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Neural Network-Based Failure Rate for Boeing-737 Tires

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This paper presents an artificial neural network (ANN) model for forecasting the failure rate of Boeing-737 airplane tires. A neural model is developed using the backpropagation algorithm as a learning rule. The inputs to the neural network are independent variables and the output is the failure rate of the tire. A comparison of the neural model with the Weibull model is made for validation purposes. It is found that the failure rate predicted by the ANN is closer in agreement with the real data than the failure rate predicted by the Weibull model.

Nomenclature

C = intercept
d = integer, $1 \leq d \leq m$
$F(t)$ = failure rate at time t
i = integer, $0 \leq i \leq N'$
j = integer, $1 \leq j \leq k$
k = integer, $m \leq k \leq N + n$
k' = number, $0.65 < k' < 1$
l = number of landings
m = number of inputs to the neural network
m' = slope of a straight line
N = number of neurons in neural network
N' = number of observations
n = number of outputs to the neural network
O_s = outputs from the neural network, s varies from 1 to n
$\mathbb{O}(t)$ = $O_s(t)$
p_{hg} = hth tire of gth airplane
$R(t)$ = reliability, $1 - F(t)$
$T(t)$ = time beyond a given time, $T > t$
t = flight operational time
t_i = flight operation time, at the observation
t_{min} = minimum time t
t_r = cumulative contact time on the runway
t_0 = minimum guaranteed life of the tire
W^{hg} = weight matrix for the hth tire of the gth airplane; h varies from 1 to 4 and g varies from 1 to 5
W_{kj} = element of the weight matrix
w = independent variable in regression
X_d = input to the neural network, d varies from 1 to m
x_j = normalized X_d
x_k = activation level of the neurons
Z = dependent variable in regression
β, η = parameters of Weibull model
$\lambda(t)$ = instantaneous failure rate of the tires
ϕ = sigmoidal function

I. Introduction

AN airplane tire's life is defined by the failure or the wear limits set by controlling aviation agencies. When the tire damage caused by failure or wear reaches the wear critical limit, it is considered to be at failure. The time taken to reach this failure or critical manifestation of wear can be measured either by associated flight time or in terms of the number of landings. Assume a situation:

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

Modeling the failure rate of airplane tires accurately is of prime importance. This model should accurately predict the time of tire failure to avoid crashes during landing or takeoff. Various conventional regression models can be developed to model this failure rate. However, much interest has recently been focused on the applications of neural network in modeling,[1,2] and it was shown that the neural network performs better than the regression models.

The advantage of neural networks over statistical models lies in their ability to model multivariate problems without making complex dependency assumptions among the input variables. Furthermore, neural networks extract the implicit nonlinear relationship among the input variables by learning from the training data set. These features make neural networks good alternatives to conventional regression techniques. The objective of the present work is to build a neural network model that predicts the failure rate of airplane tires and to compare it with the regression model. The rest of the paper is organized as follows: in Sec. II, an introduction to neural networks and feedforward networks is presented; in Sec. III, the failure time data for the tires is presented; in Sec. IV, a regression model (the Weibull model) is developed; in Sec. V, a neural network model is developed; a comparison of the results obtained from the Weibull and neural network models with the real data is presented in Sec. VI; and Sec. VII concludes the paper.

II. Neural Network

A. Introduction to Neural Network

Neural networks can be described as an attempt by humans to mimic the functioning of the human brain. Meinsky and Papert[3] performed a rigorous analysis of the perceptron; they pointed out certain limitations of neuron models. Their publication nearly brought the research in this area to a halt. Much later, the work of Hopfield[4] revived interest in neural networks. Presently, research on artificial neural networks is being performed in a great number of disciplines, ranging from neurobiology and psychology to engineering sciences. An artificial neural network (ANN) has a parallel and distributed processing structure and consists of processing elements called neurons. These neurons are interconnected with the weighted unidirectional connection. Each neuron is composed of multiple inputs, one output, local memory, and activation functions. The inputs carry the weighted output of

