Neural network-based failure rate prediction for De Havilland Dash-8 tires

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Abstract

An artificial neural network (ANN) model for predicting the failure rate of De Havilland Dash-8 airplane tires utilizing the two-layered feed-forward back-propagation algorithm as a learning rule is developed. The inputs to the neural network are independent variables and the output is the failure rate of the tires. Six years of data are used for model building and validation. Model validation, which reflects the suitability of the model for future prediction is performed by comparing the predictions of the model with that of Weibull regression model. The results show that the failure rate predicted by the ANN is closer in agreement with the actual data than the failure rate predicted by the Weibull model.

Keywords: Back-propagation; Neural networks; Failure rate; Weibull regression model; Aircraft reliability; Preventive maintenance

1. Introduction

Tires of airplanes like tires of automobiles are subjected to a number of wear out processes, i.e., uniform wear, accelerated wear at certain spots, micro chipping, localized tire deformation, etc. In the case of airplanes, when the tires are in contact with the runway on landing, the conditions of wear are far more severe than the corresponding conditions in automobiles on the highways. In the case of airplanes the loads are not so uniform, there is a variety of shock loads, or a severe load spectrum is generated, which can cause accelerated wear. Since tires are important aircraft components and the safety of an aircraft greatly depends on the reliability of its tires, their periodic monitoring and preventive maintenance are essential measures to increase aircraft reliability and crucial for safe takeoff and landing. Tire life is defined by the wear limits set by controlling aviation agencies. When the tire damage due to wear out processes reaches this critical limit, the tire is considered to have failed. The time to reach this critical manifestation of wear can be measured either by associated flight time, or in terms of number of landings. It can also be written as

$$t \propto t_{\mathrm{r}} \quad \text{and} \quad t \propto l,$$

where t is the flight operational time, t_{r} is the time that the airplane tires are in contact with runway and l is the number of landings. The tire life is not a fixed value but rather a random quantity, which is determined by t, bounded by $t_0 < t < \infty$, where t_0 is the minimum expected life and can also be referred to as safe life.

Modeling the failure rate of airplane tires accurately is of prime importance. This model should accurately predict the time of failure to avoid crashes during landing or take

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off. Various conventional regression models can be developed to model this failure rate. However, much interest has recently been focused on the application of artificial neural networks (ANN) in modeling (Wu and Yen, 1992; Lu et al., 1993; Al-Garni, 1997; Al-Garni et al., 1998; Ganguli et al., 1998; Bailey et al., 2000; Pidaparti et al., 2002), and it was shown that the ANN performs better than the regression models.

The ability of ANN to model multivariate problems without making complex dependency assumptions among the input variables is an advantage over the statistical models. Moreover, ANN extracts the implicit non-linear relationships among the input variables through a learning process from the training data set. These features make neural networks a good alternative to conventional regression techniques. The objective of the present work is to build an ANN model that predicts the failure rate of De Havilland Dash-8 airplane tires and to compare it with the Weibull regression model. The rest of the paper is organized as follows: in Section 2, an introduction to neural network and feed-forward back-propagation network is presented; in Section 3, the failure time data for the tires is presented; in Section 4, a regression model (the Weibull model) and the neural network model are developed; a comparison of the results obtained from the Weibull and neural network models with the real data is presented in Section 5; and Section 6 concludes the paper.

2. Artificial neural networks (ANN)

2.1. Recent developments

The basic idea of the neural network was initiated by MuClloch and Pitts (1943). They studied the ability of a model neuron to interconnect several basic components. Later, Rosenblatt (1958) coined the name "perceptron" and devised an architecture that received much attention. However, a rigorous analysis of the perceptron, made by Minsky and Papert (1969) demonstrated that it had certain limitations. This almost brought research in this area to a halt, but later the work of Hopfield (1982) revived the interest in neural networks. Since then, a variety of ANN algorithms have been proposed and used in recent years. Presently, research on ANN is being performed in a great number of disciplines, ranging from neurobiology and psychology to engineering sciences.

2.2. ANN working methodology

A typical ANN operation starts with the training stage. This stage is conducted by using various training data sets that include the respective inputs and the corresponding desired outputs. The initial network connection weights are set to equal small random numbers. After the network is properly trained, the recall stage starts. In this stage, a set of test data is applied to the network. Afterwards, the performance of the network is analyzed. This performance depends on various factors such as the statistical soundness of the training data set, the structure and size of the network, the initial network weights, the learning strategy and input variables.

2.3. Back-propagation algorithm

Most of the currently used ANNs for process estimation or prediction problems are layered feed-forward neural networks (FNNs), also called multilayer perceptrons. The back-propagation (BP) algorithm is the most widely used learning procedure for neural networks (Rumelhart et al., 1986; Werbos, 1990; Zhu and Qi, 1997; De Jesus and Hagan, 2001; Wang et al., 2004). It is infact a gradient descent-error-correcting algorithm. Before beginning training, some small random numbers are usually used to initialize each weight on each connection. BP requires pre-existing training patterns, and involves a forward-propagation step followed by a back-propagation step. The forward-propagation step begins by sending the input signals through the nodes of each layer. A non-linear activation function, called the sigmoidal function, is usually used at each node for the transformation of the incoming signals to an output signal. This process repeats until the signals reach the output layer and an output value is calculated. The back-propagation step calculates the error by comparing the calculated and target outputs. New sets of weights are iteratively calculated, by modifying the existing weights, based on these error values until a minimum overall error, or global error is obtained. The mean-square error (MSE) is usually used as a measure of the global error (Haykin, 1999). The following logic is assumed in back-propagation (Werbos, 1990).

