MODELING OF THE FATIGUE LIFE OF ADHESIVELY-BONDED FRP JOINTS WITH GENETIC PROGRAMMING

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SUMMARY

A novel computational technique, called genetic programming, is used in this work to model the fatigue life of adhesively-bonded FRP joints subjected to tensile fatigue loading under different environmental conditions. It is proved that genetic programming can effectively interpret fatigue data, without the need for the adoption of any assumptions, and can accurately model fatigue life of the material system under investigation.

Keywords: Fatigue, genetic programming, life prediction, adhesive joints, temperature

INTRODUCTION

The effect of the environment on the fatigue behavior of adhesively-bonded joints has formed the subject of several investigations in the past, e.g. [1-5], mainly on joints used in the aerospace and/or automotive engineering domains. Previous studies showed that the fatigue behavior of the joints was considerably affected by environmental conditions. In addition, different failure modes were observed under different conditions. Cohesive failure of the adhesive occurred under hot, humid conditions. The failure mode changed to substrate failure for ambient temperature, while very rapid propagation was observed when testing at -50^{o}C. The authors [1] attributed this behavior to the increased rigidity of the adhesive as it cooled. The static and fatigue behavior of different joint types used in the aerospace industry were investigated in [2] (composite joints with film or paste adhesives, composite-to-metal joints). The same group investigated the temperature-dependent fatigue behavior of CFRP/epoxy double-lap joints over a wide temperature range of -50 to 90^{o}C [3]. Unidirectional (UD) and multidirectional (MD) adherends were used. The MD joints were shown to be stronger at low temperatures, at which, according to the authors, joint strength was determined by the peak stresses. UD joints on the other hand were stronger at high temperatures where the strength was controlled by the creep of the joints, determined by the minimum developed stresses. The fatigue damage and failure mechanism of single-lap joints composed of E-glass/polyethylene adherends and an ethyl-cyanoacrylate adhesive were investigated in [4]. The specimens were preconditioned for up to 90 days in water at different temperatures prior to testing. A significant reduction in fatigue strength was observed with increased immersion time and when the water temperature exceeded the glass transition temperature of the adhesive this reduction was accelerated. The fatigue response of adhesively-bonded pultruded GFRP double-lap joints under different environmental conditions has been investigated in [5]. Tests were performed at -35°C, 23°C and 40°C. A fourth set of fatigue data was collected from tests on preconditioned specimens in warm (40^{o}C) water. The tests were performed at 40^{o}C and at 90% relative humidity. The dominant failure mode was a fiber-tear failure that occurred in the mat layers of the GFRP laminates. In the presence of high humidity, the failure shifted to the adhesive/composite interface. Although the testing temperature was lower than the glass transition temperature of the adhesive, its influence on the fatigue life and fracture behavior of the examined joints was apparent and was aggravated by the presence of humidity

Although a lot of research efforts were devoted to the characterization of the fatigue behaviour of adhesively-bonded composite joints and composite laminates under different temperature and humidity environments, there is no common method in the literature (to the authors knowledge) for the modeling and/or the prediction of such a behavior. A limited number of modeling approaches has been published, e.g., [6-8]. However, in order to accommodate a significant number of parameters that affect the fatigue life of FRP joints, these phenomenological models adopt a lot of assumptions, e.g., [6]. Therefore, their applicability could not be validated on different material system's data.

To this end, new computational methods have been presented in the literature [9-12] and it has been proved that they can be used to accurately model the fatigue life of composite laminates under various loading patterns. In fact, evolutionary computational methods have been emerged as one of the most powerful modeling tools in a number of scientific domains. In engineering, artificial neural networks and genetic programming have been used for optimization of design methods and manufacturing processes e.g., [13]. Modeling of fatigue life of composite materials and structures is a topic that has been addressed by this type of analysis tools only the last years. Since recently, artificial neural network was the only method that was used for the fatigue life modeling of composite materials and structures [9-10]. New tools, like genetic programming and adaptive neuro fuzzy inference system were applied lately [11-12]. A novel, in this field, computational technique, called genetic programming, has been presented in [11] for the modeling of the fatigue life of multidirectional composite laminates. The same tool is used in this work to model the fatigue life of adhesively-bonded FRP joints subjected to tensile fatigue loading under different environmental conditions.