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the directly connected neurons. The incoming information of a neuron is processed by the associated nonlinear activation function (such as a sigmoidal function). The output is then distributed to other neurons as inputs. A variety of ANN configurations has been developed.[5] One of the most popular ANN configurations is the feedforward backpropagation network. The backpropagation training is a gradient descent-error-correcting algorithm. The algorithm updates the network weights in such a way that the network output is minimized. This network consists of one input layer, one or more hidden layers, and one output layer. 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 will start. In this stage, a set of test data is applied to the network. Afterward, the performance of the network is analyzed. This performance depends on various factors such as the statistical soundness of the raining data set, the structure and the size of the network, the initial network weights, and the learning strategy and input variables.

B. Feedback Network

Before we specify a learning rule, we have to define exactly how the outputs of a neural net depend on its inputs and weights. In backpropagation, we assumed the following logic[5]:

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

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

$$x_k = \phi(\text{net}_k) \qquad m < k \le N + n \tag{3}$$

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

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

where ns is the number of outputs of the neural network, and

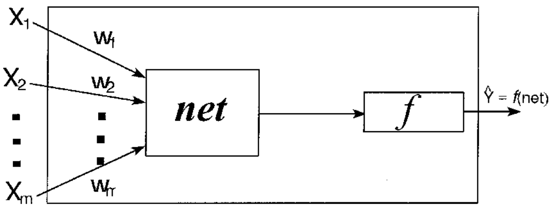

Fig. 1 Artificial neuron with activation function.

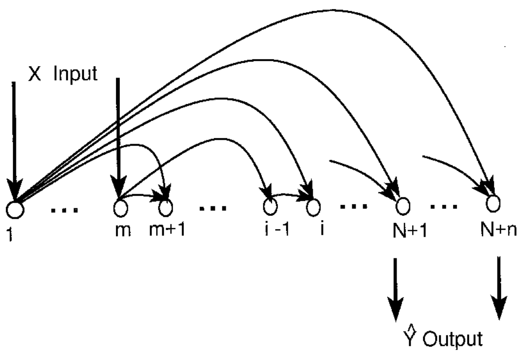

Fig. 2 Network design for backpropagation.

X_d represents the actual inputs to the network (which have to be normalized and then initially stored in x_i). The function ϕ (net) in Eq. (3) is called the activation function, and N is a constant; it can be any integer as long as it is not less than m. The value of $N + n$ decides how many neurons there are in the network (if we include the inputs as neurons). W^{hg} is the weight matrix whose size depends on the total number of neurons in the neural network. The size of the weight matrix is $(N + n)$ by $(N + n)$, which depends on the number of layers. A brief explanation of the concept of layers is given in the next section. The term ϕ(net) is called the sigmoidal function that is given as in Eq. (5). The input and output to the neuron are 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 of 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 $\boldsymbol{x}$ 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, and takes input from every cell that precedes it in the network. Even the last output cell, which generates O_s, takes input from other output cells, such as O_{s-1}.

III. 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 Series over a period of five years for a fleet of five airplanes. These five airplanes have the registration numbers 714A, 715A, 716A, 719A, and 720A. Data were collected for the four main tires of each airplane. In this type of aircraft (Boeing series), there are four tires, two on the left and two on the right. For ease of usage, we have named the five airplanes in serial order so that airplane 714A is 1, 715A is 2, 716A is 3, 719A is 4, and 720A is 5. (Example: p_{hg} represents the hth tire of the gth airplane, p_{35} refers to the third tire on the right of the fifth airplane, i.e., a 720A.) Tires 1 and 2 belong to the left, and tires 3 and 4 belong to the right of the airplane (Fig. 3). At inspection time, failure is defined whenever the tire needs to be replaced according to the aviation standards being followed. The data is obtained from the log book of each airplane. It is recorded in two forms, i.e., the number of flying hours between replacement and the number of landings between replacement.