$$x_j = \text{normalized } X_d, \quad 1 < d \leqslant m, \tag{1}$$

$$\text{net}_k = \sum_{j=1}^{k-1} W_{kj} x_j, \quad m \leqslant k \leqslant N + n, \tag{2}$$

$$x_k = f(\text{net}_k), \quad m < k \leqslant N + n, \tag{3}$$

$$O_s = x_{N+s}, \quad 1 \leqslant s \leqslant n, \tag{4}$$

$$f(\text{net}) = \frac{1}{1 + e^{-\text{net}_k}}, \tag{5}$$

where X_d represents the actual inputs to the network (which have to be normalized and then initially stored in x_i), m is the number of inputs to the network, n is the number of outputs of the neural network, W_{kj} are elements of the weight matrix, N is the number of neurons in neural network, O_s are outputs from the neural network, and x_k is the activation level of the neurons. The non-linear activation function f(net) in Eq. (5) is log-sigmoid function and it depends on the desired output data range. N is a constant, which represents the number of intermediate neurons in the neural network. It can be any integer as long as it is not less than m. The value of $N+m$ determines how many neurons are there in the network (if we include the inputs as neurons). W is the weight matrix in each layer whose size depends on the number of neurons in the corresponding adjacent layers of neural network. The input and output to the neuron is given in Fig. 1. The significance of these equations is illustrated in Fig. 2, which shows the connection in the network.

There are $N+n$ circles, representing all the neurons in the network, including the input neurons. The first m circles are copies of the inputs $X_1, X_2, \ldots, X_m$; they are included as a part of the vector x only as a way of simplifying the notation. Every other neuron is the network such as neuron number k, which calculates net_k and x_k, takes input from every cell, which precedes it in the network. Even the last output cell, which generates O_s, takes input from other output cells, such as the one whose output is O_{s-1}.

3. Tire failure time data

The data were collected from a local aviation facility in Saudi Arabia. The data represents the time-to-failure of tires for the De Havilland Dash-8 series over a period of 6 years for a fleet of three airplanes. These three airplanes have the registration numbers N724A, N725A and N759A. Data was collected for all the six tires of each airplane. In this type of aircraft (De Havilland Dash-8 series), there are six tires, two on the left, two on the right and two in the front near the nose of the airplane. For convenience, we have named the three airplanes in serial order so that airplane N724A is A, N725A is B and N759A is C. Tires are also numbered as 1 and 2 to the left, 3 and 4 to the right, and 5 and 6 in the front, as shown in Fig. 3. Tires of any of the three airplanes can be represented by P_{hg}, e.g., P_{3A} refers to the third tire on the right of the airplane A, i.e., N724A. Failure is defined whenever, at the inspection time, it is observed that the tire needs to be replaced according to the aviation standards being followed. The data, which is obtained from the logbook of each airplane, are recorded in two forms, i.e., as flying time in hours between the replacements and as number of landings between the replacements. However, in the present study, flying time is used as an indicator of life of the tires.

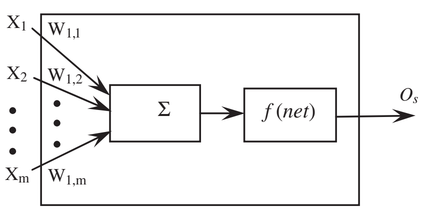

Fig. 1. Artificial neuron with activation function.

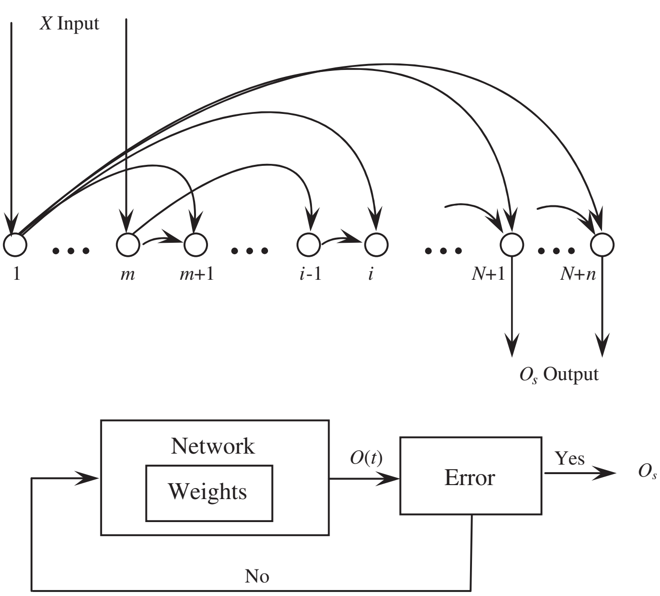

Fig. 2. Network design for back-propagation.

