Prediction of static shear force and fatigue life of adhesive joints by artificial neural network

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Abstract

In this study, a static shear force and fatigue life prediction model was developed using artificial neural network (ANN). The developed model was used to predict static shear force and fatigue life of adhesively bonded cylindrical joints for the surface roughness, bonding clearance and adherent such as steel, bronze and aluminium. The results showed that developed artificial neural network model was convenient and powerful tool for static shear force and fatigue life prediction of adhesively bonded cylindrical joints.

K e y w o r d s: adhesive joints, fatigue, bonding strength, artificial neural network (ANN)

1. Introduction

Since before recorded history, mankind has been joining materials together to create functional items. To enhance effectiveness and efficiency, many prehistoric as well as modern devices required the assembly of several components. Over time, the sophistication of joining methods has increased to include a wide variety of mechanical fasteners, numerous welding methods and the use of adhesives to hold components together [1].

Mechanical fasteners such as bolts, screws, rivets, and nails have been widely and successfully employed in building the man-made world around us. A number of advantages continue to make these appropriate joining techniques in certain instances. Using them often requires no surface preparation, although drilling is needed in most cases. Unlike many adhesives, mechanical fasteners have a very long shelf life, generally have less environmental concerns, and may facilitate repair because they can often be removed and reinstalled with little or no damage to the joined components. Mechanical fasteners facilitate inspection; a loose or missing rivet may be easily seen and repaired. However, mechanical fasteners and welds are not practical in many situations. One of the key factors is simply that drilling a hole induces stress concentrations that weaken the components to be joined. In fact, the components may need to be made thicker simply to withstand the higher stresses imposed by holes, especially loaded holes associated with load bearing mechanical fasteners [2].

Adhesive bonding is becoming an increasingly viable alternative for joining materials for structural, non-structural, and semi-structural applications. Nowadays, bonded joints are preferred over riveted, spot-welded, and fastened structures [3–5]. The use of bonded structures has been growing in the aircraft industry over the past few years. Even though flying vehicles have progressed from glorified kites to commercial jet transports, supersonic missiles and space vehicles, adhesively bonded structure has been crucial to virtually every one. The use of adhesive bonding is widespread in the aerospace industry because it has characteristics that are particularly well suited to aerospace applications: weight efficiency, sonic vibration damping, ability to easily produce aerodynamically smooth surfaces and the fatigue resistance [1].

Fatigue cracking is such a problem that a large number of joints on modem commercial aircraft are sized by fatigue considerations and not by ultimate strength requirements. Typical commercial transport aircraft may be required to fly as many as 60,000 hours over a span of 30 years and 20,000 flights, plus approximately 100,000 miles in taxi operations. During this

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period of time, commercial aircraft structures will experience thousands of fatigue cycles at high and low magnitudes under many adverse climatic conditions. On the other hand, typical military aircraft designed for 6,000 hours of service operations are subject to fatigue cycles at higher magnitudes due to extreme accelerations and manoeuvres [6].

A joint of thin components made with many small fasteners is highly susceptible to fatigue cracking because of the high stress concentrations at the edges of the fastener holes. A properly designed adhesively bonded joint eliminates or reduces the stress concentration at fasteners and increases the fatigue life of a given joint. Adhesively bonded doublers are also more effective at slowing or stopping the growth of fatigue cracks in an adjacent field than a mechanically fastened doubler. Finally, bonded components can be used to introduce dual load-carrying capability. Adhesively laminated sheets tend to resist propagation of cracks from one component to another, resulting in an inherently fail-safe design [6].

Due to the lack of reliable methods for stress analysis and fatigue life prediction, particularly for low-cycle, high-stress levels under cold (−40 ℃), wet, and room temperature conditions which are representative of service conditions where fatigue exists; many studies attempt to predict the fatigue life of adhesively bonded components. Many studies of predicting the fatigue life behaviour of adhesively bonded joints address materials, such as stainless steels [7] or composite materials [8], but only rough data are available for static shear force and fatigue life of adhesively bonded cylindrical steel, bronze and aluminium joints. Additionally many studies address fatigue performance of the adhesively bonded single-lap joints [9, 10] and many studies attempt to predict fatigue life using linear regression or similar non-adaptive methods. We have classified these as non-adaptive because the "shape" of the function is pre-determined by the authors rather than adapted to the data. In contrast, neural network methods are adaptive functions.