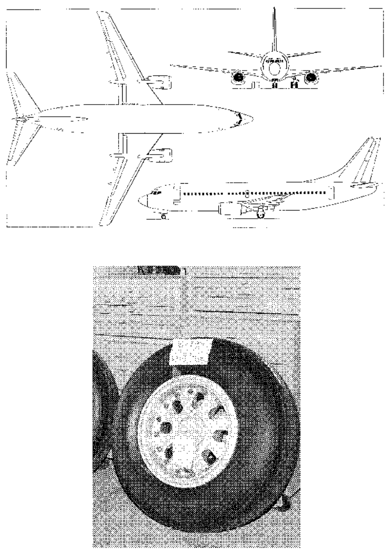

Fig. 3 Airplane and its tires.

IV. Regression Model

A. 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 in Refs. 6–8

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

where 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, as in

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

where η is a scale parameter, and β is a parameter that determines the severity of the wearout 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:

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

where t is the random variable characterizing the life of a product; $t_0 < t < \infty$, η expresses the characteristic life, and β is the shape parameter of the model; it is a nondimensional quantity and represents scatter in life. The smaller the scatter, the larger the β is, and vice versa.

B. 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,

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

Among various approaches used in fitting the Weibull model to the failure data, a procedure used by Refs. 10 and 11 is the most lucid, and it is easy to implement. This method linearizes the equation $F(t)$ as follows:

$$\ell n[1 - F(t)] = -\left(\frac{t - t_0}{\eta}\right)^{\beta}$$
$$\ell n\left\{\ell n\left[\frac{1}{1 - F(t)}\right]\right\} = \beta\,\ell n(t - t_0) - \beta\,\ell n(\eta - t_0) \tag{10}$$

Equation (10) is in the form $Z = m'w + C$, where $Z = \ell n\{\ell n[1/1 - F(t)]\}$, $w = \ell n(t - t_0)$, $m' = \beta$, and $C = -\beta\,\ell n(\eta - t_0)$. Rearranging the given failure data in ascending order, the probability distribution function $F(t)$ can be substituted by its estimate, using the median rank formula

$$F(t_i) = \frac{i}{N' + 1} \qquad 0 \le i \le N' \tag{11}$$

Linearized Eq. (10) can be fitted to the experimental data $F(t_i)$ vs $(t_i - t_0)$ for $i = 0, 1, 2, \ldots, N'$. By performing the linear regression analysis using linearly transformed Eq. (10),

Table 1 Regression analysis of the failure data (hours) of p_{35}, for Boeing series

t, h	$X_d = (t - t_0)$	$\ell n(t - t_0)$	i	$F(t_i) = [i/(N' + 1)]$	$\ell n(\ell n\{1/[1 - F(t)]\})$	Regression
39	7.8	2.05412	1	2.70270E-02	−3.597725	−4.90654
66	34.8	3.54962	2	5.40541E-02	−2.89011	−1.99107
68	36.8	3.60550	3	8.10811E-02	−2.47032	−1.88213
82	50.8	3.92790	4	0.108108	−2.16796	−1.25361
82	50.8	3.92790	5	0.135135	−1.92977	−1.25361
82	50.8	3.92790	6	0.162162	−1.73200	−1.25361
85	53.8	3.98527	7	0.189189	−1.56198	−1.14175
86	54.8	4.00369	8	0.216216	−1.41214	−1.10585
88	56.8	4.03954	9	0.243243	−1.27757	−1.03597
89	57.8	4.05699	10	0.270270	−1.15493	−1.00194
90	58.8	4.07414	11	0.297297	−1.04179	−0.968504
96	64.8	4.17131	12	0.324324	−0.936386	−0.779083
99	67.8	4.21656	13	0.351351	−0.837331	−0.680855
101	69.8	4.24563	14	0.378378	−0.743549	−0.634180
101	69.8	4.24563	15	0.405405	−0.654166	−0.634180
102	70.8	4.25986	16	0.432432	−0.568463	−0.606448
102	70.8	4.25986	17	0.459459	−0.485831	−0.606448
103	71.8	4.27388	18	0.486486	−0.405747	−0.579105
106	74.8	4.31482	19	0.513514	−0.327746	−0.499306
107	75.8	4.32810	20	0.540541	−0.251409	−0.473415
108	76.8	4.34120	21	0.567568	−0.176344	−0.447865
109	77.8	4.35414	22	0.594595	−1.02179E-01	−0.422644
109	77.8	4.35414	23	0.621622	−2.85429E-02	−0.422644
110	78.8	4.36691	24	0.648649	4.49433E-02	−0.397746
111	79.8	4.37952	25	0.675676	0.118682	−0.373162
125	93.8	4.54116	26	0.702703	0.193115	−5.80415E-02
129	97.8	4.58292	27	0.729730	0.268754	2.33692E-02
140	108.8	4.68951	28	0.756757	0.346206	0.231160
144	112.8	4.72562	29	0.783784	0.426232	0.301547
155	123.8	4.81867	30	0.810811	0.509830	0.482950
161	129.8	4.86599	31	0.837838	0.598374	0.575215
170	138.8	4.93303	32	0.864865	0.693887	0.705909
178	146.8	4.98907	33	0.891892	0.799588	0.815153
180	148.8	5.00260	34	0.918919	0.921201	0.841534
181	149.8	5.00930	35	0.945946	1.07082	0.854591
202	170.8	5.14049	36	0.972973	1.28396	1.110351

