Experimental validation of an ANN model for random loading fatigue analysis

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Abstract

The use of artificial intelligence especially based on artificial neural networks (ANN) is now prevalent in many fields of data analysis and interpretation. There have been a number of papers published in the literature on the use of ANN for fatigue characterisation. Most of these have however been developed for rather focussed application with limited capability for fatigue life prediction for a broad scope of material and loading conditions. The authors recently presented a uniquely generalised ANN model that is capable of making fatigue life prediction for a broad range of material fatigue properties and loading spectral forms. The model was developed using simulated data albeit subject to conceivable constraints between possible materials properties and load forms. This paper presents a validation of the ANN model using a Society of Automotive Engineers (SAE) random fatigue loading experimental test data. The capabilities and potentials of the model are demonstrated by comparison with the SAE random load fatigue test results and with results obtained from other predictive methods. The performance of the ANN is highly encouraging as a general tool for random loading fatigue analysis.

Keywords

Random fatigue, frequency domain, time domain, artificial intelligence, artificial neural networks, SAE

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1 Introduction

ANN has been known to provide greater scope for non-linear generalisation and ability to deal with a high number of input variables than direct application of optimisation methods [1-4] . It has therefore seen application in various fields of analysis, prediction and classification. Bhadeshia[5] indicated that fatigue is one of the most difficult mechanical properties to predict and suggested that the application of ANN could assist with the establishment of relationships between, material and loading variables especially for crack propagation life prediction. There have been a number of ANN models developed to solve different types of fatigue problems. Artymiak et al[6] demonstrated the use of ANN for the prediction of S – N curves based on a database of fatigue properties for steel alloys only. Pujol and Pinto[4] used ANN to develop cumulative fatigue damage functions based on results of experimental tests carried out on a steel alloy.

Iacoviello et al [7] introduced ANN as a tool for the analysis of the effect of stress ratio on fatigue crack propagation in a duplex steel. Marquardt and Zener [8] showed that ANN could be used to make better fatigue damage predictions by using fatigue life properties and the form of loading directly without using classical damage accumulation models. The work was based on a database of 825 experimental tests, more than half of which were carried out on ferrous materials. Kang et al [9] showed how ANN could be used to reduce computational time for fatigue damage calculation under multiaxial random loading for a component. Recently, Martinez and Ponce [10] showed that ANN could be used to predict the effect of temperature on fatigue damage during different sequences of loading of a component. In the realm of random loading fatigue, Kim et al [1] showed the possibility of using ANN to determine the stress range probability density function for two peak spectral load data type indicating that better performance is obtained compared to those developed by Wirsching-Light[11], Zhao-Baker[12], Benasciutti-Tovo[13], Tovo[14] and Dirlik[15]. As highlighted in the above review, the scope of the use of ANN in references [1,4,6,7] is rather in terms of the possibilities of range of materials, load type and fatigue component conditions.

A recent publication by the authors [16] presented a novel generalised ANN frequency domain based method for random loading fatigue analysis. The model which cover a wide range of materials, load forms and component conditions. This was done by considering material fatigue properties that cover virtually all metallic alloy property range and all conceivable component conditions such as different sizes, surface conditions, stress concentration and realistic loading spectra load forms. The generalisation was achieved by investigating and identifying the input parameters which were necessary to make generalisation for fatigue damage prediction possible under the broad scope of conditions considered. A further developed generalised model [17] which built on the previous work in [16] included the effect of mean stress due to loading.

The model developed by the authors [17] was tested previously only on simulated data. Every effort was of course made to ensure that the simulated data represented real data as much as possible. This was achieved by ensuring during the data generation stage that various choices of metal alloy, tensile strength, fatigue strength coefficient and exponent values and the root mean square value of PSD shapes were all consistent so that the corresponding fatigue damage was realistic. For unseen data, the proposed model [17] was able to generate good correlation between predicted and simulated damage for the combination of material and signal options highlighted. The model [17] gave better agreement with the rainflow cycle counting time domain approach [15] than the existing frequency domain methods [15] [19]. The correlation and regression coefficients between the ANN [17] predictions and the time domain method [15] predictions were all over 0.997 for the logarithmic damage outputs. Although this was very encouraging, it is essential to demonstrate that the models will make good predictions when used on actual experimental data. This was the motivation for this work.