In this paper, a static shear force and fatigue life prediction model are developed using Bayesian artificial neural network. Developed model is used to predict static shear force and fatigue life of adhesively bonded cylindrical joints for the surface roughness, bonding clearance and adherent, such as steel, bronze and aluminium material.

2. Experimental

In this study, steel, bronze, aluminium and Loctite 638® were used as the model adherents and adhesive, respectively. A complete description of the joint design and fatigue testing procedures can be found in [11]. Additionally, the effects of surface roughness, adherent and bonding clearance on the static shear force and fatigue behaviour of adhesively bonded cylindrical joints can be found in [12–14].

3. ANN modelling

In subsequent sections, after a brief introduction to ANN, an attempt has been made to predict static shear force and fatigue life of adhesively bonded joints by using the data from [11–14].

Neural network modelling is an empirical modelling method in which a very flexible function is fitted to a set of data by adjusting the parameters of the network, also known as the weights. Basically, artificial neural networks are computer programs designed to develop and discover new information by using the learning function like a human brain. It is very hard or impossible to develop these skills with traditional programming methods. For this reason, it can be said that artificial neural network is a computer science division about adaptive information processing developed for occasions where the programming is very hard or impossible [15].

Technically, the most basic function of artificial neural networks is determining an output set for each input set given to it. To achieve this, the network is given the ability to make generalizations by learning from sample cases. With this generalization, output sets corresponding to similar cases are determined. It is important to draw attention to a point that an artificial neural network does not give information about how it transforms an input vector to an output vector. When artificial neural networks are considered in an engineer's point of view, they can be seen as a "black box". Black boxes take information from the outside and give output to the outside. In other words, artificial neural network doesn't have the ability to explain how it forms the results. To give the artificial neural networks the ability to explain will be a very important contribution to the science world. It must be known that as number of inputs and hidden layers increase, the accuracy rate of artificial neural networks increase in the same ratio [16].

The first stage of forming an artificial neural network is to prepare a suitable database including inputs and outputs. There is no numerical limit in the data that will be used in the artificial neural network. On the contrary, an increase in the number of data increases accuracy of the model. But there is an important point here: only the data effecting outputs must be entered as the data. This rule is also valid for complex problems. To decrease the calculation time of the problem, only the most relevant parameters can be given as input. The structure of a typical feed forward network with one input, nine hidden units and two outputs as used in the present study is illustrated in

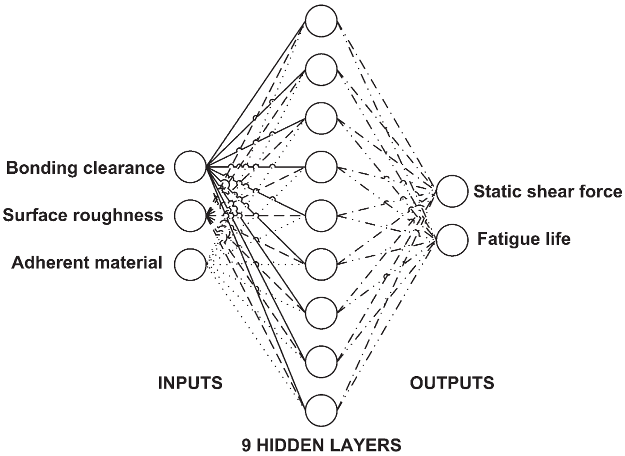

Fig. 1. The structure of a feed forward neural network with three inputs, nine hidden units and two outputs.