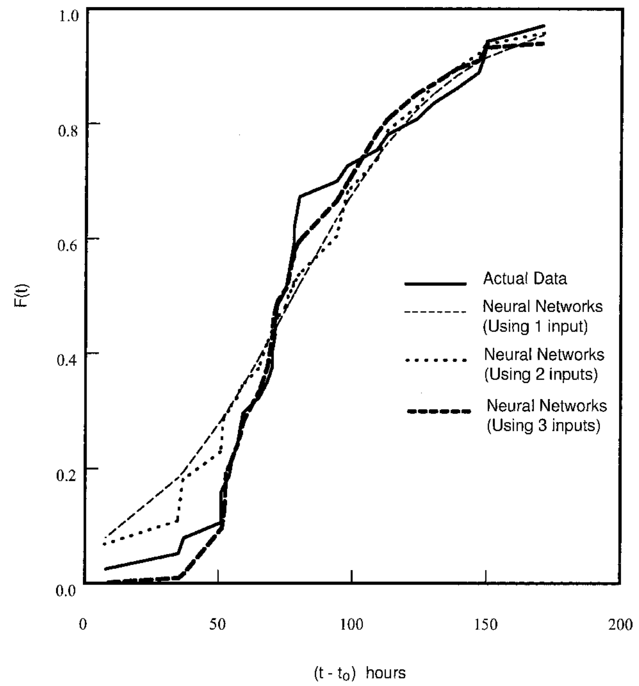

Fig. 4 Comparison of $F(t)$ against time, predicted by using one, two, and three input neural models.

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 $0.65 < k' < 1$. 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 $0.65 - 0.99 t_0$, until a good fit is obtained.

C. Reliability Analysis of Tire Failure Data in Terms of Flight Time

The reliability analysis of the tires of five aircraft is presented in this section. A spreadsheet (Quattro Pro) was used to perform this analysis. Table 1 gives the complete analysis for p_{35}. The regression output for this analysis are as follows, giving the values of the parameters of the Weibull model: constant c, -8.911; standard error, 0.418; R^2, 0.8711; number of observation N', 36; degrees of freedom, 34; w coefficient m', 1.949; standard error of coefficient, 0.1286; β 1.949; η 96.63; and t_0 31.2 (h). This procedure was adopted for analysis of the data for all five airplane tires. For brevity, the analysis tables for the tires of all five airplanes were not included.

V. Neural Network Model

A neural model is developed in this section, which models the failure rate of the tires at any given time. 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. To model accurately, three cases are presented.

