ARTIFICIAL NEURAL NETWORK APPLICATION OF MODELLING FAILURE RATE FOR BOEING 737 TIRES

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ABSTRACT
This paper presents an application of artificial neural network technique for predicting the failure rate of Boeing 737 tires. For this purpose, an artificial neural network model utilizing the feed-forward back-propagation algorithm as a learning rule is developed. The inputs to the neural network are the independent variables and the output is the failure rate of the tires. Two years of data is used for failure rate prediction model and validation. Model validation, which reflects the suitability of the model for future predictions, 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 artificial neural network is closer in agreement with the actual data than the failure rate predicted by the Weibull model. The present work also identifies some of the common tire failures and presents representative results based on the established model for the most frequently occurring tire failure.

KEY WORDS
Reliability, failure rate, modelling, back-propagation, neural networks, and Weibull regression model.

1. Introduction

The reliability of an aircraft's tires is one of the factors on which the safety of the aircraft greatly depends. Preventive maintenance and continuous monitoring of the tires are essential measures to increase both reliability and aircraft safety. Once a tire reaches the serviceability limit for any reason according to controlling aviation agencies, the tire must be removed from the aircraft for service and this event is considered as a tire failure. The time taken to reach this failure is measured by the associated flight operational time (t) or the number of accumulated aircraft landings. It can be written as:

$$t \propto t_r \qquad \text{and} \qquad t \propto l$$

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 $t_o < t < \infty$, where t_o is the minimum guaranteed life and can also be referred to as safe life.

Modeling the failure rate of airplane tires accurately is of prime interest. This model should accurately predict the time of tire failure in order to avoid crashes during landing or take-off. Various conventional regression models can be developed to model this failure rate. However, recently, a lot of interest has been focused on the applications of Artificial Neural Network (ANN) in modeling [1-9]. It is eminent from the previous work that the development of failure rate prediction model for Boeing 737 tires and its comprehensive analysis are in their infancy stage. The objective of the present work is to develop an artificial neural network model that predicts the failure rate of Boeing 737 tires based on flight operational time and identify the common tire failures. The present work also presents the failure rate analysis of most frequently occurring tire failures. The results of the ANN model are also compared with that of Weibull regression model, which has been used in the past in the aerospace, automotive, and manufacturing industries.

2. 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 Boeing 737 series over a period of two years for a fleet of five airplanes. These five airplanes have the registration numbers N737A, N738A, N739A, N743A, and N745A. Data was collected for tires of the four main landing gears of each airplane. In this type of aircraft (Boeing 737 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 five airplanes in serial order so that airplane N737A is *A*, N738A is *B*, N739A is *C*, N743A is *D*, and N745A is *E*. Tires are also numbered as 1 and 2 to the right, and 3 and 4 to the left, as shown in Fig. 1. Tire of any of the five airplanes can be represented by P_{hg}, e.g., P_{3A} refers to the third tire on the left of the airplane *A*, i.e., N737A. 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.