Table 1. Minima and maxima for each input variable included in the database

Data	Minimum	Maximum
Bonding clearance, s (mm) (Quantitative variable)	0	0.3
Surface roughness, R_a (μm) (Quantitative variable)	0.45	6.2
Adherent material (Qualitative variable)	1 (Steel)	3 (Aluminium)

Fig. 1. Additionally minima and maxima for each input variable included in the database can be seen in Table 1.

As stated above, the process of determining weight values of process elements' links in artificial neural networks is called "learning of the network". In the beginning, these weight values are randomly assigned. The aim is to find the weight values that will produce the accurate output for the examples shown to the network. Examples are shown to the network many times to find the most accurate weight values. The network having the accurate weight values means it has the ability to make generalizations about the case it represents. This process is called the learning of the network. The changes in weight values are governed under certain rules. These rules are called learning rules.

A neural network is traditionally trained by optimizing its parameters with regard to a given error function. This results in an optimum set of weights, which are in turn used to make predictions. In a Bayesian approach however, a probability distribution of weight values is fitted to the data. Where data are sparse, this distribution will be wide, indicating that a number of solutions have similar probabilities. If, on the contrary, there are sufficient data, the probability distribution for the network parameters will be narrow, indicating that one solution is significantly more probable than others [17]. For further details on the method, authors point to the review by Mackay [18].

In a first instance, half of the data sets were randomly selected from the database to serve as a test. None of these sets were used in training the present network. The remaining data were then divided in two sets, also randomly selected. The first one, containing 80 % of the lines, was used to train a number of models, while the second, containing the rest of the database, was used to validate the training and select an optimum committee of models. As mentioned earlier, this procedure has been described numerous times in the literature. In the present study, a commercial package [19] was used which implements the algorithm written by Mackay [20].

4. Results and discussion

Predicted and experimental relationship between static shear force, number of cycles to failure and bonding clearance, surface roughness of adherent material can be seen in Figs. 2–7. The results showed that developed artificial neural network model was convenient and powerful tool and provided appropriate data for static shear force and fatigue life of adhesively bonded cylindrical joints.

In Fig. 2, when the thickness of adhesive layer increased, static shear force of the joint decreased for the low surface roughness values. With increasing surface roughness value, static shear force curve was turning on the counter-clockwise direction. In the other words, there is a transition point between static shear force curves for different surface roughness values with bonding clearance about 0.2 mm. Therefore, for low bonding clearances up to 0.2 mm finer surface provides better static shear force values. With increasing bonding clearance, rough surface provides better static shear force.

As it can be seen in Fig. 3, when the thickness of adhesive film layer increased, fatigue life of the joint decreased considerably for all surface roughness values. However decreasing rate fell with increasing surface roughness values. As the bonding clearance increased twice and three times, load cycle number decreased about 40 % and 57 %, respectively for surface roughness $R_\mathrm{a} = 1.5\,\mu$m, but just 85 % and 90 %, respectively for surface roughness $R_\mathrm{a} = 6.2\,\mu$m. Higher bonding clearances may be used to compensate for differential thermal expansion or when the adhesive