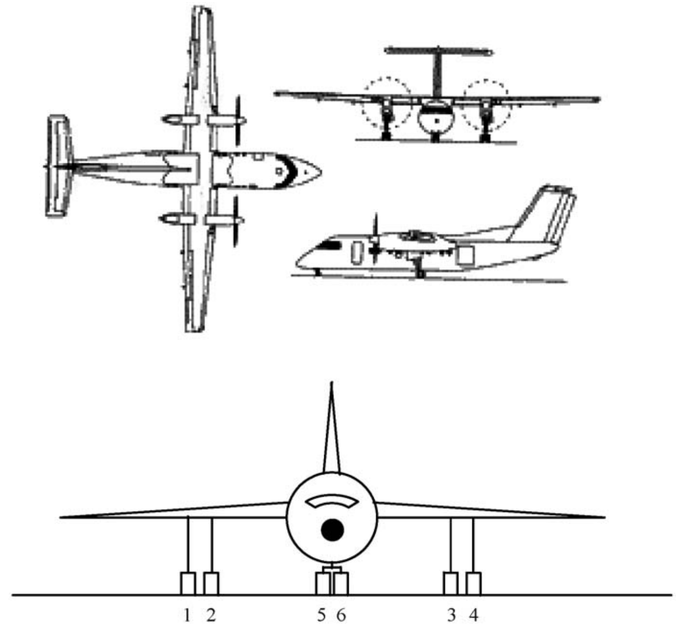

Fig. 3. Airplane and its tires.

4. Tire failure prediction models

4.1. Regression model

4.1.1. Reliability of tires in terms of flight time

The reliability $R(t)$ of a tire characterizes the probability of its survival beyond a given time t, i.e., $R(t) = P[T > t]$, and in general terms, it can be defined as (Kapur and Lamberson, 1977)

$$R(t) = \exp\left[-\int_0^t \lambda(t)\,\mathrm{d}t\right], \tag{6}$$

where $\lambda(t)$ is the instantaneous failure rate of the tires and t is proportional to t_r, which in turn, is proportional to l.

Tires are subjected to an increasing failure rate as the operational time, i.e., the number of landings, increases. Thus the most suitable characterization on instantaneous tire failure rate will be described by a power-law function of time, so that

$$\lambda(t) = \frac{\beta}{\eta - t_0}\left(\frac{t - t_0}{\eta - t_0}\right)^{\beta - 1}, \tag{7}$$

where η is a scale parameter that expresses the characteristic life and β is a shape parameter of the model that determines the severity of the wear out process. Using this power-law failure-rate model, Eqs. (6) and (7) will represent a well-known three-parameter Weibull reliability model, which can be written as follows:

$$R(t) = \exp\left[-\left(\frac{t - t_0}{\eta - t_0}\right)^{\beta}\right] \quad t > t_0, \tag{8}$$

where t is the random variable characterizing the life of the tire; $t_0 < t < \infty$.

4.1.2. Fitting the Weibull model failure data

To fit the data, the complimentary function to the reliability function $R(t)$ is often used, which is also known as the cumulative function $F(t) = 1 - R(t)$ and defines $P(T > t)$. Thus using Eq. (8), one can write

$$F(t) = 1 - \exp\left[-\left(\frac{t - t_0}{\eta - t_0}\right)^{\beta}\right] \quad t > t_0. \tag{9}$$

$F(t)$ is called failure rate at time t. Among various approaches used in fitting the Weibull model to the failure data, a procedure used by Al-Garni et al. (1995) is the most lucid, and it is easy to implement. This method linearizes the equation $F(t)$ as follows:

$$\ln[1 - F(t)] = -\left(\frac{t - t_0}{\eta - t_0}\right)^{\beta},$$

$$\ln\left\{\ln\left[\frac{1}{1 - F(t)}\right]\right\} = \beta\ln(t - t_0) - \beta\ln(\eta - t_0). \tag{10}$$

Now let

$$y = \ln\left[\ln\left(\frac{1}{1 - F(t)}\right)\right],$$

$$x = \ln(t - t_0),$$

$$m' = \beta,$$

$$c = -\beta\ln(\eta - t_0).$$

Eq. (10) is now in the form

$$y = m'x + c, \tag{11}$$

where x and y are the independent and dependent variables in regression, respectively, m' is the slope of the plot, and c is the y-intercept. After arranging the failure data in ascending order, the probability distribution function can be substituted by its estimate, using the median rank formula (Kapur and Lamberson, 1977):

$$F(t_i) = \frac{i}{N' + 1}, \quad 1 \leqslant i \leqslant N', \tag{12}$$

where N' is the number of observations. Linearized Eq. (11) can be fitted to the experimental data $F(t_i)$ versus $(t_i - t_0)$ for $i = 1, 1, 2, \ldots, N'$. By performing the linear regression analysis using linearly transformed Eq. (11), the parameters β and η can be determined. This approach implies that t_0 is known. The value of t_0 is less than $t_0 = k' t_{\min}$, where $0.65 < k' < 1$ and $t_{\min}$ is the minimum time t. A starting point can be taken as $t_0 = 0.6 t_{\min}$. If a straight line fit is poor, then this value can be adjusted between $0.65 t_{\min}$ and $0.99 t_{\min}$, until a good fit is obtained.

A spreadsheet (MS Excel) was used to perform this analysis on the tires of all the three airplanes. Table 1 gives the complete analysis for P_{5A}. The regression output for this analysis is presented in Table 2, which gives the values of the parameters of the Weibull model.

