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A FATIGUE DAMAGE ESTIMATOR USING RBF, BACKPROPAGATION, AND CID4 NEURAL ALGORITHMS

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Abstract. Fatigue damage estimation using neural networks is described in the paper. Attention is focused on the method of data generation for both the training and test data used by radial basis function (RBF), backpropagation, and CID4 algorithm used in this study. The performance results of the three neural algorithms are analyzed in terms of their strengths and weaknesses in training.

Keywords. Fatigue estimation, Neural networks.

INTRODUCTION

Machines and structures fabricated from engineering materials undergo cyclic loading which results in failure due to metal fatigue. In such situtations, it is often necessary to estimate the service life of the critical components of such systems, either for design purposes or to aid in the troubleshooting of service failures. Unfortunately, practical situations require the handling of complex geometric shapes and irregularly cycled loadings. One approach to such problems is to base life calculations on the stresses and strains that occur to the most highly stressed areas of the structure, which for argument's sake can be considered a notch. This could be done in the laboratory with typical load sequences that the structure may encounter during actual usage, or it may be done real-time [1].

It is beyond the scope of this paper to describe the details of fatigue life prediction based on cycled stresses and strains. Rather, the reader is directed to Lorenzo and Saus [2] for this information. It is sufficient to state that cycle life prediction calculations are based on the extrema stress and strain values associated with hysterisis loops (Figure 1) as created by incoming cycled stresses (Figure 2).

Figure 3 shows a block diagram of a system under development at the NASA Lewis Research Center that is designed to estimate (in real-time) temperature-influenced, cyclic damage incurred at the component critical point [2]. For this estimation, temperature from a monitored location is used with known functional relationships to generate temperature dependent values for material properties such as Young's Modulus, ultimate tensile stress, etc.. These properties are then used with the nominal stress of the critical component and a priori geometry-specific stress concentration factor, k_t, in a neural network (trained) to map nomial stress into local stress in accordance with Neuber's Rule (Equation 1) and the stress/strain equations that govern the appearance of the hysterisis loops (Equations 2 and 3).

The extrema detector monitors nominal stress to determine cycle extrema and "tags" the local strain values at the extrema for use in a subsequent damage calculation. Also, the cycle local mean stress is determined. These values, together with the temperature sensitive material properties, are then used as inputs to a neural network trained to map the values into cycle damage. This mapping is consistent with Dowling's Local Strain Approach [3]. Accumulated damage is then determined by post-processing the cycle damage by a damage accumulation law such as Palmgren-Miner, Halford-Manson Double Linear Damage Rule, etc..

As has already been pointed out, two neural networks are being used with this design. One neural net is being trained on the mapping of nominal stress into local stress, and the second is being trained to map hysterisis loop extrema stress and strain values into cycle damage. We are interested in determining the effectiveness of the RBF [4, 5], backpropagation [6], and CID4 algorithms in training these two networks. The CID4 algorithm is an extension of the CID3 algorithm[7].