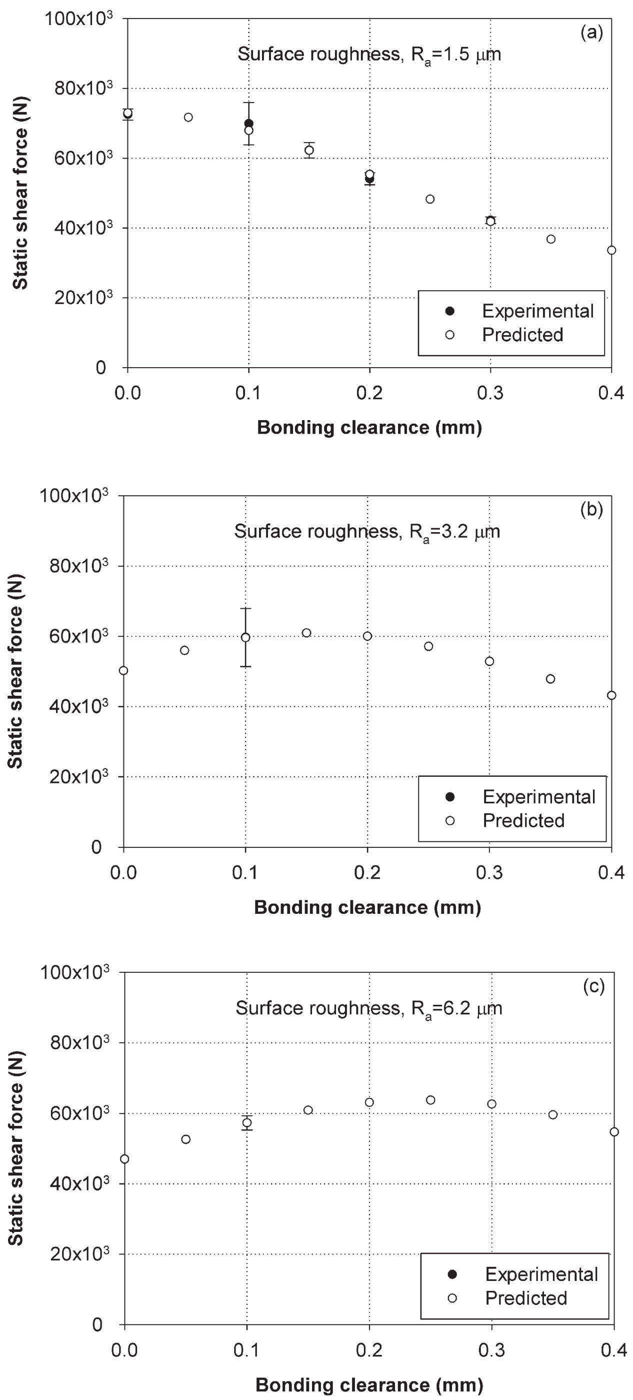

Fig. 2. Predicted and experimental relationship between static shear force and bonding clearance for different surface roughness values.

