $a°$. The reference-crack-size is commonly selected on the basis of a detectable crack by the nondestructive inspection (NDI) technique. The TTCI distribution is physically observable and can be obtain by experiments and tests results. Fatigue crack initiation and early crack growth in a SENT specimen tested with the Fokker 100 Reduced Basic (RB) gust spectrum [7] is shown in Fig. 4. The spacings of the bands on the fracture surface above the fatigue origin correspond to blocks of 5000 flights.

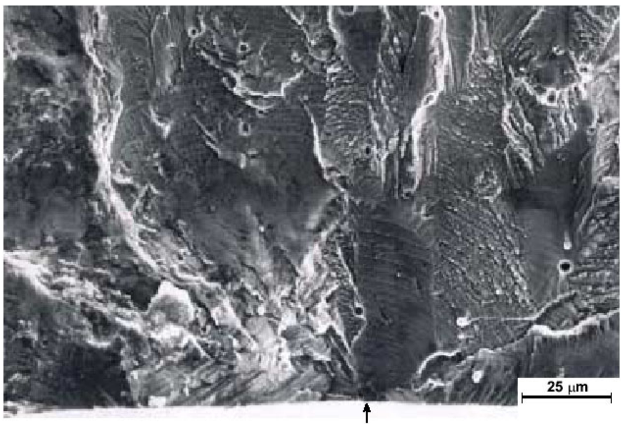


Fig. 4 – Fatigue crack initiation and early crack growth in a SENT specimen.

In region II stable fatigue crack growth conditions prevail and the fatigue crack growth rate (FCGR) is given by the well-known Paris-Erdogan relation [8-10]. In this region, generally, the Paris–Erdogan formula:

$$\frac{\mathrm{d}a}{\mathrm{d}N} = C(\Delta K)^m \quad (7)$$

is used to analyze fatigue crack growth process data and predict remaining life, where $\mathrm{d}a/\mathrm{d}N$ is the crack growth per cycle, a is the crack length, N is the number of loading cycles, ΔK is the stress intensity range, and C and m are material constants that are determined experimentally.

In the linear region II (see Fig. 3), the Paris-Erdogan Equation (7) is used as follows. Integrating

$$\int_{N_0}^{N_c} \mathrm{d}N = \int_{a_0}^{a_c} \frac{\mathrm{d}a}{C(\Delta K)^m} = \int_{a_0}^{a_c} \frac{a^{-m/2}\mathrm{d}a}{CF^m(\Delta\sigma)^m \pi^{m/2}}, \quad (8)$$

we have

$$N_c - N_0$$

$$= \frac{1}{CF^m(\Delta\sigma)^m \pi^{m/2}\left(1-\frac{m}{2}\right)}\left[a_c^{1-\frac{m}{2}} - a_0^{1-\frac{m}{2}}\right]. \quad (9)$$

Thus, the crack growth equation representing the solution of the differential equation for the Paris-Erdogan law is given by

$$N_c - N_0 = \frac{1}{q(b-1)}\left(\frac{1}{a_0^{b-1}} - \frac{1}{a_c^{b-1}}\right), \quad (10)$$

where

$$q = CF^m(\Delta\sigma)^m \pi^{m/2}, \quad b = m/2. \quad (11)$$

It should be remarked that (10) could be obtained immediately from the Paris–Erdogan law written in the form:

$$\frac{\mathrm{d}a(N)}{\mathrm{d}N} = q[a(N)]^b, \quad (12)$$

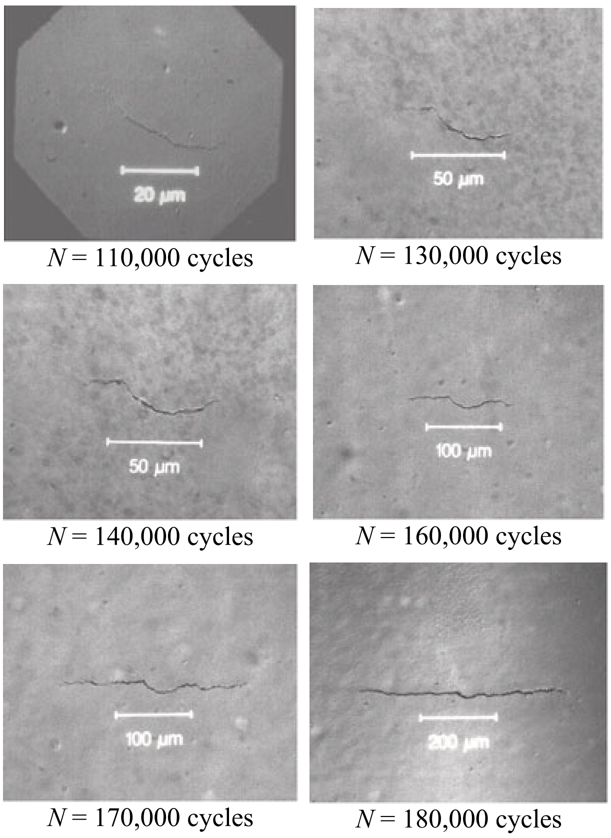
in which q and b are parameters depending on loading spectra, structural/material properties, etc.