THEORETICAL BACKGROUND

Genetic programming (GP) is a domain-independent problem-solving technique in which computer programs are evolved to solve, or approximately solve, problems. Genetic programming is a member of a broad family of techniques called evolutionary algorithms. All these techniques are based on the Darwinian principle of reproduction and survival of the fittest and are similar to the biological genetic operations such as crossover and mutation. Genetic programming addresses one of the central goals of computer science, namely automatic programming; which is to create, in an automated way, a computer program that enables a computer to solve a problem [14-15].

In genetic programming, populations of thousands or millions of computer programs are evolved for hundreds, or thousands of generations. This evolution is done using the Darwinian principle of survival and reproduction of the fittest, along with a genetic crossover operation appropriate for mating and a mutation operator appropriate for randomly altering computer programs. A computer program that solves (or approximately solves) a given problem often emerges from this combination of Darwinian natural selection and genetic operations

Genetic programming starts with an initial population (generation 0) of randomly generated computer programs composed of primitive functions and terminals. Typically, the size of each program is limited, for practical reasons, to a certain maximum number of points (i.e. total number of functions and terminals) or a maximum depth of the program tree. Typically, each computer program in the population is run over a number of different *fitness cases* so that its fitness is measured as a sum or an average over a variety of representative different situations. For example, the fitness of an individual computer program in the population may be measured in terms of the sum of the absolute value of the differences between the output produced by the program and the correct answer (desired output) to the problem (i.e., the Minkowski distance) or the square root of the sum of the squares (i.e., Euclidean distance). These sums are taken over a sampling of different inputs (fitness cases) to the program. The fitness cases may be chosen in a random way or may be chosen in some structured way (e.g., at regular intervals) [16]. The computer programs in generation 0 (initial population) will almost always have very poor performance. Nonetheless, some individuals in the population will turn out to be somewhat more fit than others. These differences in performance are then exploited by genetic programming. The Darwinian principle of reproduction and survival of the fittest and the genetic operations of crossover and mutation are used to create a new offspring population of individual computer programs from the current population.

The reproduction operation involves selecting a computer program from the current population of programs based on fitness (i.e., the better the fitness, the more likely the individual is to be selected) and allowing it to survive by copying it into the new population.

The crossover operation creates new offspring computer programs from two parental programs selected based on fitness. The parental programs in genetic programming are typically of different sizes and shapes. The offspring programs are composed of sub-expressions from their parents. These offspring programs are typically of different sizes and shapes than their parents. Crossover operation creates new computer programs using parts of existing parental programs. Because entire sub-trees are swapped, the crossover operation always produces syntactically and semantically valid programs, as offspring, regardless of the choice of the two crossover points. Because programs are selected to participate in the crossover operation with a probability based on their fitness, crossover allocates future trials to regions of the search space whose programs contain parts from promising programs. [16]

The mutation operation creates an offspring computer program from one parental program selected based on fitness. One mutation point is randomly and independently chosen and the sub-tree occurring at that point is deleted. Then, a new sub-tree is grown at that point using the same growth procedure as was originally used to create the initial random population (this is only one of the many different ways that mutation operation can be implemented), [16].

After the genetic operations have performed on the current population, the new population of offspring (the new generation) replaces the old population (the old generation) and generation index increases by one. Each individual in the new population is then measured for fitness, and the process is repeated over many generations until the termination criterion/criteria is/are satisfied.

Genetic programming works in the following way: the available experimental data are separated, normally by using a randomization technique, to define two data sets, one designated “training set” and the other “validation set”. In these data sets the data points are divided into input and output values. The GP then develops programs that are able to describe the relation between inputs and outputs in the training data set. In a second phase, the best family of evolved programs is applied on the data provided with the validation data set. Normally, the validation data set is not used for the training of the model and development of programs. It is used only to validate the evolved programs and select the best one according to its ability to generalize (performing on data not used for training). At this stage the tool has been trained and the model has been set up. The predicting accuracy of the selected evolved programs can be tested against new data sets (test data) that have not been used at all in program development.