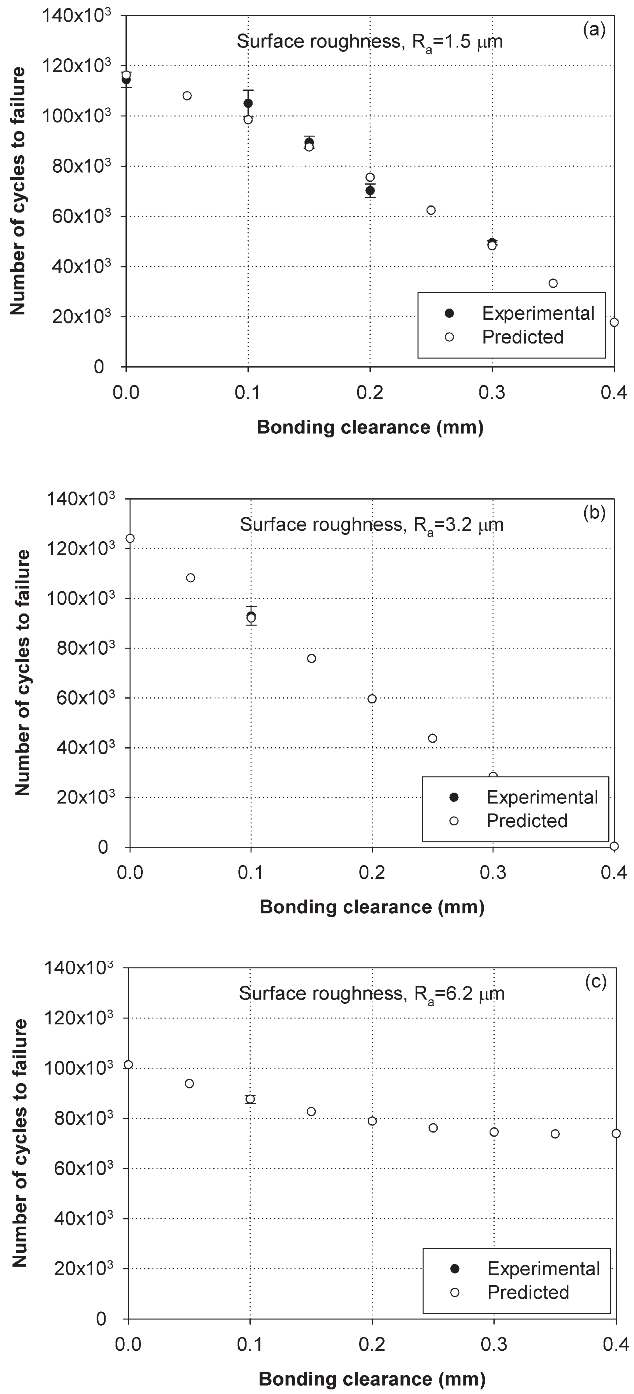

Fig. 3. Predicted and experimental relationship between number of cycles to failure and bonding clearance for different surface roughness values.

is used within existing design for maintenance purposes. Under these situations better static shear force and fatigue life can be obtained by increasing surface roughness values.

Experimental and predicted relationship between the static shear force and surface roughness results are shown in Figs. 4 and 5. When surface roughness increased, static shear force and fatigue life increase up to $R_a = 2\,\mu$m surface roughness value for all bonding clearances. With increasing surface roughness value, static shear force and fatigue life of adhesively bonded joints decreased considerably for all bonding clearance

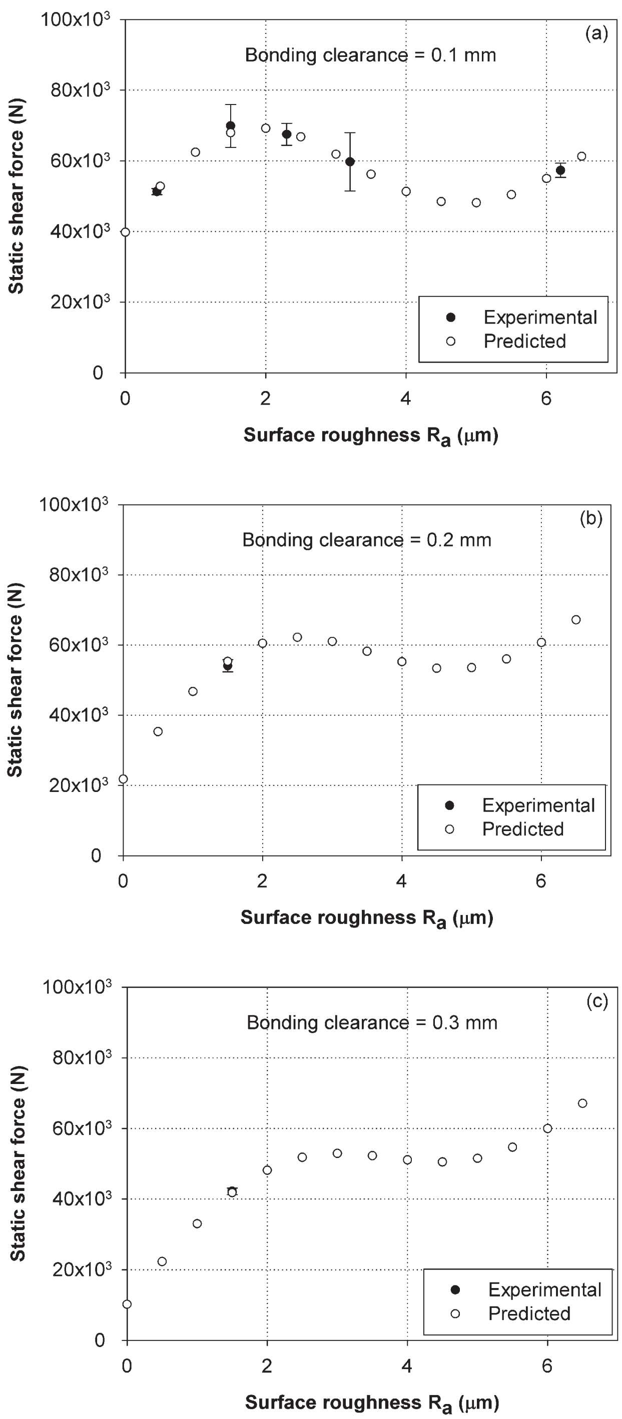

Fig. 4. Predicted and experimental relationship between static shear force and surface roughness for different bonding clearance values.