The experimental data used in this work for validation was obtained from the SAE test programme which was reported in reference [20]. The data was a result of a fairly comprehensive random fatigue loading test programme. The programme considered three component load forms, three levels of loading and two material types. The load histories represented averagely negative, positive and zero mean stress conditions and were applied to the specimens under low, medium and high load levels. The published data is a filtered form of the experimental data which means that some effect could have been lost. It nevertheless has provided basis for investigation by some authors [21]. It has served a similar purpose in this work; in this case, for validation of the ANN model. The validation was carried out by using the SAE fatigue test data and material properties in the ANN model presented in [17] and comparing the predictions obtained with actual fatigue life obtained in the SAE [20] experimental test programme. The results of the application of the model are also compared with those obtained using other existing non ANN predictive models such as Dirlik's model [15] and Nieslony [15]. This was to provide a basis of comparison of the effectiveness of the model presented in [17].

2 The ANN model

This section presents an outline of the bases and methods used for the ANN model being validated. The structure of the ANN used, the types of signals considered, the input-output parameters used, the numerical training, validation and testing of the model is highlighted in this section.

2.1 ANN architecture

Three layers of neuron as illustrated in Figure 1 which is generally accepted as sufficient to represent any non-linear function approximation [21] was used as the architecture of the ANN. The number of input, hidden and output neurons used were 11, 25 and 1 respectively. The 11 input parameters are listed later in this work in section 2.3. The result from the single output neuron was the logarithmic value of the fatigue damage. The number of hidden layer neurons tested ranged from 10 to 80 and 25 was found to be adequate. The recommendation to use about 20 times the total number of neurons [22] provided some guidance for the number of signals constructed for the ANN training and testing in the study. In order to study the effect of the density of the coverage of the sampling space, the numbers of signals constructed and tested ranged from 100 to 50,000.

2.2 Signal generation

The signals used to train the network were constructed from twelve forms of spectral shapes illustrated in Figure 2. The spectral forms included those used by Dirlik [15], Tovo 11] and Benasciutti and Tovo

[13]. In Figure 2, the frequency values q_1, q_2, f_i, $i = 1, 6$; spectral amplitudes d_i, $i=1, 3$ and shape modification parameters d_4 and d_5 were chosen using the Latin Hypercube Sampling (LHS) [23] experimental design approach [24]. This facilitated effective coverage of the fatigue loading space. The range of the material properties, i.e. the ultimate tensile strength, S_u, fatigue strength coefficient *a* and strength exponent *b*; and the limits of the spectral moment values m_i, $i = 0,1,2,4$ considered in the work are highlighted in Table 1.

As highlighted in the foregoing, different sample sizes ranging from 100 to 50000 were analysed in the course of the study. The materials considered in this work were metallic alloys. Fatigue material properties S_u, *a* and *b* were sampled in the range 200 – 2000 MPa, 1.17 S_u to 13.61 S_u and -0.0850 to -0.333 respectively. The range for the strength accommodates most alloys known from copper to maraging steels; both the fatigue strength exponent *b* and strength coefficient *a* covered all typical or plausible values [17]. These *a* and *b* values are dependent on factors such as size, surface finish, type of loading and notch factor. For every combination of spectra parameters, the corresponding time domain signal for the selected spectrum was generated using equation (1) [25],

$$x_n(t) = \sum_{k=1}^{N} [2G_x(f_k)\Delta f]^{1/2}[\cos(2\pi ft + \phi_{k,n})] \quad (1)$$