In the present paper, genetic programming is used for the modeling and subsequent prediction of the thermomechanical behavior of double-lap adhesively-bonded pultruded joints. GP is used as a stochastic non-linear regression tool as one output (number of cycles to failure) is assigned to a number of input parameters (Load level, testing temperature and testing humidity). During the process, computer programs are evolved to describe the relation between the output and input parameters i.e., output=f(input), or for the present case:

$$N_f = f(F,\ T,\ RH) \tag{1}$$

Where N_f, denotes the number of cycles to failure when the maximum applied cyclic load is F, under testing temperature, T, and relative humidity RH. The selected program (the best fitted one according to the criterion of minimizing the error between the targeted output and the selected program output in the training data set) is used to predict outputs for artificial input variables in an applied data set.

EXPERIMENTAL PROGRAM

Balanced adhesively-bonded double-lap joints (DLJs), composed of pultruded GFRP laminates bonded by an epoxy adhesive system, were tested under axial tensile fatigue loads in four different environments in [5]. The objective of the experimental program was to demonstrate the influence of temperature and humidity on the fatigue behavior of the examined structural components. For all the cases investigated, the Load-N (*F-N*) curves were derived.

The geometry of the examined joint configuration is shown schematically in Fig. 1. All specimens were manufactured in ambient laboratory conditions. After manufacture, all specimens were cured in ambient laboratory conditions (23^{o}C±5^{o}C, 50%±10% RH) for ten days.

All tests were carried out on an INSTRON 8800 universal testing rig of 100 kN capacity under load control. An environmental chamber was used to control temperature and humidity during testing. Deviations of approximately ±1°C were recorded for the temperature, while ±2% differences in relative humidity were observed. Frequency was kept constant at 10 Hz for all joints, while the stress ratio ($R=\sigma_{min}/\sigma_{max}$) was equal to 0.1, resulting in a tension-tension fatigue loading. The frequency of 10 Hz was chosen as a compromise between testing time and hysteretic heating effects. Four different load levels were predetermined for each condition (after an iterative pre-study) to collect experimental data in the range between 10^2 and 10^7 cycles.

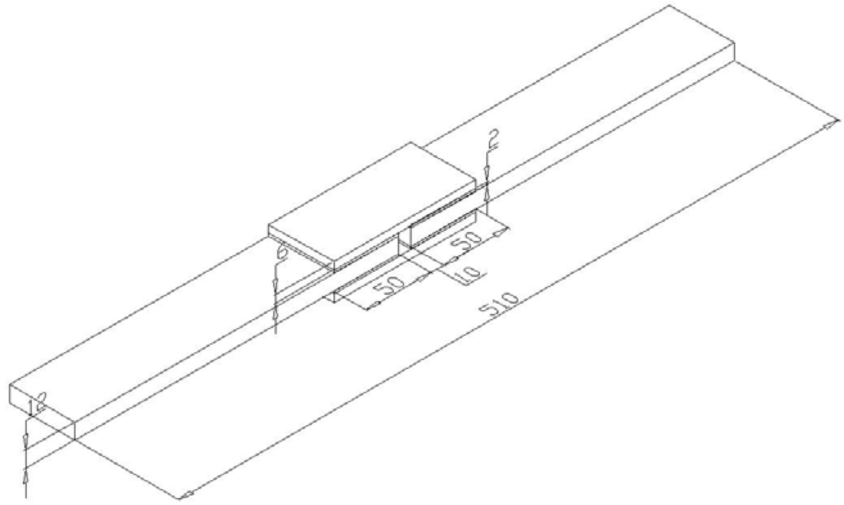

Figure 1. Geometric configuration of test specimen. [5]

The tests were performed under four different controlled environmental conditions: a temperature of -35°C±1°C (humidity cannot be controlled for negative temperatures), a temperature of 23°C±1°C and relative humidity of 50%±2%, a temperature of 40°C±1°C and relative humidity of 50%±2% and finally, a temperature of 40°C±1°C and relative humidity of 90%±2%. The temperature and humidity ranges were selected in accordance with the properties of the adhesive (which has a glass transition temperature of approximately 50°C) and the operational conditions of the joints as parts of engineering structures. Prior to testing, the specimens were placed inside the chamber for an appropriate time period (approximately 90 min for temperatures above zero and 150 min for the negative temperature) in order to attain the predetermined temperature and humidity levels. Special preconditioning was required for the specimens that were tested at high temperature and high relative humidity. Preliminary quasi-static tests showed that moisture absorption was initially rapid and reached saturation after 70 days. The ultimate load of the joints decreased with increased moisture concentration and also reached a plateau after 70 days. Based on these tests, the fatigue specimens were preconditioned for 70 days in a warm water bath at a temperature of 40°C.