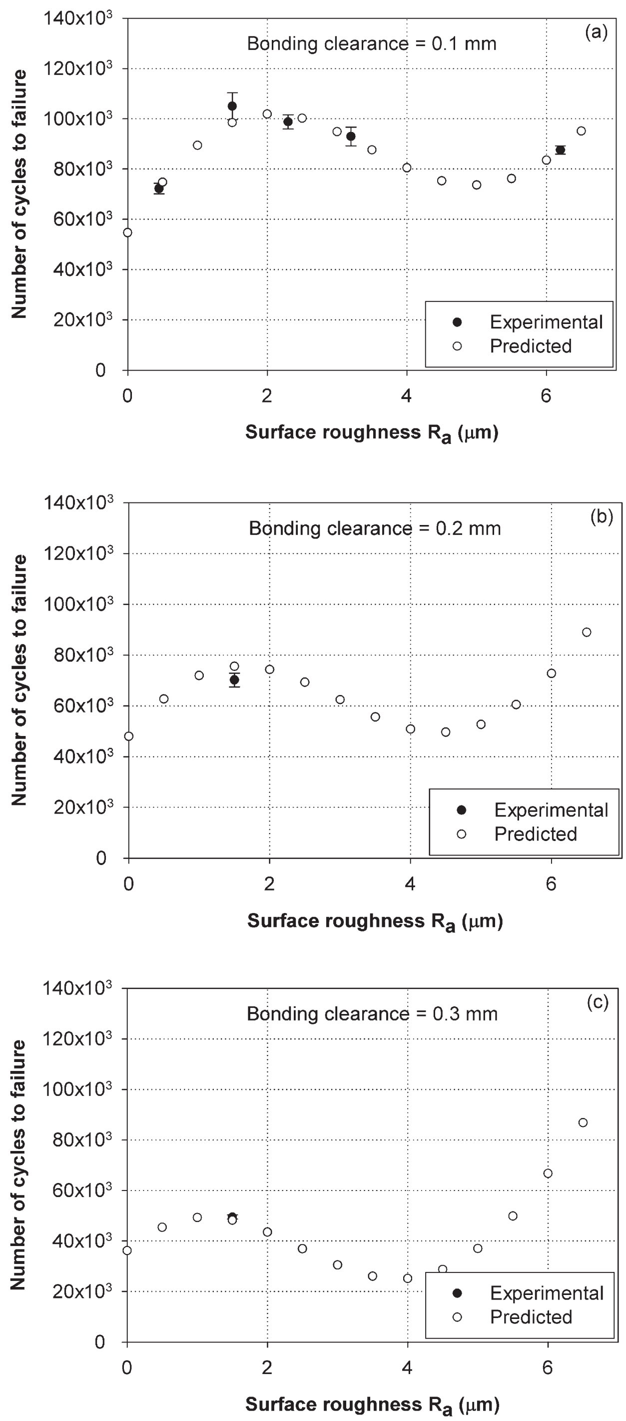

Fig. 5. Predicted and experimental relationship between number of cycles to failure and surface roughness for different bonding clearance values.

values. Similarly, as can be seen on Figs. 4 and 5, better static shear force and fatigue life from thicker adhesive layers can be obtained by increasing surface roughness values. The reason of these transition points may be complex interaction between adhesion mechanism such as mechanical interlocking and wetting.