Where, n is the sample number, *N* is the number of discretisation of the power spectral densities (PSD) G_x, with $f_k = (k - 0.5)\Delta f$ and $\phi_{k,n}$ are mutually independent random phase angles distributed uniformly over the range 0 to 2π. The maximum frequency considered for the fatigue data in the study was 200 Hz. The sampling frequency used varied from the corresponding Nyquist frequency of 400 Hz to 6.40 kHz. The higher sampling frequencies were considered in the light of recent findings [26]. Up to 5000 discretisation of the frequency range and 32000 time steps were considered. In order to introduce a mean stress effect, the signal was then randomly shifted along the stress ordinate so that in general $S_m \neq 0$ [17]. The final *x(t)* obtained was then scaled so that the highest peak or deepest valley lied within 5 to 83% of the ultimate tensile strength value. The mean stress values incorporated ranged from -0.6 to 0.6S_u. This scaling reduced the possibility of any of the time data leading to extremely low values of oscillation that would not be representative of a fatigue phenomenon. This process provided a pool of input and output data for the training of the ANN as described in section 2.3. The signals were analysed using ANN structures described in the foregoing as well as using an in-house rainflow cycle counting routine for fatigue damage predictions. For each signal and corresponding material fatigue properties, the corresponding fatigue damage intensity (i.e. damage per second) for was determined using the rainflow cycle counting and Miner's cumulative damage rule as the target result values.

2.3 ANN Input - output

The number of inputs used for the neural network was 11 in total. This included fatigue material properties, a and b and the ultimate tensile strength, S_u ; four spectral moments m_i, $i = 0,1,2,4;$ the Goodman parameter α_m that accounts for the mean stress effect in a global sense; a mean complementary parameter $\alpha_c = 1 - \alpha_m$; and two crest parameters γ_p and γ_n. The crest parameters were respectively equal to the ratios of maximum and minimum stress in the signal to the ultimate tensile strength of the material. Further description of these parameters can be found in reference [17]. The logarithmic value of the damage *E(D)* was used as the output target value. This helped to reduce the impact of the spread of the damage values which was broad by several orders.

2.4 Training, validation and testing

The training process used in the work was based on the feedforward – backpropagation multilayer perceptron (MLP) method. The training proceeds by feeding known inputs into the network and obtaining its corresponding predictions for the output. In this process, each internal and output neuron received a weighted sum of the input from the preceding neurons. The output from each neuron was transformed by an activation function before being used as an input for the next layer of neurons. The sigmoid function which is numerically desirable in the perceptron model because it ensures that all values passing to the next neuron lie in a range such as [0,1] was used between the input and hiding layer. The output layer used a linear transfer function, to ensure that erroneous outputs were easy to identify rather than being tempered by the sigmoid transfer function effect.

The output from an ANN does not in general match the known output corresponding to the inputs used from the data set, at least in the first feedforward through process. The mis-match error is a function of the weights associated with the neurons. The aim of the training is to determine the weights associated with the neurons that minimise the error. The minimisation process was carried out iteratively in many stages. Various error reduction backpropagation algorithms have been devised for the training of networks. One of the methods used in this work was based on the +Rprop algorithm which is known to have excellent convergence characteristics [27]. The parameters required for the optimal convergence of the training in this approach has been identified for most problems and are not dependent on trial and error [27]. For research flexibility purposes, the implementation of the ANN in this work was also carried out using a set of in house routines developed in a MATLAB [28] environment. The Levenberg Marquardt error backpropagation and weight correction method in MATLAB ANN tool box was used. The use of MATLAB provided faster processing of data and the prediction was also equally good as in the in-house programs.

After experimenting with various proportions, the percentages of data finally used for training, validation and testing were 70, 15 and 15% respectively. The training process was based on 70% of the total data generated. A validation set which was 15% of the total number of signals, was used to independently check the performance of the ANN weights obtained in the training process. This was to ensure that the ANN model had not simply over fitted or memorised the relationship between the training data and the output but actually developed the capability to make a prediction for an unseen set of data. The validation set was used to detect when the tendency for overfitting was about to set in and the training process was stopped at this stage. The final 15% data set was used to provide an independent test of the ANN model. The data used in this process was different from the data used for the training and validation steps. It should be noted that the validation discussed here is part of the common terminology used for ANN model development in the literature. It is not validation using experimental test data which is the main objective of this paper. It should furthermore be stated that in some ANN development cases however, all the data used for training, validation and testing could be completely or partly experimental. No experimental data was used in the development of the ANN model presented in [17].