4.2. Neural network model

In this section, an ANN is developed to model the failure rate of the tires. The input to the neural network is time in hours and the output to the neural network is the failure rate corresponding to that time. Since the present study represents a dynamic system, which is one whose state varies with time, a model known as autoregressive model that uses inputs corresponding to previous points in time can be used (Haykin, 1999). For such purpose, three cases are studied:

(1) One input $m = 1$, one output $n = 1$, and six intermediate neurons $N = 6$.
(2) Two inputs $m = 2$, one output $n = 1$, and six intermediate neurons $N = 6$.
(3) Three inputs $m = 3$, one output $n = 1$, and six intermediate neurons $N = 6$.

For 2nd and 3rd case, one and two previous time inputs are taken, respectively, for each time input. The activation function (log-sigmoid function) takes the input and squashes the output into the range 0 to 1 as shown in Fig. 4. This function is commonly used in multilayer networks that are trained using the back-propagation algorithm and also this function is differentiable. The predicted failure rate can be found by using the forward-pass calculation Eqs. (1)–(4). The training of the neural network is carried out using the back-propagation technique (Haykin, 1999). The objective is to minimize the sum squared error given by

$$\text{error} = \sum (F(t) - O(t))^2.$$

Here, $F(t)$ is the actual failure rate, and $O(t) = O_s$ is the final output which is calculated from the neural network model. The number of passes is usually set to a high

Table 1
Regression analysis of the failure data (h) of P_{5A}, for Dash-8

i	t_i (h)	$X_d=(t_i–t_0)$	ln $(t–t_0)$	$F(t_i)=\left(\frac{i}{N'+1}\right)$	$\ln\left[\ln\left(\frac{1}{1-F(t_i)}\right)\right]$	Regression
1	57	22.8	3.1268	0.0357	−3.3141	−4.3211
2	80	45.8	3.8243	0.0714	−2.6022	−2.3957
3	91	56.8	4.0395	0.1071	−2.1775	−1.8015
4	98	63.8	4.1558	0.1429	−1.8698	−1.4807
5	102	67.8	4.2166	0.1786	−1.6260	−1.3128
6	108	73.8	4.3014	0.2143	−1.4223	−1.0787
7	116	81.8	4.4043	0.2500	−1.2459	−0.7946
8	117	82.8	4.4164	0.2857	−1.0892	−0.7611
9	122	87.8	4.4751	0.3214	−0.9474	−0.5992
10	122	87.8	4.4751	0.3571	−0.8168	−0.5992
11	123	88.8	4.4864	0.3929	−0.6952	−0.5680
12	125	90.8	4.5087	0.4286	−0.5805	−0.5065
13	128	93.8	4.5412	0.4643	−0.4714	−0.4168
14	131	96.8	4.5726	0.5000	−0.3665	−0.3299
15	134	99.8	4.6032	0.5357	−0.2649	−0.2456
16	134	99.8	4.6032	0.5714	−0.1657	−0.2456
17	136	101.8	4.6230	0.6071	−0.0679	−0.1908
18	137	102.8	4.6328	0.6429	0.0292	−0.1639
19	137	102.8	4.6328	0.6786	0.1266	−0.1639
20	148	113.8	4.7344	0.7143	0.2254	0.1168
21	155	120.8	4.7941	0.7500	0.3266	0.2815
22	155	120.8	4.7941	0.7857	0.4321	0.2815
23	167	132.8	4.8888	0.8214	0.5439	0.5430
24	168	133.8	4.8963	0.8571	0.6657	0.5637
25	168	133.8	4.8963	0.8929	0.8036	0.5637
26	169	134.8	4.9038	0.9286	0.9704	0.5842
27	172	137.8	4.9258	0.9643	1.2036	0.6450

Table 2
Regression output for failure data (h) for P_{5A}

Constant C	−12.9523
Std. error	0.3335
R^2	0.9150
No. of observations N'	27
Degree of freedom	25
Std. error of coefficient	0.1683
β	2.7604
η	143.2873
t_0	34.2

number. The initial error is high because the initial weights were assigned randomly. As the network is trained, the error decreases and converges to a minimum value. The comparison of all three cases is presented in Fig. 5. The average percentage difference of the failure rate with that of the actual data is found to be 19.84%, 8.56% and 5.66% for neural networks having one, two and three inputs, respectively. Moreover, with informal visual inspection of Fig. 5, it can be observed that the neural network model with three inputs is closer to the actual data than other cases (i.e., 1 and 2 inputs). Therefore, three input neural network model has been adopted for the present study.

The working flow chart of the entire neural network analysis is shown in Fig. 6 and the neural network architecture employed is shown in Fig. 7. The sizes of the weight matrices W_1, W_2 and W_3 are 2×3, 4×2 and 1×4, respectively. Training the back-propagation network requires the following:

(1) Select the training pair from the training set; apply the input vector to the network input terminal.
(2) Calculate the output of the network (using the Eqs. (1)–(4), forward pass).
(3) Calculate the error (the difference between the network output and desired output).
(4) Adjust the weights of the network in a way that minimizes the error. It would quicken the process if the weights not being used are zeroed out.
(5) Repeat steps 1–4 for each vector in the training set until the error for the entire set is acceptably low. Steps 1 and 2 constitute the forward while steps 3 and 4 are the reverse passes.