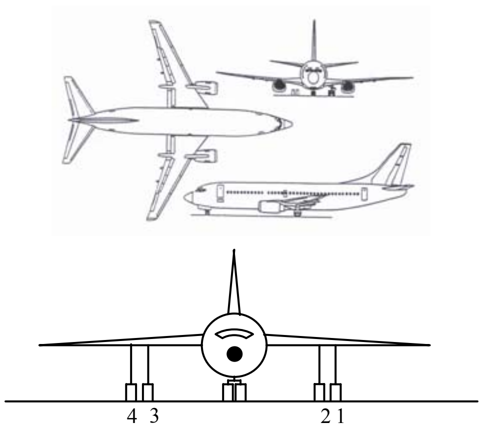

Figure 1. Boeing 737 Airplane Sketch for Four Main Brake Assemblies

3. Tire Failure Prediction Models

3.1. Artificial Neural Network (ANN)

3.1.1. Introduction

An ANN is an information processing system that has certain performance characteristics in common with biological neural networks. ANNs are computational systems that mimic the biological neural networks of the human brain. An artificial neural network is a collection of neurons that are interconnected with the weighted unidirectional connection. Neurons are grouped into layers. A multi-layer network usually consists of an input layer, one or more hidden layers, local memory, activation functions, and an output layer. The inputs carry the weighted output of the directly connected neurons. The incoming information of a neuron is processed by the associated non-linear activation function (such as a sigmoid function). The output is then distributed to other neurons as inputs [8]. The basic idea of the neural network was initiated by MuClloch and Pitts [10]. They studied the ability of a model neuron to interconnect several basic components. Later, Rosenblatt [11] coined the name “perceptron” and devised an architecture that received much attention. However, a rigorous analysis of the perceptron, made by Minsky and Papert [12] demonstrated that it had certain limitations. This almost brought research in this area to a halt, but later the work of Hopfield [13] revived the interest in neural networks. Since then, a variety of ANN algorithms have been proposed and used in recent years. Presently, research on artificial neural networks is being performed in a great number of disciplines, ranging from neurobiology psychology to engineering sciences.

3.1.2. Back-Propagation Algorithm

Some other algorithms also are in use such as Radial Bases Function NN (RBF), Recurrent NN, Hopfield NN, Self Organizing Map (SOM), etc [14]. The back-propagation (BP) algorithm is among the popular learning algorithms for neural networks [15-18]. BP algorithm is the simplest and well known for its good performance. It is in fact 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 nonlinear activation function, called the sigmoid 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 [14]. The following logic is assumed in back-propagation [15]:

$$x_j = normalized\ X_d \qquad 1 < d \le m \tag{1}$$

$$net_k = \sum_{j=1}^{k-1} W_{kj} x_j + b_j \qquad m+1 \le k \le N+n \tag{2}$$

$$x_k = f(net_k) \qquad m+1 \le k \le N+n \tag{3}$$

$$O_s = x_{N+s} \qquad 1 \le s \le n \tag{4}$$

$$f(net_k) = \frac{1}{1+e^{-net_k}} \tag{5}$$

Where m is the number of inputs to the network, n is the number of outputs of the ANN, and X_d represents the actual inputs to the ANN (which have to be normalized and then initially stored in x_j). The non-linear activation function f (net_k) 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 ANN. 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 neuron). W is the weight matrix in each layer whose size depends on the number of neurons in the corresponding adjacent layers of ANN. W_{kj} are the elements of the weight matrix. The term x_k is called the “activation level” of the neuron, and O_s is the output from ANN. The notational input and output to the neuron and the network design of back-propagation are shown in Fig. 2.

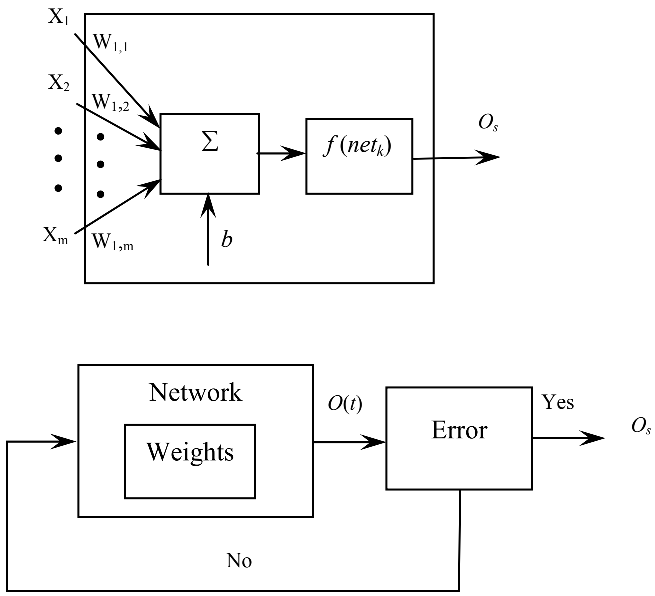

Figure 2. Artificial Neuron with Activation Function and Network Design of Back-Propagation