The initial crack size, a_0, is usually either found by inspection (in this case, $a_0 = a°$) or a reasonable minimum size of crack is assumed for the analysis (in this case, a_0 is approximately between 0.02 and 0.05 mm that was found through quantitative fractography for typical aircraft metallic materials [11]).

The critical crack size, a_c, is found from:

$$a_c = \frac{1}{\pi}\left(\frac{K_c}{F\sigma_{\max}}\right)^2, \tag{13}$$

where K_c is the critical value of stress intensity, K, which at the point of fracture is known as fracture toughness. When the combination of stress and crack size reach the fracture toughness of the material, failure occurs. Knowing the fracture toughness, K_c, of the material, we can use the stress intensity solution (67) to determine the critical crack length a_c (if we know the stress level σ), or the stress level $\sigma_{\max}$ (if we know the crack size a). For example, progression of small crack growth with cycling is shown in Fig. 5.



N = 110,000 cycles; N = 130,000 cycles; N = 140,000 cycles; N = 160,000 cycles; N = 170,000 cycles; N = 180,000 cycles

Fig. 5 – Progression of small crack growth with cycling.

The traditional analytical method of engineering fracture mechanics (EFM) usually assumes that crack size, stress level, material property and crack growth rate, etc. are all deterministic values which will lead to conservative or very conservative outcomes. However, according to many experimental results and field data, even in well-controlled laboratory conditions, crack growth results usually show a considerable statistical variability (as shown in Fig. 6).

There are many factors influencing fatigue crack growth, including random material inhomogeneities, loading frequency, stress ratio, loading waveform, geometric size of components and specimens, composition, concentration and temperature of environment mediums, metallurgical composition and heat treatment of materials and many other factors.

From experimental investigations [12-13], fatigue crack growth appears as a process with random properties. These random properties seem to vary both (1) from specimen to specimen and (2) during crack growth.

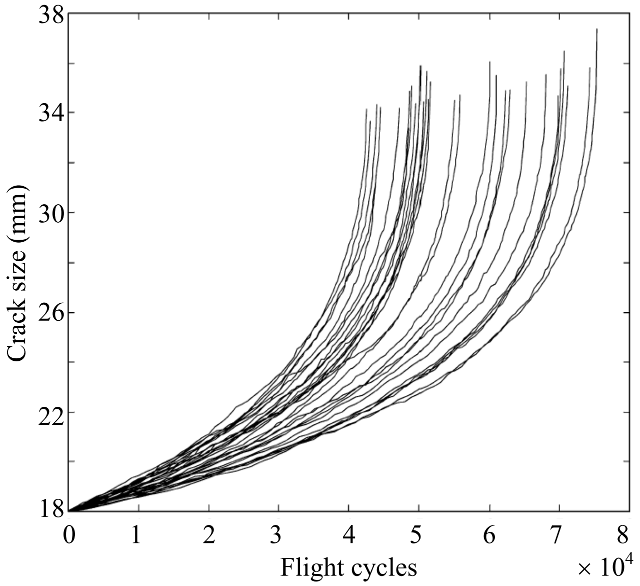


Fig. 6 – Fatigue crack propagation curves.