The above steps can easily be understood by the flow chart shown in Fig. 8.

5. Model adequacy and comparison

Evaluating the model adequacy is an important part of any model-building problem. The idea is to examine whether the fitted model is in agreement with the observed data. An informal visual assessment method has been adopted. Fig. 9(a) shows a comparison between the actual and the predicted failure rate for the P_{1A}, using a neural network and the Weibull model. For the performance evaluation of the neural network model and the regression model, a predictive accuracy of the two models for the given tire data has been compared. Figs. 9(a)–(f) show the actual failure rate, the predicted failure rate from the neural network model, and the predicted failure rate from the Weibull regression model for the six tires of the first airplane, i.e., 724A. In general, it is observed from the results in Figs. 9(a)–(f), 10(a) and (b), 11(a) and (b) that the neural network model predicts the failure rate better than the Weibull regression model. The results can be considered in two groups (groups A and B). Group A is when the rate of $F(t)$, with respect to (t_i—t_0), is large at the earlier stage or becomes large after a short time, and/or if there is no major change in the rate of $F(t)$ that takes place and remains that way for a longer time, e.g., Fig. 9(a) for the first tire of the first airplane, P_{1A}. Group B is

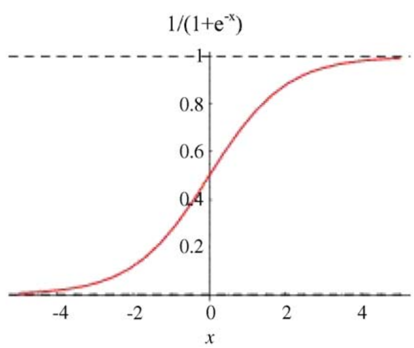

Fig. 4. Log-sigmoid function.

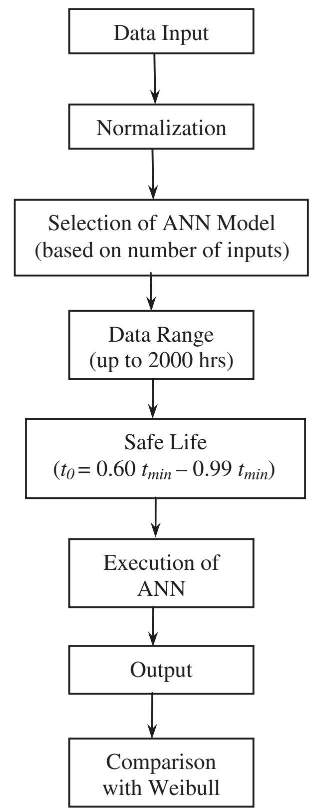

Fig. 6. Flow chart of neural network analysis.

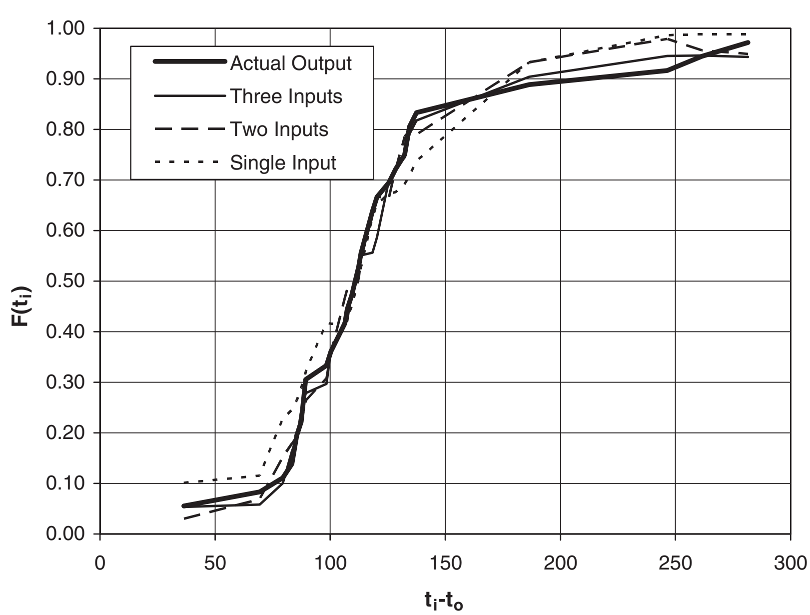

Fig. 5. Comparison of failure rate $F(t)$ against time, predicted by using one, two and three input neural network.