3.1.3. ANN Model for Present Analysis

In this section, an artificial neural network 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 ANN is the failure rate corresponding to that time. The activation function (log-sigmoid function) takes the input and squashes the output into the range from 0 to 1 as shown in Fig. 3. This function is commonly used in multi-layer 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. The objective is to minimize the sum of mean square error give by:

$$error = \sum \left(F(t) - O(t)\right)^2 \tag{6}$$

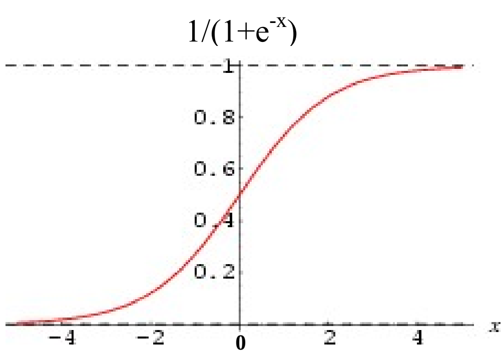

Figure 3. Log-Sigmoid Function

Where $F(t)$ is the actual failure rate in terms of time (hours). $O(t)$ is the final output in time (hours), which is calculated from the ANN model. The number of passes is usually set to a high 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. 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 [14]. Therefore, for ANN model selection, only data in terms of time in hours from the same source is taken and following four cases are studied:

1) One input $m = 1$, one output $n = 1$, and four intermediate neurons $N = 4$,
2) Two inputs $m = 2$, one output $n = 1$, and four intermediate neurons $N = 4$,
3) Three inputs $m = 3$, one output $n = 1$, and four intermediate neurons $N = 4$,
4) Four inputs $m = 4$, one output $n = 1$, and four intermediate neurons $N = 4$.

For 2nd, 3rd, and 4th case, one, two and three previous time inputs are taken, respectively, for each time input. The comparison of all four cases is presented in Fig. 4(a). The average percentage differences of the failure rate with that of the actual tire failure data are found to be 15.65%, 10.11%, 6.60%, and 5.80% for ANN having one, two, three, and four inputs, respectively. It is evident from the percentage differences that the ANN results improve as the number of inputs increase but the model with four inputs does not bring drastic improvement in results from that of three inputs. Therefore, three inputs ANN model has been adopted for the present study.

Furthermore, the analysis was also extended to study the effect of the number of intermediate neurons as shown in Fig. 4(b). The percentage differences for two, four, six, ten, and fifteen intermediate neurons came out to be 16.06%, 10.31%, 5.42%, 4.55%, and 4.23%, respectively. It is obvious from the percentages that little improvement has been achieved by increasing the number of neurons beyond six at the expense of more complexity in the network and program execution time. Hence, six intermediate neurons are selected for the analysis. The ANN model of the present study uses single intermediate layer of neurons since single layer is commonly used and gives reasonable results [3]. The ANN architecture employed is shown in Fig. 5. The sizes of the weight matrices W_1 and W_2 are 6x3 and 1x6, respectively.

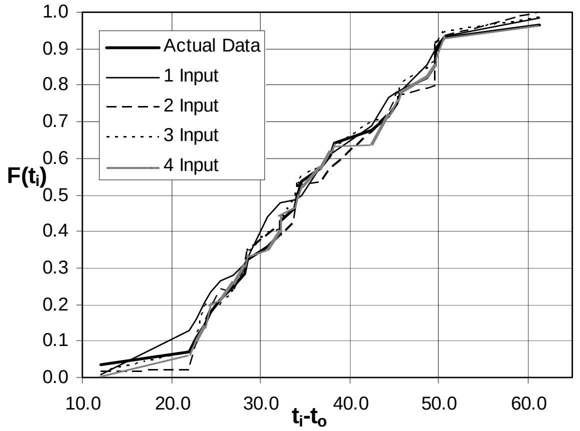

Figure 4(a). Comparison of Failure Rate $F(t)$ Against Time, Predicted by using One, Two, Three, and Four Inputs Neural Network