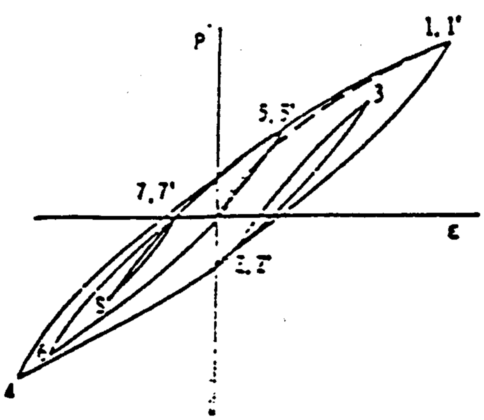

Figure 1. **Hysterisis Loop on the stress/strain plane.**

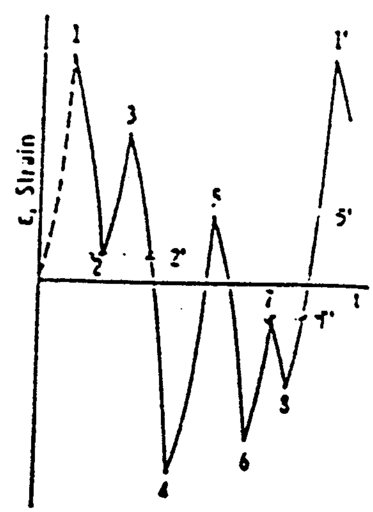

Figure 2. **Incoming cycled strain vs. time.**

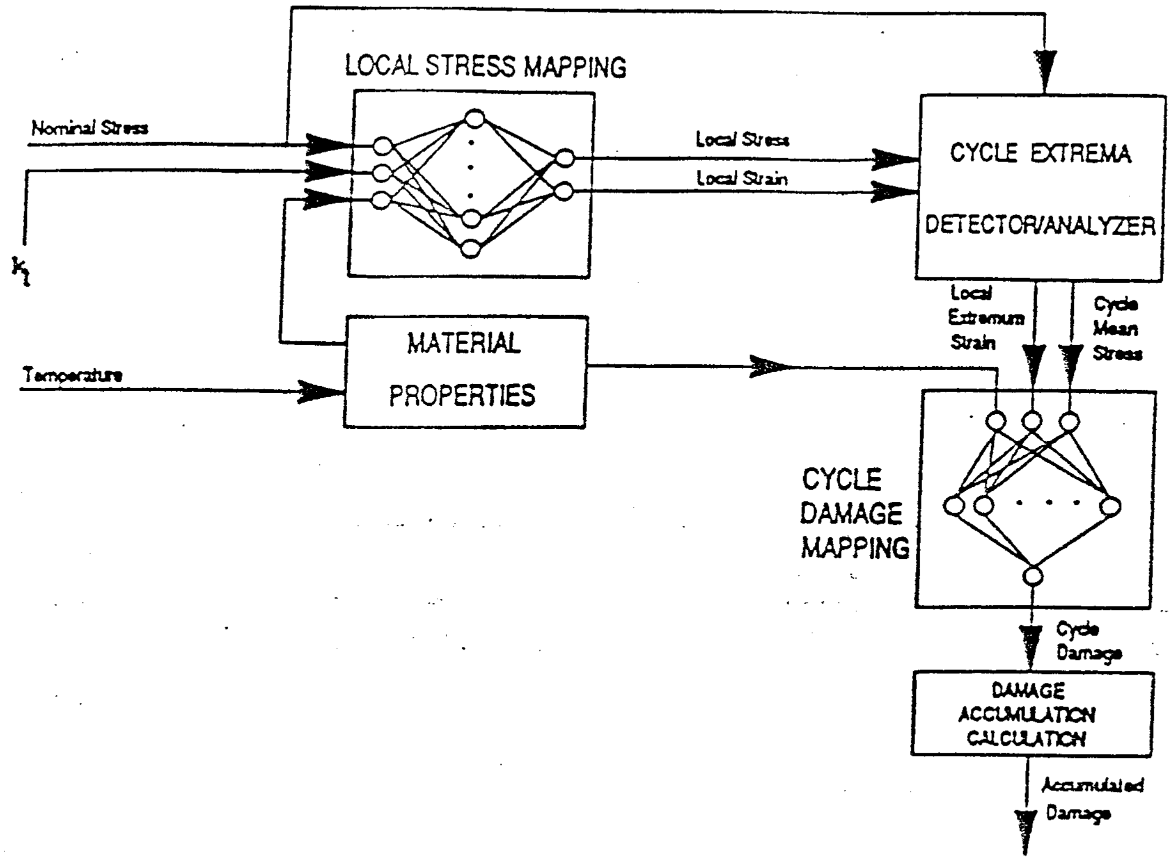

Figure 3. Temperature Sensitive Neural Damage Estimator.

PREPARATION OF TRAINING DATA

Estimation of local stress

The governing equations behind the mapping of nominal stress into local stress are as follows:

$$\left(\sigma\varepsilon E\right)^{\frac{1}{2}} = k_t S \tag{1}$$

$$\varepsilon = \varepsilon_r + \frac{(\sigma - \sigma_r)}{E} + 2\left(\frac{(\sigma - \sigma_r)}{2A}\right)^{\frac{1}{S}} \tag{2}$$

$$\varepsilon = \varepsilon_r - \frac{(\sigma_r - \sigma)}{E} - 2\left(\frac{(\sigma_r - \sigma)}{2A}\right)^{\frac{1}{S}} \tag{3}$$

Equation (1) is a form of Neuber's Rule that applies when the critical component being monitored experiences gross elastic deformation only. Under these conditions it effectively relates to the local stress, S_{nom}. Equations (2) and (3) relate the local stress to the local strain within the context of a hysterisis loop. Equation (2) governs the increasing stress/strain portion of the loop and equation (3) governs the decreasing portion. In these equations, ε_r and σ_r refer to the local strain and local stress reference points, within the loop. The variable, A, is defined as the ratio of σ'_f to $(\varepsilon'_f)^s$, where σ'_f is the elastic strainage versus life coefficient, and ε'_f is the inelastic strainage versus life coefficient. The variable, s, is defined as the ratio of b to c, where b is the exponent on cyclic life for elastic strainage versus life, and c is the exponent on cyclic life for inelastic strainage versus life.