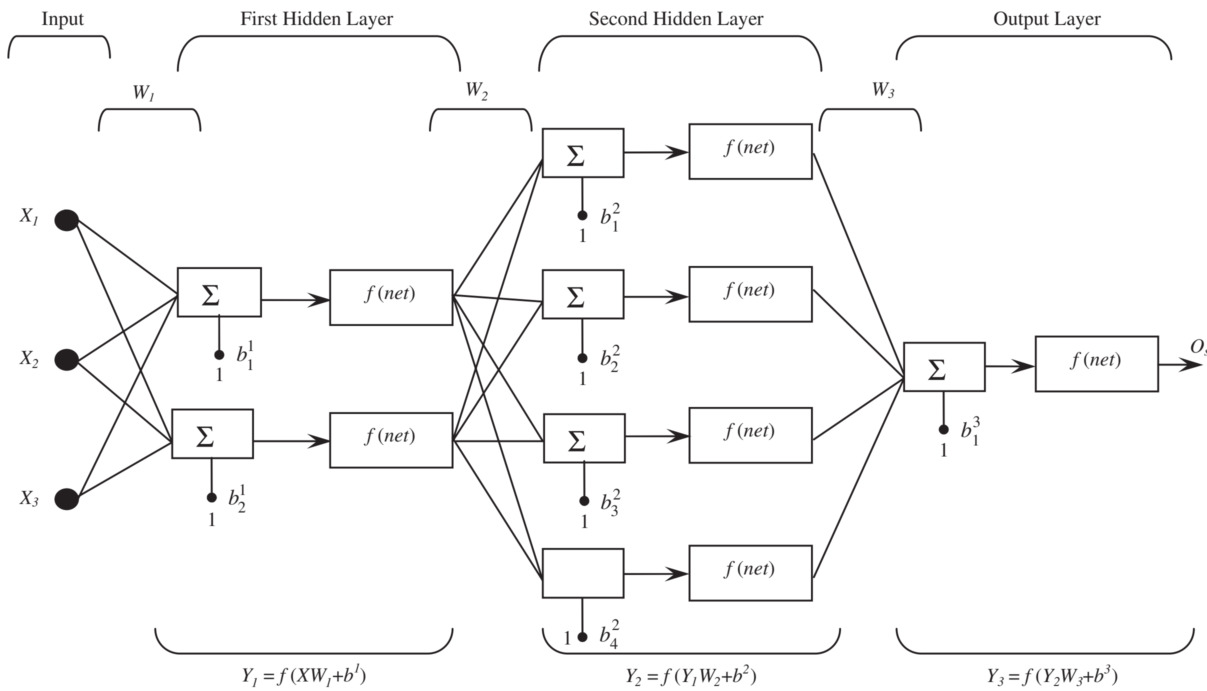

Fig. 7. Neural network architecture.

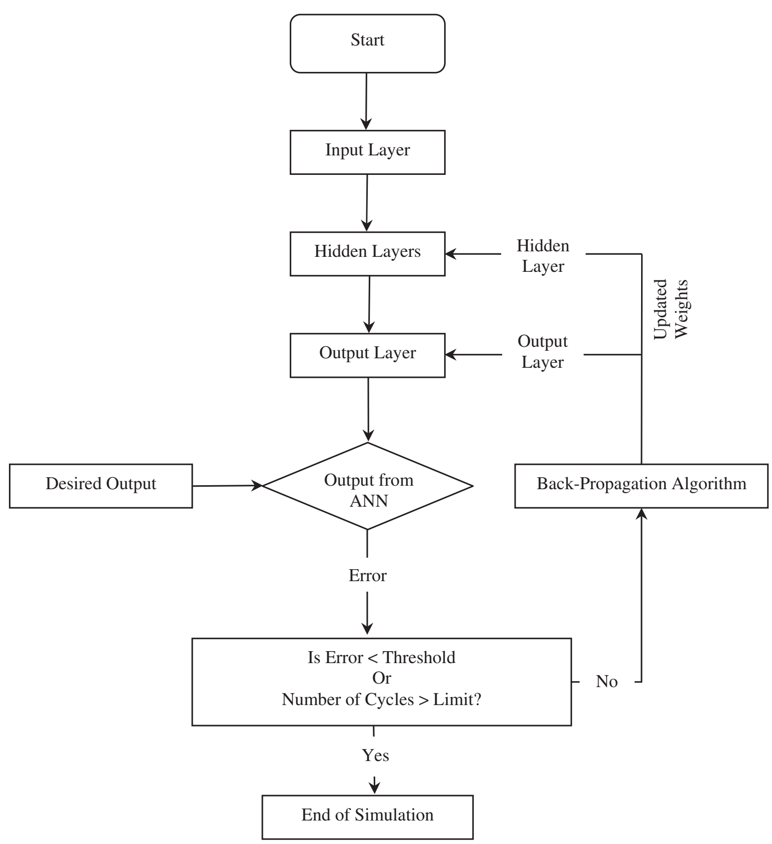

Fig. 8. Flow chart of neural network algorithm.

when the rate of $F(t)$, with respect to $(t_i - t_0)$, at the earlier stage is small and remains small for a long time, and/or if there is a major change in the rate of $F(t)$ that takes place and remains that way for a long time, e.g., Fig. 10(a) for the second tire of the second airplane, P_{2B}.