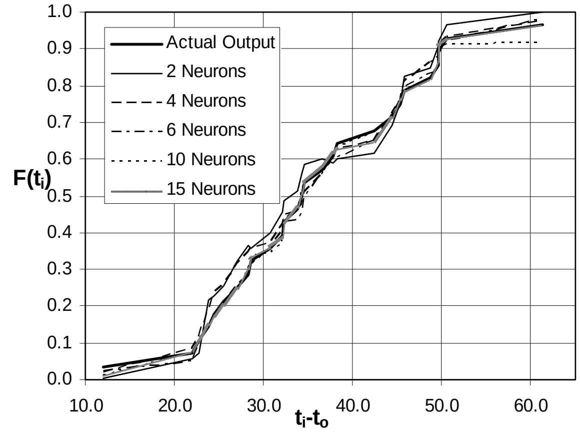

Figure 4(b). Comparison of Failure Rate $F(t_i)$ Against Time, Predicted by using 2, 4, 6, 10, and 15 Neurons

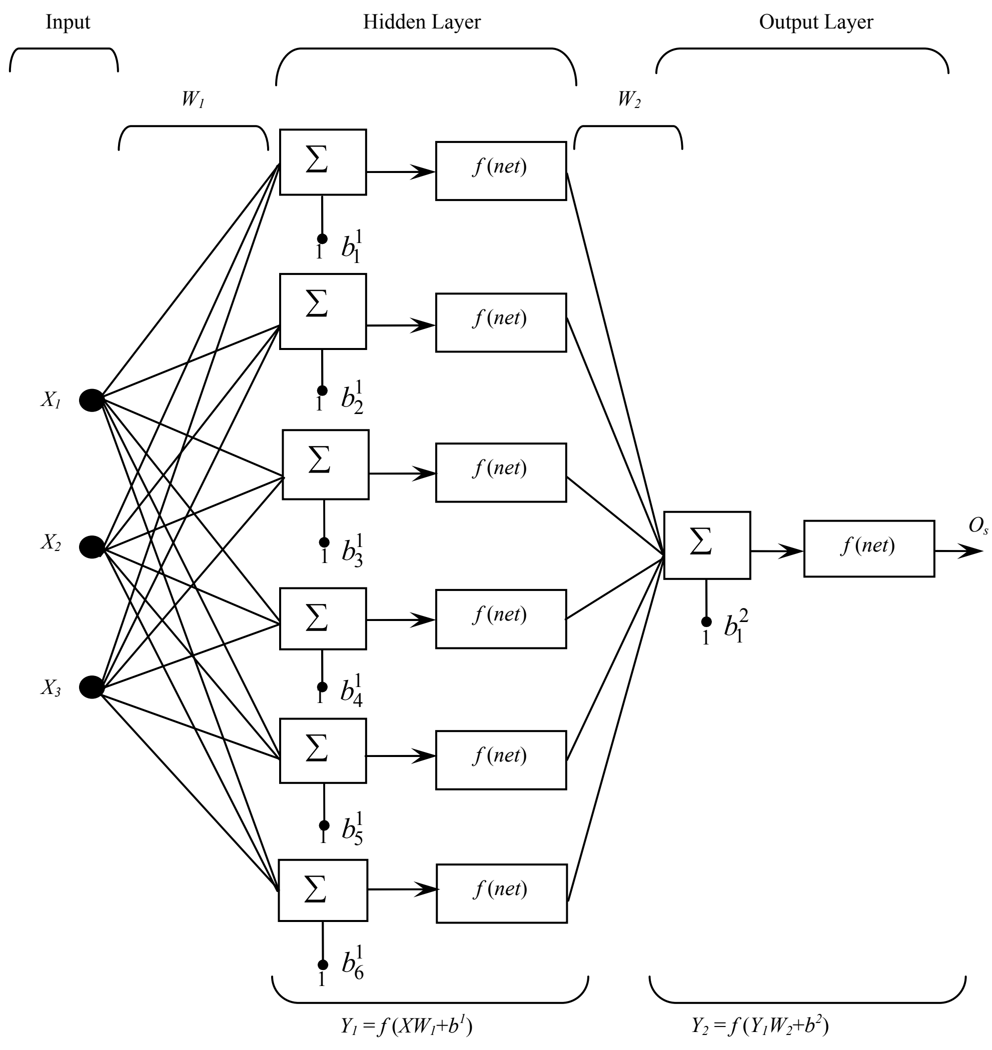

Figure 5. ANN Architecture

3.2. Weibull Regression Model

Weibull regression method can be used to model a wide range of life distributions characteristic of engineered products. It has been in use successfully for years in many fields including aerospace as one of the decision making tool to identify and eliminate costly and unexpected part failures, and provide an optimal maintenance strategy, particularly when an aging mechanism is involved with increasing failures [19]. The reason Weibull regression method was used in the past years is its ability to provide reasonably accurate failure analysis and failure forecast with extremely small samples. 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 [20, 21]:

$$R(t) = \exp\left[-\int_0^t \lambda(t)dt\right] \tag{7}$$

Where $\lambda(t)$ is the instantaneous failure rate of the tire 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

$$\lambda(t) = \frac{\beta}{\eta - t_0}\left(\frac{t - t_0}{\eta - t_0}\right)^{\beta - 1} \tag{8}$$

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. (7) and (8) will represent a well known three-parameter Weibull reliability model, which can be written as follows:

$$R(t) = \exp\left[-\left(\frac{t - t_0}{\eta - t_0}\right)^{\beta}\right] \qquad t > t_0 \tag{9}$$

Where t is the continuous variable characterizing the life of the tires; $t_o < t < \infty$. To fit the data, the complementary 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. (9), one can write

$$F(t) = 1 - \exp\left[-\left(\frac{t - t_0}{\eta - t_0}\right)^{\beta}\right] \qquad t > t_0 \tag{10}$$