3 Experimental data

The validation in this work was based on experimental data obtained by the Society of Automotive Engineers [20]. The data came out of an initiative of the SAE Fatigue Design and Evaluation Committee to test component under real load histories and to compare the experimental results to those of cumulative damage fatigue life estimates procedures. While it was not the intention of the committee to produce standard load histories or spectral for components, the load histories selected were typical for ground vehicle industry and admittedly limited. The aim of the program was to provide a database that can be used generally to evaluate methods of fatigue life prediction methods.

The tests consisted of two different notched hot rolled steel specimens made of Man-Ten and RQC-100 steel alloy materials. The material properties of Man-Ten and RQC-100 are listed in Table 2. The time loading histories consist of (i) that of a mounting bracket with 5936 reversals, predominantly a zero mean signal and represents a narrow-band signal; (ii) a vibration loading history of a transmission torque of a tractor with 1705 reversals, a positive mean with radical changes in the mean load; and (iii) a time load history of an automobile suspension component with 2056 reversals having highly compressive mean stress. The total number of reversals in each spectrum was considered as one block of loading and the fatigue life in the study was the number of blocks loading till of the component failure occurred. Figure 2 shows the three time histories developed by SAE, which were used in this study.

3.1 Geometry and description of the fatigue test experiment

Drawing on six months of discussions, the SAE Fatigue and Design Evaluation committee came up with a test specimen, which was relatively stiff and had a notch for consideration of stress concentration effects. The specimen also had negligible critical dimensions with all surfaces in the as received condition and permitted the study of both crack initiation and propagation [20]. The geometry of the

SAE notched specimen is shown in Figure 3. The experiments were conducted by applying the load on the specimen through a monoball fixture which facilitated compression and tension loading, Figure 4 shows the experimental assembly of the notched specimens.

3.2 Fatigue strength coefficients and exponents

The S – N curves of materials were generally determined using small plane specimens with excellent surface condition and without geometric factors that could cause stress concentration. The properties obtained in this way are usually modified in order to be applicable to components with real features such as fillets, notches and holes that cause stress concentration. Three nominal stress methods considered by Dirlik [15] to account for the effect of stress concentration for the SAE tests specimens were applied in this study. The modification of the plain specimen fatigue properties *a* and *b* to account for the stress concentration effect are presented in Tables 3 and 4. The methods were described as Nominal Stress Methods 1, 2 and 3 and are henceforth referred to in this work as NS-1, NS-2 and NS-3 methods. Table 4 contains the modified S – N curve properties *a'* and *b'* in terms of the stress concentration factor K_t for the test specimens and the original fatigue properties *a* and *b* given in Table 3.

4 FEA Fatigue analysis

4.1 Fatigue damage analysis using nominal fatigue life parameters

The SAE Notched specimen was modelled in SolidWorks software package [29] and it was exported to ANSYS Workbench [30] environment for analysis. Material properties of both Man-Ten and RQC-100 were put in the ANSYS Workbench material library. The model applied load using bearing contact option for the three holes on the component. The directions of the force between the pivot point of the mono-ball joint and the three holes on the component were specified by the direction from the centre of the holes to the centre of the pivot. This loading option methods are available in ANSYS and SolidWorks packages. The same loading method was applied at the two ends of the compact tension component. Rigid body motion under this loading condition was avoided by selecting the ' inertia relief' option. This means that no displacement boundary conditions were required in order to allow the solver to complete the analysis. The SAE fatigue test used three load levels 71.2, 35.6 and 15.6 KN for bracket and transmission load histories and 71.2, 40.0 and 26.7 KN for suspension load histories respectively. These load sets were used in the validation studies.

As highlighted in Section 3.2, the analysis carried out was based on an S-N approach with the stress concentration accounted for by the modification of the fatigue properties. This is the usual approach for the application of the S-N curve and the empirical procedures behind the method. The stress concentration factor of 3.05, given by SAE was based on a nominal stress calculated by assuming that the test specimen was a simple beam subjected to an offset load causing a combination of axial and bending stress. In order to avoid double accounting for the stress concentration effect, the nominal loads applied in the FEA analysis were based on the loading forces divided by the stress concentration factor of 3.05. The element used in the ANSYS analysis by were a mixture of solid tetrahedral and hexahedral type elements of the quadratic order of displacement approximation. Focussed element mesh was used around the notch while free mesh was used elsewhere. Mesh effect test analysis was carried out to ensure that the stress at the root of the notch converged. The element dimension around the notch was approximately 0.5 mm for the converged results around the notch. The elements remote to this region were about 5 mm side length. The converged value of the stress at the root of the notch was 34.6MPa / KN. The data points in the three SAE time histories were given in a normalised form to lie between -1 and 1. The actual stress history in any case was obtained by multiplying the normalised SAE time history by the maximum stress obtained at the root of the notch from the FEA linear elastic static analysis. The time scale was represented by a nominal unit of 1 s, corresponding to 1 Hz.