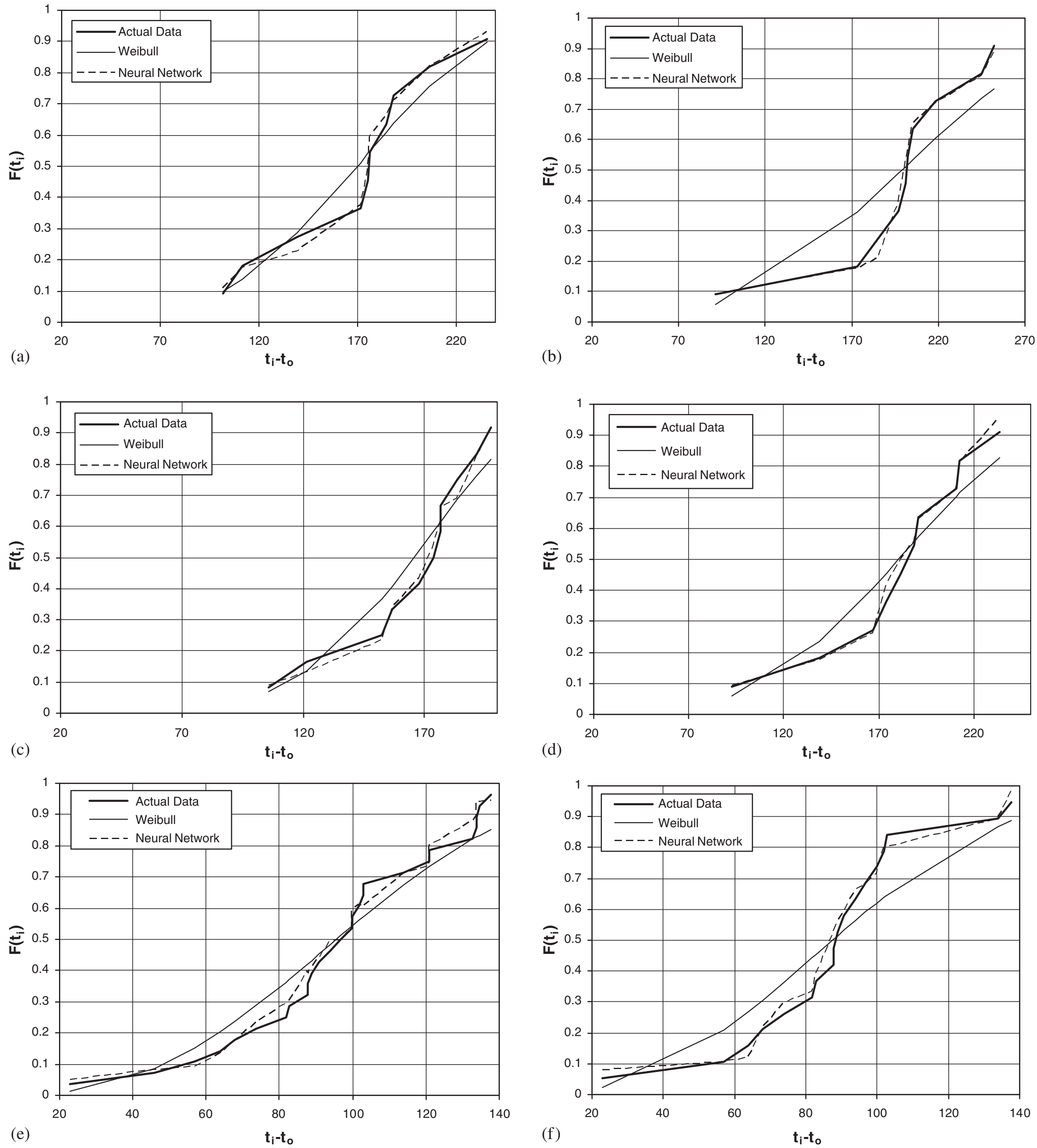

Fig. 9. (a) Failure $F(t)$ for the Dash-8 tire P_{1A} versus failure data (h). (b) Failure $F(t)$ for the Dash-8 tire P_{2A} versus failure data (h). (c) Failure $F(t)$ for the Dash-8 tire P_{3A} versus failure data (h). (d) Failure $F(t)$ for the Dash-8 tire P_{4A} versus failure data (h). (e) Failure $F(t)$ for the Dash-8 tire P_{5A} versus failure data (h). (f) Failure $F(t)$ for the Dash-8 tire P_{6A} versus failure data (h).

Group A can be considered as 10 tires, i.e., P_{1A}, P_{3A}, P_{4A}, P_{1B}, P_{3B}, P_{4B}, P_{5B}, P_{6B}, P_{1C} and P_{5C}. Group B can be considered as eight tires, i.e., P_{2A}, P_{5A}, P_{6A}, P_{2B}, P_{2C}, P_{3C}, P_{4C} and P_{6C}. The first airplane is taken as a typical case as shown in Figs. 9(a)–(f) for tires P_{1A}, P_{2A}, P_{3A}, P_{4A}, P_{5A} and P_{6A}, respectively. For the other airplanes, representative results are shown in Figs. 10(a) and (b) and 11(a) and (b) for tires $P_{2B \text{ and } 4B}$ and $P_{1C \text{ and } 2C}$, respectively. For group A, the first, third and fourth tires of first airplane (P_{1A}, P_{3A} and P_{4A}); fourth tire of second airplane (P_{4B}), and first tire of third airplane (P_{1C}) are shown in Figs. 9(a), (c) and (d), 10(b), and 11(a), respectively. For group B, second, fifth and sixth tires of first airplane (P_{2A}, P_{5A} and P_{6A}); second tire of second airplane (P_{2B}), and second tire of third airplane (P_{2C}) are shown in Figs. 9(b), (e), (f), 10(a), and 11(b), respectively.