A great number of stochastic models that account for the random behavior have been proposed. They are based either on suitable "randomized" empirical crack growth laws or on data fitting [14-15]. There are several randomizations possible: q could be a random variable and b a constant; b could be a random variable and q a function of b; or both q and b could be random variables. This approach to the probabilistic modelling of material inhomogeneity captures the first type of inhomogeneous behavior, but not the second. A second probabilistic approach is to let the coefficients of the growth law be constants, but allow the fatigue crack growth rate to randomly deviate from the growth law from point to point along the crack path. This approach captures the second type of inhomogeneous behavior, but not the first. Models based on stochastic differential equations, in fact, are suited to account for this type of variability. E.g. Tsurui et al. [16] and Tang and Spencer [17] proposed crack growth equations with a time-correlated stochastic process. A model with a jump process has been introduced by Lin *et al.* [18]. As the correlation should rather be attributed to the spatial dimension, Ortiz and Kiremidjian [19] proposed a model, where the correlation of the stochastic process depends on the crack length. Markov chain models [20] reflect the fact that the load process is often discretized into independent events. They can be directly fitted to experimental data. However, this makes predictions for other load conditions or geometrical configurations a difficult task. This problem can be circumvented by using a suitable stochastic crack growth model for the determination of the transition probabilities [21]. A combination of the two approaches described above allows one to capture both types of inhomogeneous behavior.

The aircraft industry has leaded the effort to understand and predict fatigue crack growth. They have developed the safe-life or fail-safe design approach. In this method, a component is designed in a way that if a crack forms, it will not grow to a critical size between specified inspection intervals. Thus, by knowing the material growth rate characteristics and with regular inspections, a cracked component may be kept in service for an extended useful life. This concept is shown schematically in Fig. 7.

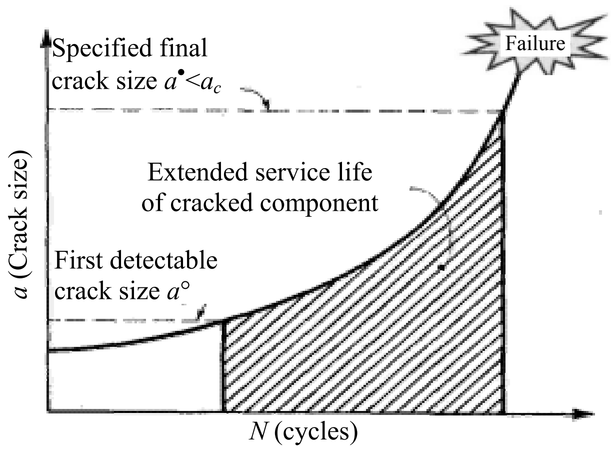


Fig. 7 – Extended service life of a cracked component.

It should be noted that it is very difficult to analyze and predict fatigue life of different fatigue structures under various surroundings. Even if a suitable formula can be applied, the calculated result will be conservative for its generality.

In this paper, the authors attempt to forecast what will happen to the structure according to the current work condition, and to predict the fatigue life of structures during the continuous learning process by ANN technique.

In recent years, an artificial neural network (ANN) has emerged as a new branch of computing, which tries to mimic the structure and operations of biological neural systems. An ANN is able to learn by example and does not have to know the theory behind a phenomenon. This quality is useful to describe problems where the relationships of inputs and outputs are not clear enough or the solutions are not easily formulated in a short time.

Pidaparti and Palakal [22] developed an ANN model to represent the fatigue crack growth behavior under spectrum loading. The inputs were information about the features in the spectrum loading and crack growth behavior, and the output was the corresponding loading cycles. A material parameter network for modified Paris Law was also developed in their study.

Haque and Sudhakar [23] described an ANN model to analyze corrosion fatigue crack growth rate in dual phase steel. The inputs were the stress intensity factor range, ΔK, and volume percent of martensite content and outputs were crack growth rate. Six groups of da/dN versus ΔK relationship corresponding to different martensite contents were trained, and the neural network (NN) analysis provided a good match with the experimental data.

Aymerich and Serra [24] used a neural network to predict fatigue strength of a graphite-peek composite with 63% of fiber content. The input parameters were the number of cycles at failure and the stacking sequence of the laminate. The neural network used showed the capability of predicting fatigue life for laminated composites.

Lee et al. [25] investigated the feasibility of using ANN to predict fatigue lives of five carbon and one glass fiber-reinforced laminates. A three-parameter Weibull distribution was used to estimate the number of cycles for various levels of failure probability from experimental data. The peak stress, minimum stress and the failure probability level were the most appropriate inputs from the root-mean-square trials. They applied ANN to train fatigue data for four CFRP systems to predict the response of HTA/982. The results showed the log-life was well within the normal experimental spread of data for composite materials.