$F(t)$ is failure rate at time t. Among various approaches used in fitting the Weibull model to the failure data, a procedure used by Sheikh et al. [21] is the most lucid and easy to implement. This method linearizes the equation as follows:

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

$$\ln\left\{\ln\left[\frac{1}{1 - F(t)}\right]\right\} = \beta \ln(t - t_0) - \beta \ln(\eta - t_0) \tag{11}$$

Now let

$$y = \ln\left[\ln\left(\frac{1}{1 - F(t)}\right)\right]$$
$$x = \ln(t - t_0)$$
$$m' = \beta$$
$$c = -\beta \ln(\eta - t_0)$$

Equation (11) is now in the form

$$y = m'x + c \tag{12}$$

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 [20]:

$$F(t_i) = \frac{i}{N' + 1} \qquad 1 \le i \le N' \tag{13}$$

Where N' is the number of observations. Linearized eq. (12) can be fitted to the experimental data $F(t_i)$ versus (t_i-t_o) for i = 1, 2, 3, 4, ……., N'. By performing the linear regression analysis using linearly transformed eq. (12), the parameters β and η can be determined. This approach implies that t_o is known. The value of t_o is equal to $k'\, t_{min}$, where $0.65 < k' < 1$ and t_{min} is the minimum time t. A starting point can be taken as $t_o = 0.6\, t_{min}$. 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 four airplanes. Thus, as a representation, the failure rate model for P_{4B} is:

$$F(t) = 1 - \exp\left[-\left(\frac{t - 21.66}{95.76 - 21.66}\right)^{1.85}\right] \tag{14}$$

All the tires were analyzed. The representative results are summarized in Table 1 for airplane B. As indicated earlier, the airplane has four tires on the four main landing gears of each airplane, two on the right (P_{1g} and P_{2g}) and two on the left (P_{3g} and P_{4g}) as shown in Fig. 1. A comparative assessment of the Weibull reliability parameters of the tires indicates the following.