1) One input $m = 1$, one output $n = 1$, and two intermediate neurons $N = 2$.

2) Two inputs $m = 2$, one output $n = 1$, and three intermediate neurons $N = 3$.

3) Three inputs $m = 3$, one output $n = 1$, and four intermediate neurons $N = 4$.

The activation function used is ϕ. The predicted failure rate can be found by using the forward-pass calculation equations [Eqs. (1–4)]. The training of the neural network was carried out using the backpropagation technique.[5] The objective is to minimize the sum squared error given by

$$\text{error} = \sum [F(t) - \copyright(t)]$$

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 reduces and converges to a minimum value. Comparison of all three cases is presented in Fig. 4.

The objective of training the network is to adjust the weights so that the applications of a set of inputs produce the desired set of outputs. Training assumes that each input vector is paired with a target vector representing the desired output. Together, these are called a training pair. Usually a network is trained over a number of training pairs. Before starting the training process, all of the weights must be initialized to small random numbers. Training the backpropagation network requires the following:

1) Select the next training pair from the training set; apply the input vector to the network input terminal.

2) Calculate the output of the network [using 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, steps 3 and 4 are the reverse pass.

A sample calculation of the forward pass is given in the Appendix. For each tire we end up with one weight matrix. For example, W^{35} refers to the weight matrix of third tire of the fifth airplane, that is, a 720A:

$$W^{35} = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ -03.41602 & -1.07709 & -1.25859 & 0 & 0 \\ 0.439663 & 1.45472\text{E-}02 & 2.72656 & -13.1454 & 0 \end{bmatrix}$$

VI. 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. We have adopted an informal visual assessment. We have modeled the neural network using one, two, and three inputs. The failure

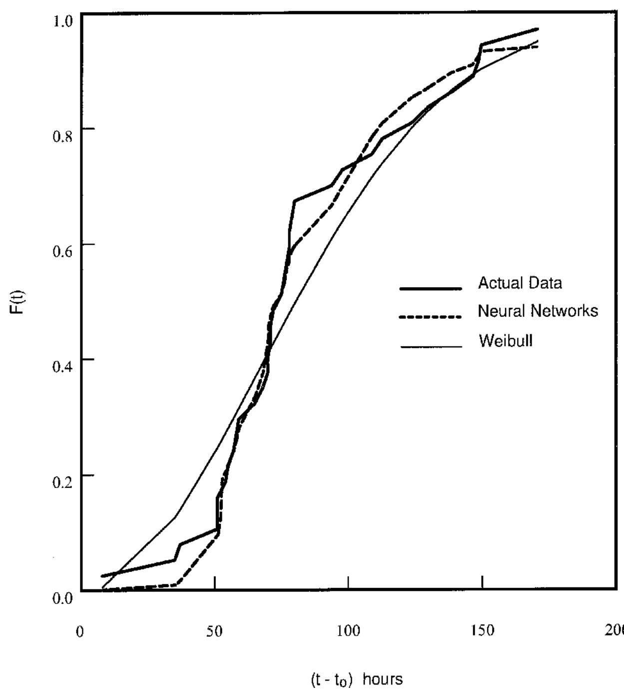

Fig. 5 $F(t)$ for Boeing tire p_{35} vs failure data (hours).