Artymiak et al. [26] applied ANN to estimate finite life fatigue strength and fatigue limit. The notch factor, tensile strength, yield strength and nominal stress were employed as input parameters. The output parameter was the endurable number of load cycles. The results showed that NN was capable of describing the expected S–N curve.

Pleune and Chopra [27] studied the effect of light water reactor coolant environments on fatigue resistance of plain carbon steel and low alloy steel using ANN. The authors showed that ANN had a great potential of predicting environmentally influenced fatigue. The ANN output of the effects of sulfur content, strain rate and temperature on the fatigue lives in air showed good agreement with the statistical model.

Venkatesh and Rack [28] developed an ANN for predicting the elevated temperature creep fatigue behavior of Ni-based alloy INCONEL 690. Five extrinsic parameters (strain range, tensile strain rate, compressive strain rate, tensile hold time, and compressive hold time) and one intrinsic parameter (grain size) were training inputs. Fatigue life defined by complete fracture of the specimen was the predicted output. Close agreement between experimental and predicted life for the test points was observed with the NN approach.

Fujii et al. [29] used a Bayesian NN for analysis of fatigue crack growth rate of nickel-based super-alloys. The database consisted of 1894 combinations of fatigue crack growth and 51 inputs. The output was the logarithm of fatigue crack growth rate. A group of seven of the best models showed minimum test error and provided a close agreement with experimental data. This NN method demonstrated the ability of revealing new phenomena in cases where experiments cannot be designed to study each variable in isolation.

Biddlecome et al. [30] developed an optimization based NN method to predict fatigue crack growth and fatigue life for multiple site damage panels. In the NN optimization each neuron represented a hole and contained pertinent information relevant to existing crack conditions. As the crack extended, the neuron gained energy. A set of energy functions was developed to define how the neurons gain energy as the system begins to converge to an optimal solution. The proposed NN was able to detect a panel failure and provide the path of crack propagation.

Kang and Song [31] determined the crack opening load the input of 100 data points of the differential displacement signal on the loading stage. The accuracy and precision of the prediction of crack opening point by the NN were estimated for 42 different cases, and the results were in good agreement with experiments.

Al-Addaf and El Kadi [32] used ANN to predict fatigue life of unidirectional glass fiber/epoxy composite laminates with a range of fiber orientation angles under various loading conditions. The best set of inputs was the fiber orientation angle, stress ratio and maximum stress. The data points for different fiber orientation angles and load ratios were tested. Although a small number of experimental data points were used for training, the results were comparable to other current methods for fatigue life prediction.

Han et al. [33] discussed an ANN method aided by a special learning set to calculate the fatigue life of flawed structures. The input data included dimensions of the fracture section, defect information and stress value. The learning results from calculated fatigue life of the back propagation (BP) network alone and from BP network with a special learning set were compared with the experimental fatigue life. The results showed the feasibility of a NN in treating fatigue life calculation problems of flawed structures both for the special learning set and normal learning set.

Choi et al. [34] presented models to predict the fatigue damage growth in notched composite laminates using an ANN, which was found to work better than the Power Law model as a predictive tool for split growth. ANN models showed the ability to capture more of the nonlinear characteristics. The linear cumulative damage rule worked well when combined with ANN models.

Smith et al. [35] explored the use of the ANN to predict the plate end debonding in FRP-plated RC beams. The ANN trained with existing data showed relatively accurate predictions, and indicated capability to be applied in parametric study and structural design to provide new insights and predictions.

In this paper, a model for predicting the fatigue crack growth by ANN is presented, which does not need all kinds of materials and environment parameters, and only needs to measure the relation between *a* (length of crack) and *N* (cyclic times of loading) in-service. The feasibility of this model was verified by some examples. It makes up the inadequacy of data processing for current technique and on-line monitoring. Hence it has definite realistic meaning for engineering application.

2. ARTIFICIAL NEURAL NETWORKS

An ANN can be considered as a black box that has the capacity to predict an output pattern when it recognizes a given input pattern [36].

The neural network must first be "trained" by processing a large number of input patterns and evaluating the output that resulted from each input pattern. Once trained, the neural network is able to recognize similarities when presented with a new input pattern, and is able to predict an output pattern.