5 Results

In this section, the procedures developed and used in the work were first validated against published data and against the results obtained using the ANSYS FE commercial package. This is followed by the assessment of the performance of the ANN model obtained from different training processes. The performance of the ANN model with various options are then compared with the SAE experimental fatigue results as well as with the results of predictions making us of other methods such as Dirlik frequency domain model [15] and Nieslony's mean stress effect modification method [19]. This latter approach is henceforth referred to as Nieslony's method.

5.1 Verification of time domain procedures

It is helpful to verify the time domain rainflow cycle counting and Miner's damage accumulation calculation procedures developed and used in this work. This is essential because the time domain predicted damage values were used as the target value for the training of the ANN. The problems considered here for the verification were based on the SAE test specimen illustrated in Figures 3 and 4. The specimens were subjected to the three test histories shown in Figure 2 and three load levels of between 15.60 kN and 71.20 kN. The two materials, MAN-TEN and RQC – 100 used by the SAE were considered. The fatigue material properties used are as given in Tables 3 and 4. This problem was solved by Dirlik [15] using the direct time domain rainflow cycle counting and Miner's damage accumulation method. The same problem was analysed herein using FE Fatigue in ANSYS. Figure 5(a) shows the von Mises stress distribution obtained for the RQC-100 material and bracket stress history using ANSYS and also the corresponding fatigue results based on the time domain rainflow cycle counting and Miner's rule for a load of 71.2 kN. The life obtained in blocks is plotted in Fig 5(b). Similarly, results for the transmission stress history under the same conditions as in Figure 5 are shown in Figure 6. The time domain rainflow cycle counting and Miner's rule method results obtained by (i) Dirlik [15] for the loading condition and those obtained in the present work (ii) using the ANSYS FE Fatigue [30] and (iii) time domain routines developed in Matlab in this work are compared in Table 5. The results obtained using the different life – stress, NS-1, NS-2 and NS-3 formulas given in Table 3 vary but are all reasonably close at least in the context of scatter of fatigue life results.

As can be seen in Table 5, the results from the rainflow cycle counting fatigue analysis carried out in this work agrees closely with those obtained using ANSYS. The same nominal stress analysis methods and material properties were of course used in both cases. The minor discrepancies between the results could be due to the differences in the intermediate steps used in the interpretation of the rainflow cycle counting algorithm. The results of the rainflow cycle counting analysis carried out herein and those of the ANSYS package agree generally well with those previously obtained by Dirlik [15]. The areas of differences are primarily where low loads were applied**.** As can be seen in Table 5, the results of the three nominal methods NS-1,2,3 are generally conservative relative to the experimental results. The NS-2 method is the least conservative with respect to the SAE [20] experimental results than the other two methods. For efficient design considerations, the fatigue life parameters, based on NS – 2, which are given in Table 3 were used for the fatigue life prediction in all the results following.

The agreement of the results obtained from the developments in this work with those obtained by Dirlik [4] previously and those obtained from ANSYS provided basis for confidence in the procedures developed for the analysis carried out.