FATIGUE LIFE MODELLING USING GENETIC PROGRAMMING

In the context of the present paper, the fatigue data of the pultruded joints were treated as follows: All fatigue data except those recorded at 40°C/50% *RH* were used for the training of the model; a total of 36 fatigue results, one for each tested joint. A training data set was created by using the maximum applied cyclic load *F*, the testing temperature, *T*, and the relative humidity *RH* as input variables. The corresponding to each set of input parameters number of cycles to failure, N_f, was set as the only output. The training file contained the data that the tool used for learning. In other words, the fitness function was calculated using the training file. Given the number of input and output parameters in the training set, the process is characterized as a non-linear stochastic regression analysis. During the training phase the genetic programming tool established several relations (by regression analysis) in the form of computer programs between the input and output variables. Using an iterative process the parameters of the established relations were adjusted in order to minimize the difference between the theoretical and the real outputs. The same set of data was used for the validation of the modeling.

A test, or applied, data set was subsequently constructed, containing input data for which the output will be calculated by the selected evolved program, herein the data for the 40°C/50% *RH* loading case. The same model (the selected evolved program) can be stored and potentially be used to predict other output values for a new applied input data set.

The training efficiency of the genetic programming tool was very good. As depicted in Fig. 2 where target output is compared with the best program output after the training process, the coefficient of multiple determination (R^2) was 0.91.

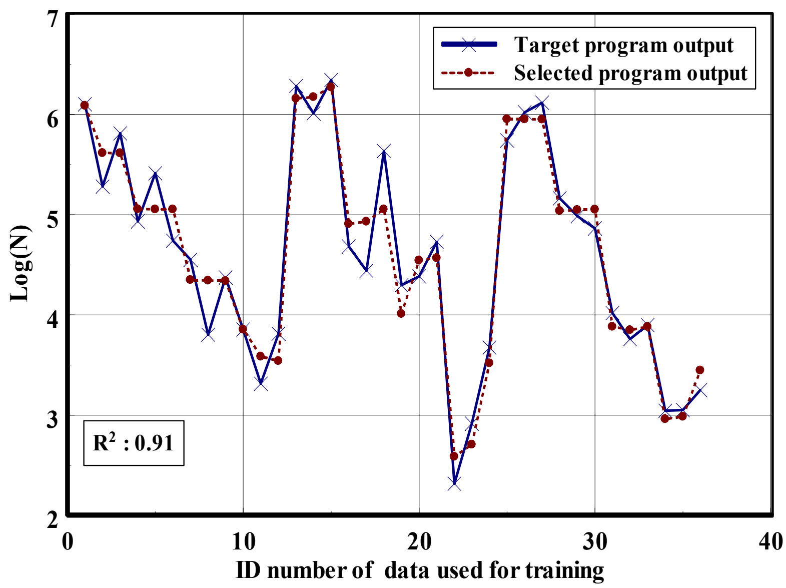

Figure 2. Modeling accuracy of GP.