Neural networks are based on models of biological neurons and form a parallel information processing array based on a network of interconnected artificial neurons (also called cells, units, nodes, or processing elements). The function of artificial neurons is similar to that of real neurons: they are able to communicate by sending signals to each other over a large number of biased or weighted connections. Each of these neurons has an associated transfer function which describes how the weighted sum of its inputs is converted to an output.

Computational models of a neural network try to emulate the physiology of real neurons. There are two principal functions for artificial neural networks. One is the input–output mapping or feature extraction. The other is pattern association or generalization. The mapping of input and output patterns is estimated or learned by the neural network with a representative sample of input and output patterns. The generalization of the neural network is an output pattern in response to an input pattern, based on the network memories that function like the human brain. Therefore, a neural network can learn patterns from a sample data set and determine the class of new data based on previous knowledge.

Differing types of neural networks have evolved based on the neuron arrangement, their interconnections and training paradigm used. There are adaptive resonance theory, back-propagation, Boltzmann network, Hopfield network, general regression, learning vector quantization, modular neural network, neocognitron, probabilistic neural network, and so on. In general, the neural networks are trained either supervised or unsupervised learning paradigms. In the supervised learning case, the network is presented with pre-selected signals defining the various classes and is trained to recognize them. Back-propagation, Boltzmann, and Hopfield networks are prominent examples under this category. Neocognitron and adaptive resonance theory networks fall under the second category. The unsupervised learning algorithms are often used in pattern recognition applications. Patterns are recognized by the neural nets based on the features present in them.

Among the various types of neural networks, the multi-layer perceptron trained with the back-propagation algorithm (back-propagation neural network) has been proved to be most useful in engineering applications [37-45]. Thus back-propagation neural network is used in this application study. The back-propagation network is given its name due to the way that it learns by back propagating the errors in the direction from output neurons to input neurons.

The structure of a single artificial neuron is shown in Fig. 8. The weighted sum of input components are calculated as

$$S_j = \sum_{i=1}^{n} w_{ij} x_i - \theta_j, \tag{14}$$

where S_j is the weighted sum of the jth neuron for the input received from the preceding layer with n neurons, w_{ij} is the weight between the jth neuron and the ith neuron in the preceding layer, x_i is the output of the ith neuron in the preceding layer, and θ_j is the intrinsic threshold that can be treated as an individual weight with a negative sign. Once the weighted sum S_j is computed, the output of the jth neuron y_j is calculated with a sigmoid function as follows:

$$y_j = f(S_j) = \frac{1}{1+\exp(-\eta S_j)}, \tag{15}$$

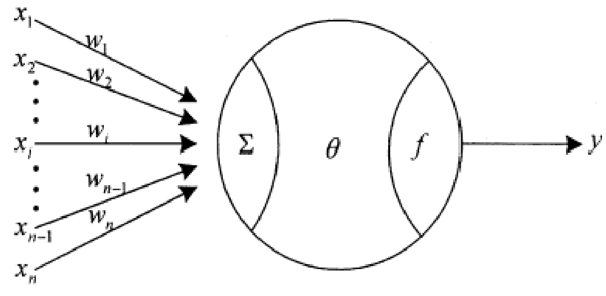


Fig. 8 – Schematic structure of an artificial neuron with input units.

where η is a constant used to control the slope of the semi-linear region. The sigmoid nonlinearity activates in every layer except the input layer.

The multi-layer perceptron network comprises an input layer, an output layer and a number of hidden layers. The presence of hidden layers allows the network to represent and compute more complicated associations between patterns. Many researchers proved that the multi-layer perceptron with three layers can perform arbitrarily complex classi.cation while the complexity is dependent on the number of neurons in the hidden layer. The number of neurons in each layer may vary dependent on the problem. The basic structure of a feed-forward, back-propagation network based on the multi-layer perceptron is shown in Fig. 9. Propagation takes place from input layer to the output layer. There is no connectivity between neurons in a layer. This type of neural network is trained using a process of supervised learning in which the network is presented with a series of matched input and output patterns and the connection strengths or weights of the connections automatically adjusted to decrease the difference between the actual and desired outputs. A gradient search technique is used to minimize a cost function which is equal to the mean square difference between the desired and the actual network outputs. The training of the network is carried out through a large number of training sets and training cycles (epochs). The criterion for convergence is determined by the root mean square error which adds up the squares of the errors for each neuron in the output layer, divides by the number of neurons in the output layer to obtain an average, and then takes the square root of that average. The root mean square error is expressed as

$$\varepsilon_{\mathrm{RMS}} = \sqrt{\frac{\sum_{i=1}^{m}(d_i - y_i)^2}{m}}, \tag{16}$$

where d_i and y_i are the desired and actual output values for ith output neuron, and m is the number of neurons in the output layer.