As it can be seen in Figs. 6 and 7, when the different adherent was used, static shear force and fatigue life values of the joint changed considerably. The highest joint strength in bronze adherent and the lowest joint strength in aluminium adherent have been obtained. The static shear force and fatigue life of

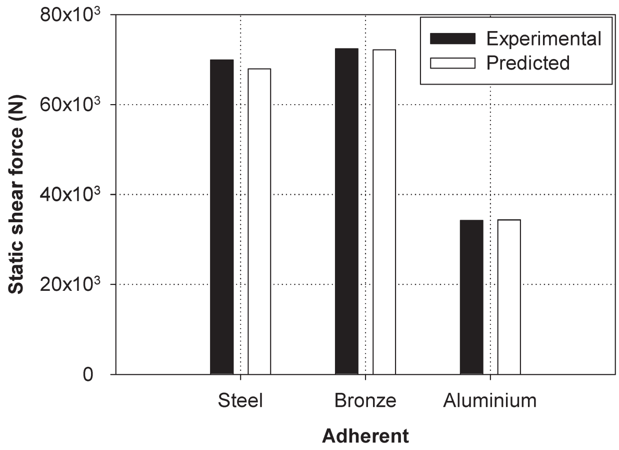

Fig. 6. Predicted and experimental relationship between static shear force and adherent material.

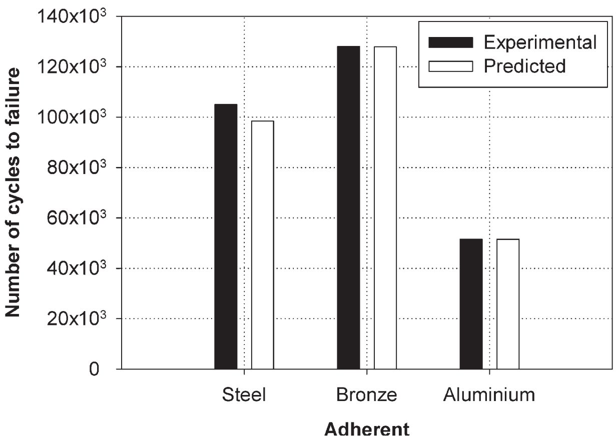

Fig. 7. Predicted and experimental relationship between number of cycles to failure and adherent material.

steel joints have been obtained about 100 % more than the static shear force and fatigue life of aluminium joints. Aluminium has weak bonding forces with adhesive materials due to the passive Al_2O_3 layer on the surface of material. As it can be seen from the results, anaerobic adhesive is not suitable for aluminium materials. Fatigue life of bronze joint is 20 % higher than the fatigue life of steel joints. The bronze materials have higher surface activity than aluminium materials, due to the high surface energy of copper.

5. Conclusions

ANN method was applied for the prediction of the static shear force and number of cycles to failure of adhesively bonded cylindrical joints for the surface roughness, bonding clearance and adherent such as steel, bronze and aluminium. The following main conclusions may be drawn from the results of the present study:

1. The ANN model indicates that the design parameters, bonding clearances, surface roughness and adherent have a direct independent influence on the static shear force and fatigue life. Effects of bonding clearance, surface roughness and adherent on the static shear force and fatigue life are explained below:

– When the thickness of adhesive film layer increased, fatigue life of the joint decreased considerably for all surface roughness values. However decreasing rate was more rapid for lower surface roughness values.

– There is a transition point between static shear force curves for different surface roughness values at 0.2 mm of bonding clearance. Therefore, for low bonding clearances up to 0.2 mm finer surface provides better static shear force values. With increasing bonding clearances, rough surface provides better static shear force.

– Significant variations were observed in static shear force and fatigue life values of the joint when the different adherent was used. The highest joint strength was obtained in bronze adherent while the lowest value was obtained in aluminium adherent. Therefore, anaerobic adhesive is not suitable for bonding of aluminium materials; it is suitable for the copper and copper alloys.

2. The ANN model can be used as estimation techniques to predict the static shear force and fatigue life of the statically and dynamically loaded cylindrical components.

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