By individually substituting equations (2) and (3) into equation (1), the following two equations results:

$$\sigma^2 + \sigma(E\varepsilon_r - \sigma_r) + 2\sigma E \left(\frac{\sigma - \sigma_r}{2A}\right)^{\frac{1}{s}} = (S_{eff})^2 \tag{4}$$

$$\sigma^2 - \sigma(E\varepsilon_r - \sigma_r) - 2\sigma E \left(\frac{\sigma_r - \sigma}{2A}\right)^{\frac{1}{s}} = (S_{eff})^2 \tag{5}$$

where, S_{eff} is the product of k_t and S_{nom}. Equation (4) provides a relationship between local stress, the material-specific parameters A and E, the reference local stress and strain coordinates of a hysterisis loop, and the nominal stress. This equation holds for the increasing portion of the stress/strain hysterisis loop whereas Equation (5) holds for the decreasing portion. Together these equations were used to randomly generate 15,121 input vectors for the neural network training set, where the form of $[E_i, A_i, \varepsilon_{ri}, \sigma_{ri}, (S_{eff\,i})^2, E_d, A_d, \varepsilon_{rd}, \sigma_{rd}, (S_{eff\,d})^2, \sigma]$ where the subscript i refers to increasing values and the subscript d refers to decreasing values. If a created vector was for the purpose of training the neural network on the increasing portion of the hysterisis loop, then all the values in the vector with a "d" subscript received a zero placeholder value. Conversely, a zero placeholder value was used for all the "i" subscripted values when the created vector was designed to train on the decreasing portion of the loop. The training data set consisted of 1,000 vectors for the half-amplitude portion of the hysterisis loop, 6,986 vectors for the increasing portion of the hysterisis loop, and 7,135 vectors for the decreasing portion of the hysterisis loop. The test data set that was created consisted of 150 vectors, with 50 vectors for each of the described portions of the hysterisis loop.

The randomly generated values for E, A, and S_{eff} were bounded by material properties of MAR-M-246 (Hf-Mod) and by typical service conditions experienced during a Space Shuttle Main Engine (SSME) mission {MAR-M-246 (Hf-Mod) is the turbine blade material in the SSME's High Pressure Fuel Turbine}. For these given constraints, the ranges for the parameters become: 111 < E < 131 GPa, 2.89 < A < 3.20 (dimensionless), and 0 < (S^2_{eff}) < 15 GPa.

In preparing the training data for the RBF network, 600 vectors were initially selected randomly from the original 15,121 vectors. The OLS selection method [8] was then performed to select 80 of the most significant regressors. For training the backpropagation network, all 15,121 vectors were used after their order has been randomly shuffled.

<u>Strain life equation</u>

The relationship between strain, ε, and the number of cycles to failure, N, is given by the following equation [1]:

$$\varepsilon = \frac{\sigma'_f - \sigma_m}{E}(2N)^b + \varepsilon'_f(2N)^c \qquad (6)$$

ε is the amplitude of the strain in the particular stress-strain hysterisis loop. σ'_f, b, ε'_f and c are material constants. Simplifying (6) gives the following:

$$\frac{\sigma'_f - \sigma_m}{E}(2N)^b + \frac{\varepsilon'_f}{\varepsilon}(2N)^c = 1 \qquad (7)$$

let

$$\alpha = \frac{\sigma'_f - \sigma_m}{\varepsilon E}, \quad \beta = \frac{\varepsilon'_f}{\varepsilon}, \quad X = (2N)^c, \quad \text{and} \quad s = \frac{b}{c} \qquad (8)$$

equation (7) now becomes:

$$\alpha x^2 + \beta x = 1 \qquad (9)$$

let

$$u^s = \alpha x^s \qquad (10)$$

equation (9) now becomes:

$$u^s + \frac{\beta u}{\alpha^{1/s}} = 1 \qquad (11)$$

$$\text{let } a = \frac{\beta}{\alpha^{1/s}} \qquad (12)$$

which results in the following:

$$u^s + au = 1 \tag{13}$$

The values for s and a that are of interest to us lie in the range of $0.1 < s < 0.3$ and $0.0 < a < 150.0$. Due to the fact that a spans a relatively wide range, log(a) was used as an input to the network instead.