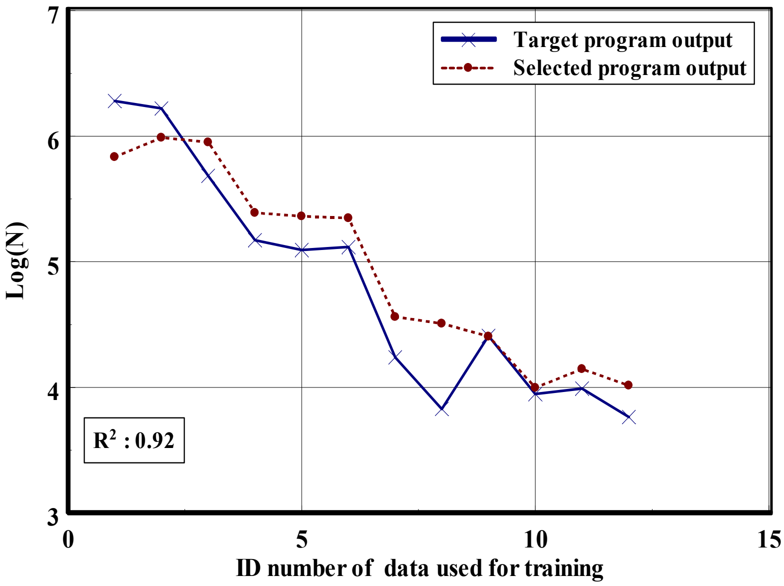

Figure 3. Predicting accuracy of GP.

The same comment applies also on the prediction efficiency of the emerged GP model. As presented in Fig. 3, the predicting ability of the developed model is excellent presenting an R^2 value of 0.92.

This excellent modeling and predicting accuracy of the developed model is depicted on the derived S-N curves as well, see Fig. 4, for the modeling and Fig. 5 for the fatigue life prediction of the “unseen” during training data set.

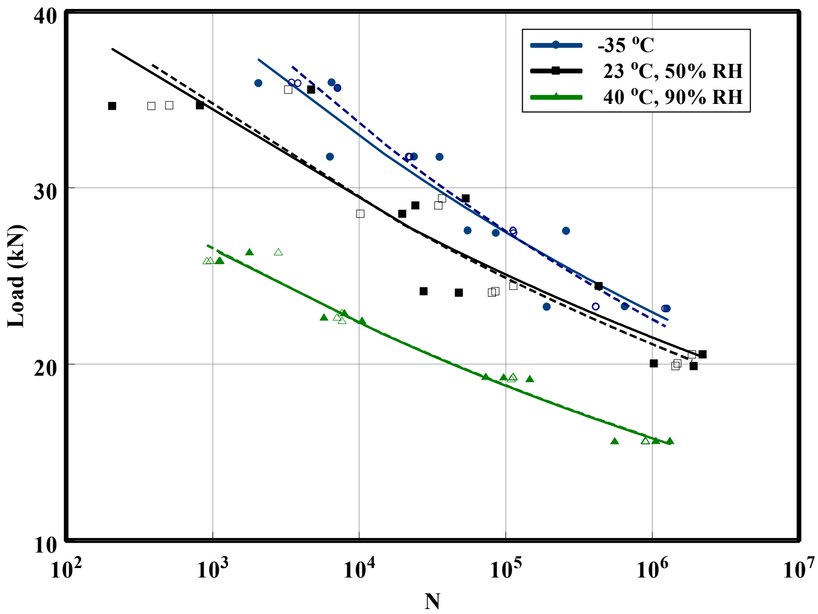

Figure 4. Modeled fatigue data by using genetic programming. Open symbols with dashed curves correspond to model output. Experimental results are presented by closed symbols and solid lines.

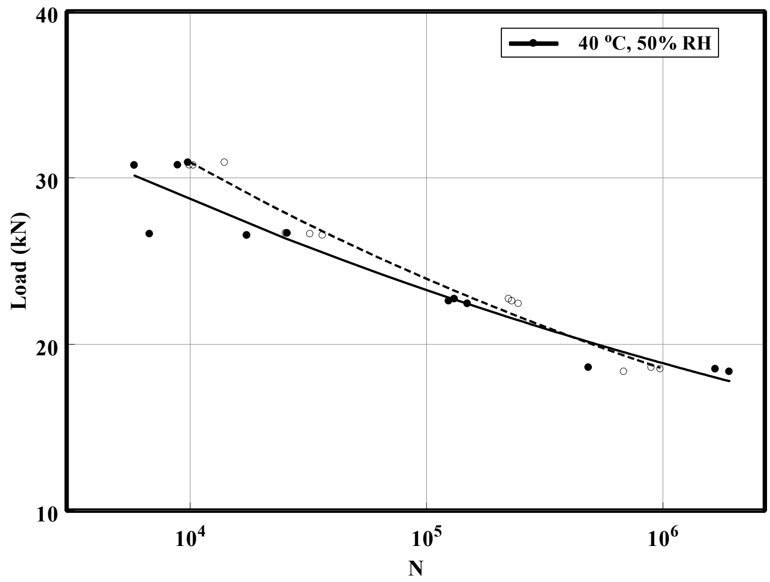

Figure 5. Prediction of the S-N curve at 40°C and 50% RH based on five runs.