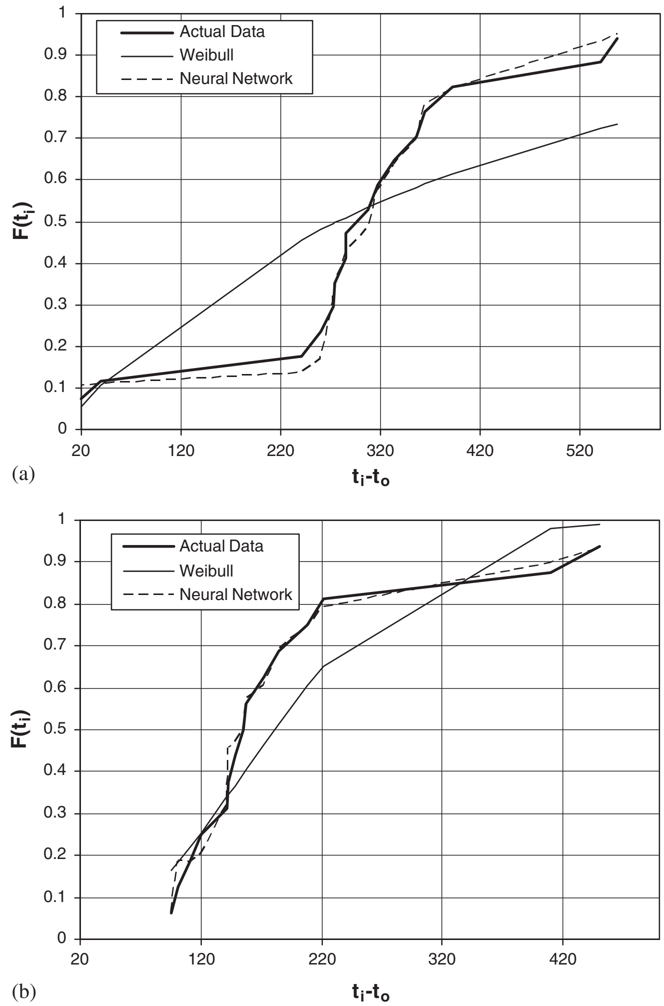

Fig. 10. (a) Failure $F(t)$ for the Dash-8 tire P_{2B} versus failure data (h). (b) Failure $F(t)$ for the Dash-8 tire P_{4B} versus failure data (h).

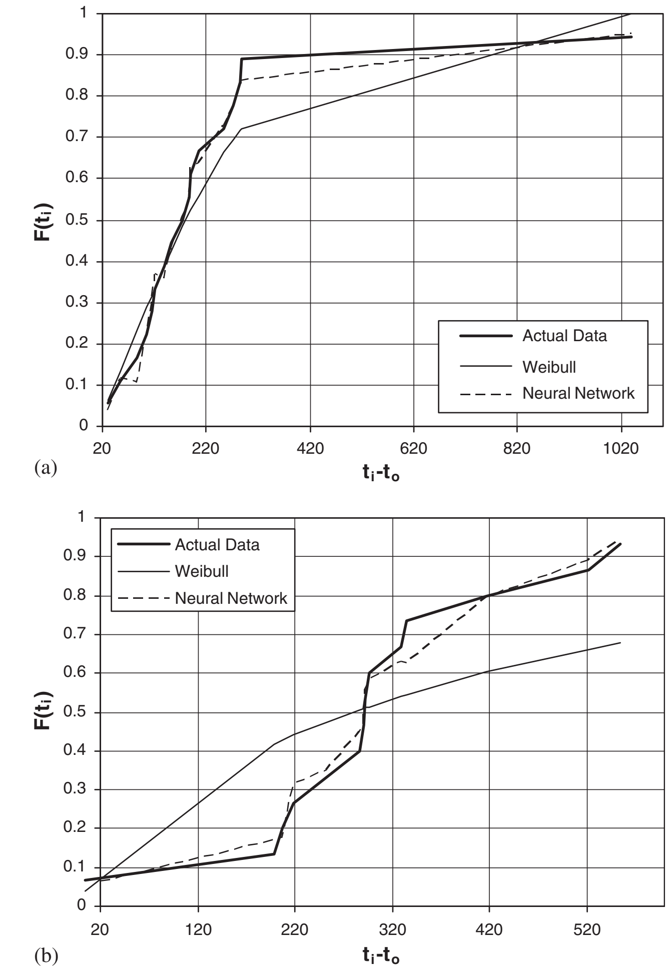

Fig. 11. (a) Failure $F(t)$ for the Dash-8 tire P_{1C} versus failure data (h). (b) Failure $F(t)$ for the Dash-8 tire P_{2C} versus failure data (h).

6. Conclusions

In this study, failure rate of the tires of three De Havilland Dash-8 airplanes is modeled using both neural network and Weibull regression models. A two-layered neural network model is used in the present study. A comparative study shows that the three input neural network model performs much better with lesser percentage difference from the actual data than the two and one input models as also verified by visual inspection. With the fact that such comparative analysis finds its applications in various technical and non-technical fields, the results cannot be generalized for all. Hence from the comparison between neural network and Weibull regression models in the present application of failure rate prediction for aircraft tires, it can be concluded that the neural network predicts better than the Weibull regression model, particularly when the rate of $F(t)$ with respect to $(t-t_0)$ at the earlier stage is small and remains small for a long time, and/or if there is a major change in the rate of $F(t)$ that takes place and remains that way for a long time.

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