The training data consists of 1000 examples, with values for s and log(a) as desired inputs, and values for log(u) as the desired output. The test data consists of 500 examples. As this is a large amount of data, the OLS selection method [8] was used to select 40 of the most significant regressors to be used by the RBF and CID4 algorithms. For training the backpropagation network, all 1000 vectors were used after they were shuffled.

NETWORK TRAINING

RBF networks were set up and the output layer weights trained using the mean squared error reduction method. For the estimation of local stress, the network architecture ranged from 10 hidden layer nodes to 80 hidden layer nodes. For the strain life equation network, the number of hidden layer nodes used were between 5 and 40. The networks were considered as being trained when further training did not reduce the mean squared error significantly.

Backpropagation networks with a varying number of hidden layer nodes were also trained with the data. For the estimation of local stress, the number of hidden layer nodes were varied from 10 to 80 nodes. For the strain life equation network, the number of nodes used ranged rom 1 to 200. All available training vectors were used to train the backpropagation networks. The only other preprocessing done on the training data was to shuffle the order of the vectors.

A third type of network, CID4, was also trained for the strain/life equation network. CID4 is a modification of CID3 [7], and is designed to produce continuous outputs as opposed to CID3's discrete outputs. As with CID3, the purpose of the CID4 algorithm is to self-generate a feed-forward neural network architecture.

RESULTS

Estimation of local stress

RBF networks using between 10 and 80 OLS selected centers were trained and tested. Tables 1, 2 and 3 show the results for the RBF networks in the estimation of local stress for the half-amplitude portion, the increasing portion, and the decreasing portion of the hysterisis loop. Each table represents 50 test vectors, and the RMS error, maximum absolute error, and minimum absolute error for the results in each range are shown. Backpropagation networks with a single hidden layer were trained and tested for a comparison. The same number of hidden layer nodes were used as with RBF, and the results are tabulated in the same tables.

Table 1: Estimation of local stress, σ ($0.079710 \leq \sigma \leq 0.596300$), half-amplitude portion of hysterisis loop.

Nodes in hidden layer	Max |Error|		Min |Error|		RMS Error	
	RBF	BP	RBF	BP	RBF	BP
10	0.086032	0.124964	0.007517	0.000257	0.059094	0.031943
15	0.111770	0.085847	0.002863	0.000224	0.046960	0.044738
20	0.064428	0.124505	0.000089	0.000018	0.034792	0.033254
30	0.091182	0.099148	0.000130	0.000485	0.020357	0.046933
40	0.084311	0.082168	0.000025	0.000064	0.023143	0.039963
80	0.085218	0.092078	0.001180	0.000975	0.019786	0.048271

Table 2: Estimation of local stress, σ ($0.122858 \leq \sigma \leq 0.668162$), increasing portion of hysterisis loop.

Nodes in hidden layer	Max |Error|		Min |Error|		RMS Error	
	RBF	BP	RBF	BP	RBF	BP
10	0.275974	0.111326	0.000179	0.000380	0.115555	0.036853
15	0.803522	0.082045	0.000303	0.000825	0.316865	0.020396
20	0.739676	0.110819	0.000282	0.000113	0.307492	0.034786
30	0.344249	0.087030	0.000636	0.000265	0.126532	0.025485
40	0.199992	0.065920	0.000209	0.002545	0.072287	0.026008
80	0.422291	0.083754	0.000066	0.000309	0.155670	0.023723

Table 3: Estimation of stress, σ ($0-0.552853 \leq \sigma \leq 0.673437$), decreasing portion of hysterisis loop.

Nodes in hidden layer	Max |Error|		Min |Error|		RMS Error	
	RBF	BP	RBF	BP	RBF	BP
10	0.900898	0.723849	0.007848	0.055201	0.470344	0.410336
15	1.038687	0.910845	0.009654	0.000791	0.507341	0.376398
20	1.121955	0.707541	0.004256	0.068561	0.486491	0.411298
30	1.207734	0.700115	0.010072	0.077343	0.461352	0.410519
40	1.144810	0.826479	0.004247	0.060604	0.447510	0.383865
80	1.071518	0.878858	0.024079	0.048025	0.373368	0.387680

Strain life equation

Table 4 shows the results of the RBF networks when tested with 500 test vectors. The desired outputs ranged from -2.4813 to -0.04477. The RMS error column gives the root-mean-squared error over all the 500 test vectors, and the minimum errors and the maximum errors give the absolute values for the best and the worst predictions that were made. Tables 5 and 6 show the results using backpropagation and CID4, respectively.