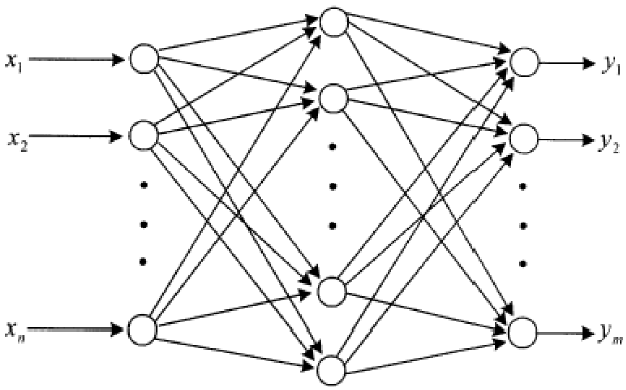


Fig. 9 – A typical multi-layer percetron neural network.

3. DEVELOPMENT OF AN ANN MODEL

Under a given working condition and loading, the data monitoring for the given equipment without affecting its normal work is called on-line monitoring. Of all factors that affect corrosion fatigue crack growth, the one by one corresponding relation of a and N is the main display of fatigue life (a indicates the length of crack, N indicates the cyclic times of loading or action cycle of equipment).

After lots of simulation and calculation, the authors adopted the three-layer back-propagation neural network as the model in this paper. There is one input element whose input value is the real length of crack growth and one output element whose output value is the cyclic times of loading.

It only needs five or six data to construct the normal model. We should get a measure value continuously to build a predicting model for on-line monitoring, that is to say, new data should be taken as the reference point. If there are k–1 data to build a predicting model at the beginning, we can predict the kth and its following data. When we get the kth data and incorporate it into the original set as new information, we should delete old information and always keep k–1 data points to construct a predicting model for the next step. That is to say every data set learns a part of $a \sim N$ curve similarly.

The interval between two data should not be too long, if not, the precision and safety will not be guaranteed.

The three-layer back-propagation neural network was constructed using MATLAB software [46].

In this study, the fatigue crack growth data were divided into two groups, a training set and a test set. The training set of the fatigue crack growth data was used to train the network and the trained ANN was evaluated with the test set, exclusively. The performance of the trained ANN was tested by evaluating the coefficient of determination (R^2), standard error of calibration (SEC), standard error of prediction (SEP), and bias [47].

The coefficient of determination, R^2, is used to measure the closeness of fit and can be defined as:

$$R^2 = 1 - \frac{\sum(y - y_{\mathrm{predicted}})^2}{\sum(y - y_{\mathrm{mean}})^2}, \tag{17}$$

where y is the actual measured value, $y_{\mathrm{predicted}}$ is the predicted value by the trained ANN and y_{mean} is the mean of the y values. Clearly, the coefficient of determination is a reasonable measure of the closeness of fit of the trained ANN, since it equals the proportion of the total variation in the dependent variable, in this study the number of cycles that is explained by the trained ANN. The coefficient of determination cannot be greater than 1. A perfect fit would result in R^2=1, a very good fit near 1, and a poor fit would be near 0.

The SEC measures the scatter of the actual measured values (y) about the values calculated by the trained ANN ($y_{\mathrm{predicted}}$) and can be defined as [47]:

$$\mathrm{SEC} = \left[\sum \frac{(y - y_{\mathrm{predicted}})^2}{n - p - 1}\right]^{1/2}, \tag{18}$$

where n is the number of data and p is the number of variables.

The trained ANN was then used to predict the number of loading cycles using the measured data that were not used in training the ANN.

The bias and SEP represent the mean and standard deviation of the differences between the actual measured values of the number of loading cycles and the predicted values of number of loading cycles, and are given by the following equations [48]:

$$\mathrm{bias} = \frac{\sum(y - y_{\mathrm{predicted}})^2}{n}, \tag{19}$$

$$\mathrm{SEP} = \left[\sum \frac{[(y - y_{\mathrm{predicted}}) - \mathrm{bias}]^2}{n-1} \right]^{1/2}. \quad (20)$$

4. EXAMPLE

The material used for the present example was 0Cr18Ni9 austenitic stainless steel. Center crack tension specimens were machined for tests. Cyclic loading with sinusoidal waveforms at 5 Hz was used in tests. The pre-made crack length was 7.0 mm. Crack growing length was monitored by microscope.