1) The minimum guaranteed life t_o of the tires for the whole fleet of five airplanes is in the range from 7.54

h to 46.97 h. The average value of t_o for the whole fleet is $\bar{t}_0 = \sum t_{0i}/20 = 31.74$ h.

2) The scale parameter η varies from 76.08 h to 110.70 h. The average value of η for the whole fleet is $\overline{\eta} = \sum \eta_i/20 = 86.28$ h.

3) A shape factor $\beta > 1$ is observed in each of the tires of the five airplanes. The values of β higher than 1 reflects a time-dependent wear/failure rate or an increasing wear/failure rate of the tires. The range of β observed is from 1.09 to 3.54. The average value of β for the whole fleet is $\overline{\beta} = \sum \beta_i/20 = 2.62$.

Table 1. Comparison of Life of Tires of Aircraft *B* as a Function of Time (hours)

Tire	t_o (h)	η (h)	β	Average Life $\overline{T}$ (h)
P_{1B}	7.54	110.70	1.09	79.49
P_{2B}	13.33	95.52	1.46	76.69
P_{3B}	29.32	90.98	2.31	81.84
P_{4B}	21.66	95.76	1.85	81.84

indicates a constant failure rate over time and implies random failures. In this case, one can suspect random events such as maintenance errors, human errors, Foreign Object Damage (FOD). β>1 indicates an increasing failure rate over time. The most common causes of failures in this range are corrosion, erosion, fatigue cracking, cuts, flat spots, worn out, etc. The values of β in the present work for all the tires of all airplanes come out to be more than 1. The replacements involving such failure rates that increase with time can be scheduled and hence can be modelled to develop the prediction pattern of the failure rates. Table 2 presents the common failures of tires for the whole fleet of airplanes with total number and percent contribution of each failure in the fleet.

4. Results 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. Owing to space limitations, only a representative sample of the results of airplanes *A* and *E* will be presented. Figure 6(a) shows a comparison

Table 2. Top Ten Failures Identified in the Fleet of all Five Airplanes

Sr. No.	Failure Causes / Airplanes	*A*		*B*		*C*		*D*		*E*		Total	
		No.	%	No.	%	No.	%	No.	%	No.	%	No.	%
1	Worn Out	83	86.4	78	84.8	79	80.6	99	93.4	96	88.1	435	86.8
2	Cord Shown	9	9.4	9	9.7	11	11.2	7	6.6	5	4.6	41	8.2
3	Flat Spot	1	1.1	-	-	4	4.1	-	-	4	3.7	9	1.8
4	Deep Cut	3	3.1	1	1.1	3	3.1	-	-	1	0.9	8	1.6
5	Leaking Badly	-	-	1	1.1	1	1.0	-	-	-	-	2	0.4
6	Low Pressure	-	-	1	1.1	-	-	-	-	1	0.9	2	0.4
7	Tie Bolt Sheared	-	-	1	1.1	-	-	-	-	-	-	1	0.2
8	Leaking	-	-	1	1.1	-	-	-	-	-	-	1	0.2
9	Cut	-	-	-	-	-	-	-	-	1	0.9	1	0.2
10	Side Cut	-		-	-	-	-	-	-	1	0.9	1	0.2
Total		96		92		98		106		109		501	

The airplane components are replaced due to many reasons. This can be better understood by examining the mortality characteristics of airplane components [22, 23]. Practically, β<1 indicates that the part has a decreasing failure rate over time and implies infant mortality. This can be caused by a variety of factors, including design flaws, misassembly, and poor quality control. β=1 between the actual and the predicted failure rate with respect to time (hours) for P_{2A} using Artificial Neural Network (ANN) and the Weibull regression model. For the performance evaluation of the ANN and the Weibull models, a predictive accuracy of the two models for the given tires data has been compared. For time (hours) input data, Figs. 6(a)–(d) show the actual failure rate, the predicted failure rate from the ANN model, and the predicted failure rate from the Weibull regression model for the four tires P_{2A}, P_{3A}, P_{3E}, and P_{4E}. The results can be considered in two groups (group G_1 and G_2). Group G_1 is when the rate of $F(t_i)$, with respect to $(t_i\text{-}t_o)$, 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 $F(t_i)$ that takes place and remains that way for a longer time, e.g., Fig. 6(a) for the 2nd tire of airplane A, P_{2A}. Group G_2 is when the rate of $F(t_i)$, with respect to $(t_i\text{-}t_o)$, 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 $F(t_i)$ that takes place and remains that way for a long time, e.g., Fig. 6(b) for the 3rd tire of airplane A, P_{3A}.