5.2 Effect of the number of samples used in training ANN

As indicated in reference [17], the weights obtained by training the ANN with over 5000 signal samples gave more consistent results when tested against un-seen signals than for lower number of signals. Up to 50,000 signals were used in the reference. Preliminary tests carried out on validation against experimental data in this work showed that weights obtained from training with 10,000 signals or more gave consistent agreement with experimental results. In view of this observation, five set of ANN weights were obtained from signal sizes of 10,000 to 50000 in increments of 10,000. ANN procedures include statistical operations such as the initial randomisation of the starting weights. This means that different weights were obtained each time the training process was carried out. This therefore meant that different results were obtained when weights from different training processes were used for prediction. The results obtained from using different weights were in most cases reasonably close. There were nevertheless instances where the differences were significant. The committee of machines approach [31] which involves statistical averaging is a method of avoiding the effect of outlier predictions that can occur from ANN predictions. In this work two committee of machines averaging methods were used. In the first case, ANNr, an average of the logarithmic damage values from the five weight sets were taken before getting the antilog to obtain the actual damage value. In the second case, ANNs, a simple average of the damage obtained from the five weight sets was taken to be representative. The predictions obtained using the five sets of weights and those obtained using the committee of machines are summarised in Table 6. All SAE data for the two materials, three load levels and three mean stress levels were considered.

It can be seen in Table 6 that the ANNr predictions generally agreed better with the experimental results than the ANNs method. ANNs results compared well with experimental results especially for the high and medium loads but less so for the low loads except for the bracket spectrum. This is partly due to the fact that low loads can give rise to high number of cycles to failure. It can be seen that the results are more sensitive to outlier predictions from the sets using the ANNs predictions. The ANNr procedure which involves taking the average of the log of damage and then converting to actual value showed less sensitivity to extreme values from the predictions of individual ANN predictions. The ANNr averaging approach was therefore adopted in subsequent analysis as basis for comparison of predictions with experimental results.

5.3 Comparison of results of ANN with other methods and SAE experimental results

The aim of this section is finally to compare the results obtained from ANNr prediction with the SAE experimental fatigue test results for three different loads levels, three signal types and two materials. This gives a total of 18 result cases. In these 18 cases however only in 14 cases were there two or three repeat tests results available. The results obtained in this work are also compared with those computed using rainflow cycle counting and Miner's rule and use of Dirlik [15] frequency domain and Nieslony's method [19].

The results from the different fatigue prediction methods are presented in Table 7. The table gives numerical values that allow comparison of the predictions against the full experimental results from SAE. For ease of visualisation of trends, it was found helpful to plot the results from ANNr against those from other methods and SAE experimental results in Figures 7 and 8. The error bar in Figures 7 and 8 represents lower and upper one standard deviation from the mean of the SAE experimental results [20]. As can be seen in Table 7, this range covers the range of the experimental results presented very well. As can be seen from the table and especially the figures, the results from Dirlik's method [15] were generally very conservative and the results of Nieslony's method [19] were generally not consistent with experimental results.

There are 18 SAE experimental result cases from 3 component types, 3 load levels and two material types. There are 16 cases with at least 2 or 3 repeat test results. The performance of ANNr is compared for these 16 cases with those of Dirlik [15], Nieslony [19] and the rainflow counting methods [15] methods in terms of how many predictions were within the range of experimental results, under predicted or over predicted the number of blocks to failure. As can be seen in Table 8, the ANNr results fell within the experimental range more than for the Dirlik and Nieslony predictions. The percentage of the results within the range were 37.50 and 18.75 and 18.75% respectively. The rainflow counting method predictions were within the range of experimental results for 43.75% of the cases but over predicted in 37.50 % of the experimental test cases with repeat results. The ANNr results over predicted in 12.50% of the cases compared to 18.75% for Nieslony's method. Dirlik's method under predicted in 81.25% compared to 50% and 18.75% respectively for the ANNr and rainflow counting methods. The work in references [16,17] shows that Dirlik's prediction could also over predict in some cases. This observation is also supported by the work of Quigley and Lee [32] who reported up to 30% over prediction of fatigue life. These results show that further wide experimental validation testing is required for all the methods in order to establish appropriate factor of safety that will lead to efficient design rather than excessively over conservative.

6 Discussion

As can be seen in Figures 7 and 8, the ANN_r results correlate well with the experimental results and generally lower than the experimental results. The results also show that ANN has given closer prediction to rainflow counting and experimental results than other existing frequency domain methods.