Table 4: Statistics for the estimation of log(u) (life), RBF network.

Number of RBF centers, OLS selected	Approximate training time	RMS Error	Minimum Absolute Error	Maximum Absolute Error
5	0.2 min	0.04472	0.00005	0.35515
6	0.25 min	0.11370	0.00006	0.30190
10	0.45 min	0.02580	0.00006	0.09339
11	0.5 min	0.04613	0.00008	0.19424
12	0.6 min	0.04524	0.00007	0.22369
20	1.5 min	0.048272	0.00013	0.10065
40	3.33 min	0.048152	0.00030	0.09624

Table 5: Statistics for the estimation of log(u) (life), backpropagation.

Number of hidden layer nodes.	Approximate training time	RMS Error	Minimum Absolute Error	Maximum Absolute Error
1	1.3 min	0.04050	0.00012	0.11006
3	5 min	0.04362	0.00018	0.11006
5	7 min	0.03924	0.00034	0.10127
7	12 min	0.04446	0.00016	0.13405
10	15 min	0.04199	0.00006	0.13433
20	40 min	0.04888	0.00013	0.21529
200	24 hr	0.04734	0.00004	0.240454

Table 6: Statistics for the estimation of log(u) (life), CID4 algorithm.

Number of training vectors (OLS selected)	Network Architecture	Approximate training time	RMS Error	Minimum Absolute Error	Maximum Absolute Error
20	2:2:2:2:2:1	1 min	0.16272	0.00058	0.33292
40	2:2:2:2:2:2:2:1	2.17 min	0.14968	0.00023	0.28879

DISCUSSION

In estimating the local stress, we see from Table 1 and 8.2 that the RBF network gave RMS errors in the range of 0.019786 - 0.59094 for the half-amplitude hysterisis loop estimations. This works out to approximately 2 - 6% of the domain of σ ($-0.552853 < \sigma < 0.673437$). The backpropagation network gave RMS errors in the range of 0.031943 - 0.048271, which works out to approximately 3 - 5%. For estimations on the increasing portion of the hysterisis loop, Table 2 indicates that the errors are approximately 7 - 30% for RBF and 2 -

4% for backpropagation. For the decreasing portion of the hysterisis loop, Table 3 indicates that the errors are approximately 35 - 46% for RBF and 35 - 39% for backpropagation. In general, the use of a larger number of hidden layer nodes means a a general decrease in error, though the trend might not be smooth. Varying the number of nodes had more effect for the RBF network than for the backpropagation network.

The results obtained for the the strain/life function (shown in Tables 4, 5 and 6) suggest that the approximated function is quite simple. An increase in the number of hidden layer nodes does not cause a significant reduction in the RMS error. In fact, as the number of nodes in the hidden layer was increased, there was a slight increase in the RMS error for both the RBF and the backpropagation networks. There was a minimum error for the RBF network using 10 hidden layer nodes, and similarly the backpropagation network using 5 hidden layer nodes had a slightly smaller RMS error than the other configurations. This could possibly mean that the larger networks were over-trained, explaining the slight increase in error when using more than the optimum number of nodes. It is also interesting to note that the backpropagation network with only one hidden layer node performed well. This again suggests that the desired mapping function is simple.

For similar sized networks, the time required to train an RBF network was over 20 times shorter than the time required to train a backpropagation network. However, the time required to select the 40 centers out of the 1000 training examples (2 hours) should also be taken into consideration. The CID4 network required slightly more training time than RBF. The advantage with CID4 is that it self-generates its own architecture. However, the results obtained had an RMS error much larger than that obtained with RBF or backpropagation.

Although the two system modules discussed in this paper were trained using data obtained from mathematical calculations, there are two major advantages gained by using neural networks over numerical methods to come up with the desired estimations. First, a trained neural network usually gives its output much faster than numerical approximation. Second, using neural networks provides the flexibility for training the system with empirical data, should it ever be desired. Third, we have shown how neural networks can be integrated into a large, complex systems.

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