Group G_1 can be considered as eleven tires, i.e., P_{2A}, P_{4A}, P_{1B}, P_{2B}, P_{2C}, P_{3C}, P_{1D}, P_{3D}, P_{1E}, P_{2E}, and P_{4E}. Group G_2 can be considered as nine tires, i.e., P_{1A}, P_{3A}, P_{3B}, P_{4B}, P_{1C}, P_{4C}, P_{2D}, P_{4D}, and P_{3E}. For group G_1, the 2nd and 4th tires (P_{2A} and P_{4E}) of airplanes A and E are shown in Figs. 6(a) and (d), respectively. For group G_2, 3rd tires (P_{3A} and P_{3E}) of airplanes A and E are shown in Figs. 6(b) and (c), respectively.

From the results shown in Table 2, it is observed that among all the failures of the tires, worn out condition is the most frequently occurring failure comprising 86.80% of all the failure conditions. Therefore, based on the obtained statistics, this type of failure becomes the candidate to develop the failure rate prediction model. Figure 7 presents a sample plot of $(t_i\text{-}t_o)$ versus $F(t_i)$ based on the worn out failure data of 3rd tire of airplane D, i.e., P_{3D}. It is, therefore, evident from the results that ANN model has proven to be more responsive to changes in the failure rate and predicts the failure rate better than the Weibull regression.

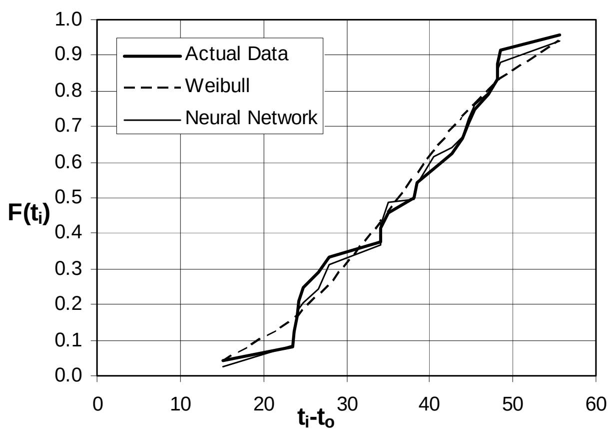

Fig. 6(a). Failure Rate $F(t_i)$ for Boeing 737 Tires P_{2A} versus Failure Data (h) using Time Parameter

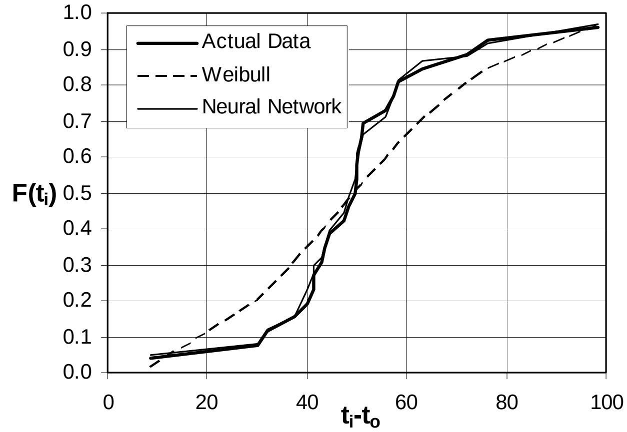

Fig. 6(b). Failure Rate $F(t_i)$ for Boeing 737 Tires P_{3A} versus Failure Data (h) using Time Parameter