It was surprising that the time domain rainflow cycle counting method using Miner's rule to determine damage showed some undesirable features. It over predicted life in 37.50 % of the experimental cases and under predicted in 18.75 % of the cases with repeat results. This observation was surprising because the rainflow cycle counting method is the most acclaimed time domain method for fatigue prediction [33]. The implication of this is that more caution is required in the use of the method alone for design because of lack of certainty with regards to the conservativeness of the prediction results in comparison to likely experimental performance. Dirlik's prediction were consistently

As in Dirlik's results [15], the choice of the method used to account for stress concentration effect in life stress calculation leads to variabilities in predictions. No single method among the three cases NS-1, NS-2 and NS-3 gave consistently closer result to the experiment for all signal types, load levels and material types. In this study as in Dirlik's [15], the choice of a helpful approach may depend on experience of actual component failure tests. The choice may then be useful for subsequent analysis and design.

The ANN results as can be seen in section 5.3 agreed more generally with experimental results than those from frequency domain based methods such as Dirlik and Nieslony methods. The agreement of ANN in this work with experimental results for two materials, three component types and three load levels has provided some validation for the ANN model.

It should be noted that the closeness between the ANN_r results and time domain rainflow counting results was lower than anticipated. The present thought about this is that the SAE data is a filtered data [20] which might have had some of the underlining frequency content removed. Although present results are encouraging, further elaborate experimental work will need to be carried out to demonstrate the full potential of the ANN approach.

7 Conclusion

The paper presents the results of validation studies carried to verify the likely performance of ANN analysis procedures developed by the authors. The results of the ANN prediction agreed reasonably well and consistently with experimental SAE results under various materials, component type and load levels which were considered. The predictions of fatigue life by ANN model were generally lower compared to experimental results. Although rainflow cycle counting results appear to be closer to experimental results in magnitude, the performance however showed both conservative and non-conservative predictions. The ANN results generally agreed better with the rainflow and experimental results than the Dirlik and Nieslony's prediction methods. It is remarkable that the ANN model results agree well with experimental testing results even though the spectral types do not explicitly match the spectral patterns used for the ANN model development. The results of the validation show that the ANN model along with other methods is a viable life prediction method for consideration for random fatigue loading problems. Further testing needs to be carried out for all the prediction methods in order to establish choice of factors of safety that will lead to efficient fatigue design of components. This work has shed further light on likely performance of ANN and those of existing methods by using the SAE random loading fatigue results.

8 References

[1] Kim,Y., Kim, H., and Ahn, I-G.(2016) 'A study on the fatigue damage model for Gaussian wideband process of two peaks by an artificial neural network'. *Ocean Eng* ; 111:310–22.

[2] Hernandez-Gomez, L.H., Durodola, J.F., Fellows, N.A. and Urriolagoitia-Calderón, G., 2005. Locating defects using dynamic strain analysis and artificial neural networks. In *Applied Mechanics and Materials* (Vol. 3, pp. 325-330). Trans Tech Publications.

[3] Farley SJ, Durodola JF, Fellows NA and LH, H.-G. (2008) 'A neural network approach for locating multiple defects', *Advances in experimental mechanics,* 125(31).

[4] Pujol, J.C.F. and Pinto, J.M.A., 2011. A neural network approach to fatigue life prediction. *International Journal of Fatigue*, *33*(3), pp.313-322.

[5] HKDH, B., *Neural networks in materials science.* ISIJ international, 1999. **39**(10): p. 966-979.

[6] Artymiak, P., et al., *Determination of S–N curves with the application of artificial neural networks.* Fatigue & Fracture of Engineering Materials & Structures, 1999. **22**(8): p. 723-728.

[7] Iacoviello, F., D. Iacoviello, and M. Cavallini, *Analysis of stress ratio effects on fatigue propagation in a sintered duplex steel by experimentation and artificial neural network approaches.* International Journal of Fatigue, 2004. **26**(8): p. 819-828.

[8] Marquardt, C. and Zenner, H., 2005. Lifetime calculation under variable amplitude loading with the application of artificial neural networks. *International journal of fatigue*, *27*(8), pp.920-927.

[9] Kang, J.Y., Choi, B.I., Lee, H.J., Kim, J.S. and Kim, K.J., 2006. Neural network application in fatigue damage analysis under multiaxial random loadings. *International journal of fatigue*, *28*(2), pp.132-140.