CONCLUSIONS

This study proved the ability of novel computational tools to model and predict the fatigue life behaviour of adhesively-bonded joints under different thermomechanical conditions. GP modeling is not based on any assumptions, for example that the data follow a specific statistical distribution, or that the *F-N* curve is described by a power curve equation or else. Moreover, the process does not take the mechanics of each material system into account. GP is a material-independent data-driven method that correlates input with output values in order to establish the fittest model for the establishment of a relationship between them. In that context the proposed method can be easily applied on any material, provided that an adequate amount of data exists.

References

[1] Gilmore RB, Shaw SJ. The effect of Temperature and humidity on the fatigue behavior of composite bonded joints. Composite Bonding, ASTM STP 1227, 1974.

[2] Ashcroft IA, Hughes DJ, Shaw SJ. Adhesive bonding of fibre reinforced polymer composite materials. Assembly Autom 2000; 20(2):150-161.

[3] Ashcroft IA, Hughes DJ, Shaw SJ, Wahab MA, Crocombe A. Effect of temperature on the quasi-static strength and fatigue resistance of bonded composite double lap joints. J Adhesion 2001;75:61-68.

[4] Ferreira JAM, Reis PN, Costa JDM, Richardson MOW. Fatigue behaviour of composite adhesive lap joints. Compos Sci Technol, 2002;62(10-11):1373-1379.

[5] Zhang Y, Vassilopoulos AP, Keller T, Fatigue failure of adhesively-bonded structural joints for fiber-reinforced polymer composites. Compos Sci Technol, 2009 in press.

[6] Miyano Y, Nakada M, Muki R. Prediction of fatigue life of a conical shaped joint system for reinforced plastics under arbitrary frequency, load ratio and temperature. Mech Time-Depend Mat, 1997;1:143-159

[7] Malvade I, Deb A, Biswas P, Kumar A. Numerical prediction of load-displacement behaviors of adhesively bonded joints at different extension rates and temperatures. Comp Mater Sci, 2009;44(4):1208-1217

[8] Miyano Y, Nakada M, Kudoh H, Muki R. Prediction of tensile fatigue life for unidirectional CFRP. J Compos Mater, 2000;34(7);538-550

[9] Vassilopoulos AP, Georgopoulos EF, Dionyssopoulos V. Modelling fatigue life of multidirectional GFRP laminates under constant amplitude loading with artificial neural networks. Adv Compos Letters, 2006;15(2):43-51

[10] Vassilopoulos AP, Georgopoulos EF, Dionyssopoulos V. Artificial neural networks in spectrum fatigue life prediction of composite materials. Int J Fatigue, 2007;29(1):20-29

[11] Vassilopoulos AP, Georgopoulos EF, Keller T. Comparison of genetic programming with conventional methods for fatigue life modelling of FRP composite materials. Int J Fatigue, 2008;30(9):1634-1645

[12] Vassilopoulos AP, Bedi R. Adaptive Neuro-Fuzzy Inference System in modelling fatigue life of multidirectional composite laminates. Comp Mater Sci, 2008;43(4):1086-1093

[13] Kradinov V, Madenci E, Ambur DR. Application of genetic algorithm for optimum design of bolted composite lap joints. Compos Struct, 2007;77(2):148-159.

[14] Koza J.R., Genetic Programming: A Paradigm for Genetically Breeding Populations of Computer Programs to Solve Problems Technical Report STAN-TR-CS 1314, Stanford University, 1990

[15] Koza JR. *"Genetic programming: on the programming of computers by means of natural selection"*. Cambridge, MA, MIT Press, 1992.

[16] Koza JR. Genetic Programming. In James G. Williams, and Allen Kent, (editors). "*Encyclopaedia of Computer Science and Technology*". New York, NY: Marcel-Dekker, 1998;39. Supplement 24:29–43.