The testing results are shown in Table 1. Initial five couples of crack length and cyclic times of loading were selected in table as primary data sets before predicting the next. But only the next *N* is better-estimated value, and its follows only can be for reference.

Table 1. Data of specimen

a (mm)	N (test)	N (prediction)	Absolute error
7.000	0	–	–
7.810	6080	–	–
8.570	11520	–	–
9.330	16580	–	–
10.05	20680	–	–
10.58	23680	23715	35
11.14	26540	25845	695
11.88	29480	28323	1157
12.60	32500	30910	1590
13.20	34760	33543	1217

It will be noted that *N* (prediction) is the value predicted by the forward five data sets.

From Table 1 we can see that the absolute error is in the normal region with the stochastic of fatigue problem. The feasibility is shown with better calculating result.

The behavior of fatigue crack growth can be divided into two stages: stable crack growth stage and accelerating crack growth stage. To avoid damage to the testing machine caused by specimens fracturing, the upper tests were all stopped in the stable crack growth stage. According to the form of *a*~*N* curve, we can judge whether the crack state is in accelerating growth stage or not by the following criterion: when continuous several estimated values are clearly bigger than measure values. This means the crack in the component may have been in accelerating stage. Its physical meaning is that the slope of the estimated curve is clearly a lot bigger than that of real curve (Fig. 10). This is an alarm for the supervisors that the component will possibly fracture, and some protective measures should be taken.

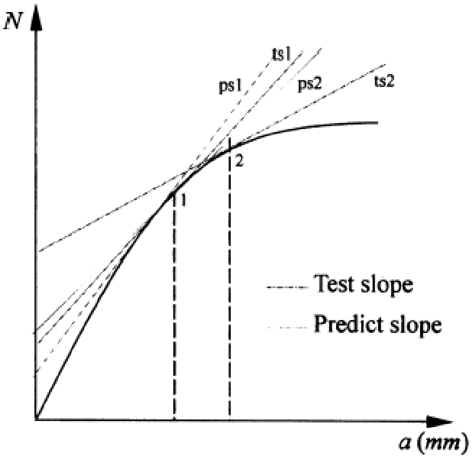


Fig. 10 – Phisical meaning of the criterion.

Using on-line data processing method the risk of equipment damage before reaching its design life is cut down, and it is a good monitoring method for extending in-service equipment, too. So material behaviors are brought into full play. It makes up for the inadequacy of causing material waste by considering safety factor in design.

Applying ANN technique to predict the fatigue life of structures, complex calculation of ΔK and determination of the constant *C*, *m* are omitted, environment factor need not be thought about, and Paris formula need not be revised and integrated. All these make the predicting method simple. It especially fits for engineering application.

ANN technique for data processing uses only one characteristic parameter. It does not consider the effect of the other parameters, in fact, the effect of all parameters were included in *a*~*N* relation. So this method focuses on certain specimens, eliminating the effect of other cases for estimating the result.

With the different effect of the changeable surroundings to the same component, the stable crack growth rate will change relevantly. So the constants *C* and *m* in Pairs formula should often change, which makes Pairs formula difficult to predict the correct remaining life. But they have the same loss-stability criterion to judge whether the crack is in accelerating growth stage or not by ANN technique. However, model of ANN can follow the change, and make the right prediction. So this technique is especially fit for on-line fatigue crack growth monitoring.

5. CONCLUSION

High levels of uncertainty in current fatigue-life prediction techniques, and the often-catastrophic nature of fatigue failure, drive the continuing effort to develop techniques for detecting and characterizing fatigue damage. In this paper, an ANN technique for data processing of on-line fatigue crack growth monitoring was developed, which has a clear criterion and makes users employ it easily without enough special knowledge. This indicates that the proposed method has the potential for practical application in more complicated problems. But as an engineering technique it should be further tested and verified in factories.

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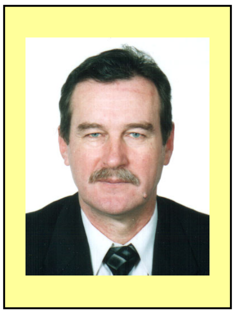

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