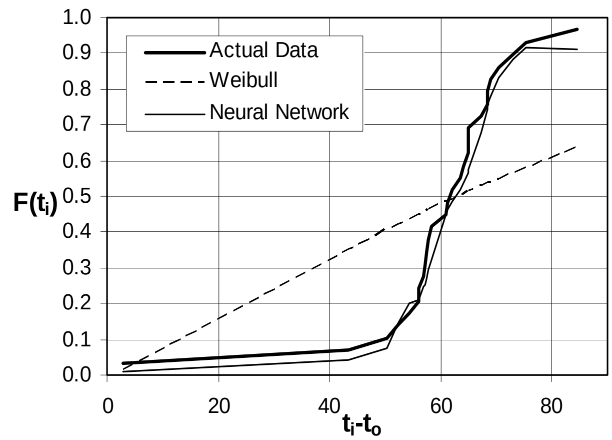

Fig. 6(c). Failure Rate $F(t_i)$ for Boeing 737 Tires P_{3E} versus Failure Data (h) using Time Parameter

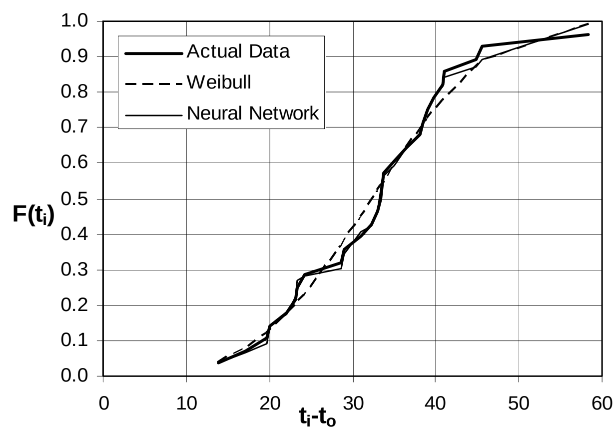

Fig. 6(d). Failure Rate $F(t_i)$ for Boeing 737 Tires P_{4E} versus Failure Data (h) using Time Parameter

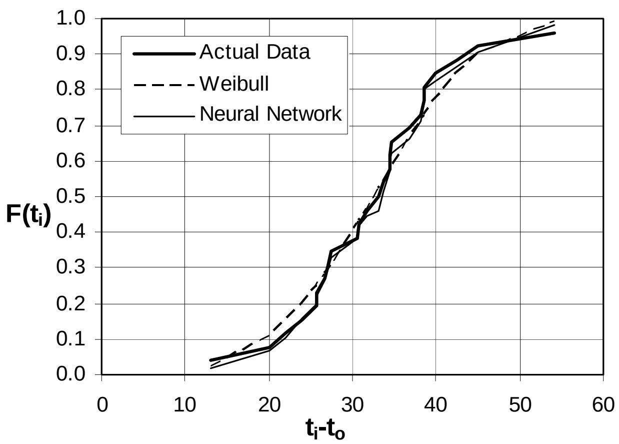

Fig. 7. Failure Rate $F(t_i)$ for Boeing 737 Tires P_{3D} versus Worn-Out Failure Data (h) using Time Parameter

5. Conclusion

In this study, failure rates of the tires with respect to time (hours) of five Boeing 737 airplanes are modelled using both artificial neural network and Weibull regression models. A one-layered neural network model is used. A comparative study shows that the three input ANN model performs much better with lesser percentage difference from the actual data than the two and one input models, and six intermediate neurons give much reasonable accuracy than lesser number of intermediate neurons 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 ANN and Weibull regression models in the present application of failure rate prediction for airplane tires, it can be concluded that the ANN model predicts better than the Weibull regression model, particularly when the rate of $F(t_i)$ with respect to $(t_i\text{-}t_o)$ 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 $F(t_i)$ that takes place and remains that way for a long time. Conclusively, the ANN model can be used to schedule a preventive policy for Boeing 737 tires replacement corresponding to an optimal level of tires reliability.

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