[10] Jimenez-Martinez, M. and Alfaro-Ponce, M., 2019. Fatigue damage effect approach by artificial neural network. *International Journal of Fatigue*, *124*, pp.42-47.

[11] Wirsching, P.H. and M.C. Light, *Fatigue under wide band random stresses.* Journal of the Structural Division, 1980. **106**(7): p. 1593-1607.

[12] Zhao, W. and M.J. Baker, *On the probability density function of rainflow stress range for stationary Gaussian processes.* International Journal of Fatigue, 1992. **14**(2): p. 121-135.

[13] Benasciutti, D. and Tovo, R., 2005. Spectral methods for lifetime prediction under wide-band stationary random processes. *International Journal of fatigue*, *27*(8), pp.867-877.

[14] Tovo, R., 2002. Cycle distribution and fatigue damage under broad-band random loading. *International Journal of Fatigue*, *24*(11), pp.1137-1147.

[15] Dirlik, T. (1985) 'Application of computers in fatigue analysis', *Ph.D. Thesis,* The University of Warwick.

[16] Durodola, J.F., Li, N., Ramachandra, S., and Thite, A. (2017) 'A Pattern Recognition Artificial Neural Network Method for Random Fatigue Loading Life Prediction' *International Journal of fatigue,* 99, pp. 55-67.

[17] Durodola, J.F., Li, N., Ramachandra, S., and Thite, A. (2018) 'Artificial neural network for random loading analysis including mean stress effect' *International Journal of fatigue,111*, pp. 321-332.

[18] Standard Practices for Cycle Counting in Fatigue Analysis, Annual Book of ASTM Standards, ASTM E 1049-85 (Reapproved 1997), 1999, vol. 03.01, Philadelphia, USA

[19] Niesłony, A., and Böhm, M. (2013) 'Mean stress effect correction using constant stress ratio S–N curves' *International Journal of Fatigue*,. 52: p. 49-56.

[20] Tucker, L., and Bussa, S. (1975) 'The SAE Cumulative Fatigue Damage Test Program'. *Society of Automotive Engineers.*

[21] Al-Asady, N.A., Abdullah, S., Ariffin, A.K., Beden, S.M. and Rahman, M.M., 2009. Comparison between experimental road data and finite element analysis data for the automotive lower suspension arm. *European Journal of Scientific Research*, *29*(4), pp.557-571.

[22] Heaton, J., 2008. *Introduction to neural networks with Java*. Heaton Research, Inc..

[23] McKay, M.D., Beckman, R.J. and Conover, W.J., 2000. A comparison of three methods for selecting values of input variables in the analysis of output from a computer code. Technometrics, 42(1), pp.55-61.

[24] Montgomery, D.C., 2000. Design and analysis of experiments. John Wiley and Sons.

[25] Shinozuka, M., 1972. Monte Carlo solution of structural dynamics. *Computers & Structures*, *2*(5-6), pp.855-874.

[26] Quigley, J.P., Lee, Y.L. and Wang, L., 2016. Review and assessment of frequency-based fatigue damage models. *SAE International Journal of Materials and Manufacturing*, *9*(3), pp.565-577.

[27] Igel, C. and Hüsken, M., 2000, May. Improving the Rprop learning algorithm. In Proceedings of the second international ICSC symposium on neural computation (NC 2000) (Vol. 2000, pp. 115-121). ICSC Academic Press.

[28] The MathWorks Inc (2018). MATLAB the language of technical computing,

[29] SolidWorks (2018), Dassault Systems

[30] ANSYS Workbench (2018), ANSYS USA

[31] Guo, J. J. and Peter, B. L., 2004. "Improving market clearing price prediction by using a committee machine of neural networks", IEEE Transactions on Power Systems. vol. 19, no. 4, pp. 1867-1876.

[32] Quigley, J. P., Lee, Y. L., 2012. 'Assessing Dirlik's Fatigue Damage Estimation Method for Automotive Applications', SAE Int. J. Passeng. Cars - Mech. Syst. 5(2):911-920.

[33] Dowling, N.E., 2012. *Mechanical behavior of materials: engineering methods for deformation, fracture, and fatigue*. Pearson.