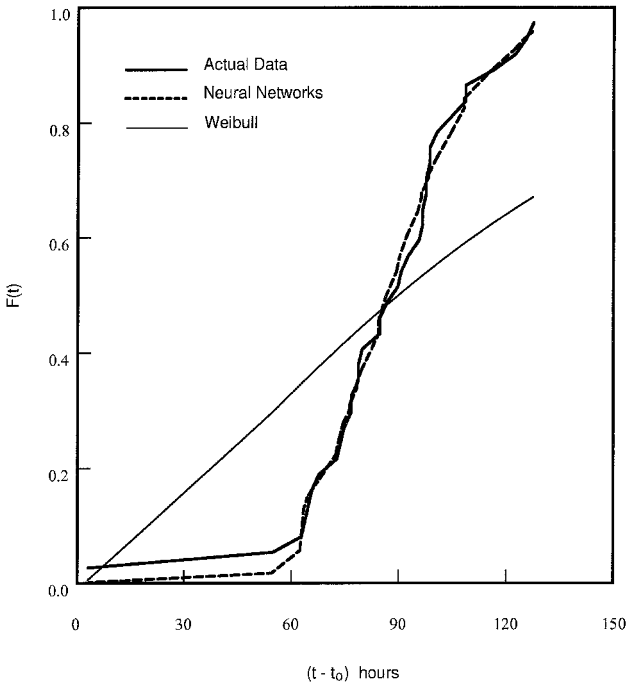

Fig. 6 $F(t)$ for Boeing tire p_{25} vs failure data (hours).

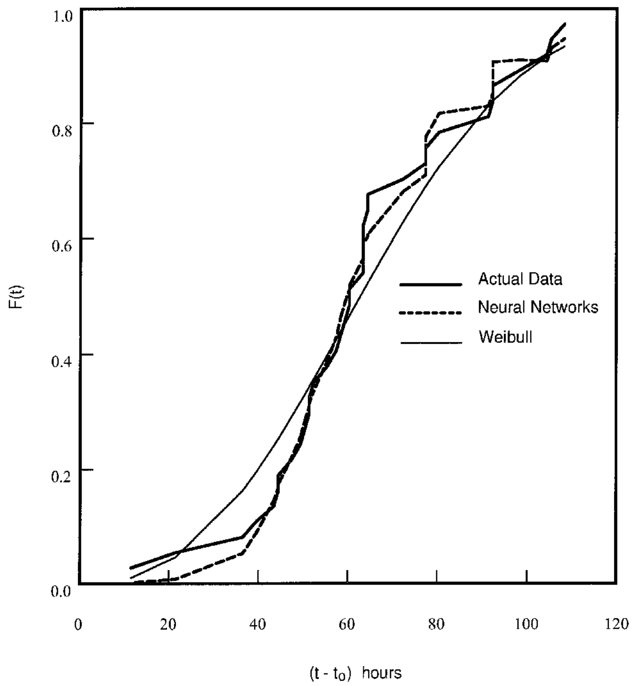

Fig. 8 $F(t)$ for Boeing tire p_{45} vs failure data (hours).

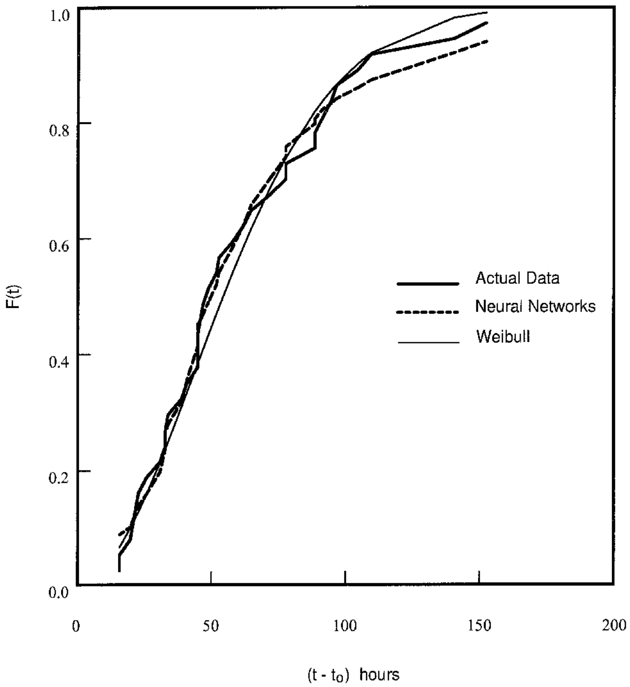

Fig. 7 $F(t)$ for Boeing tire p_{15} vs failure data (hours).

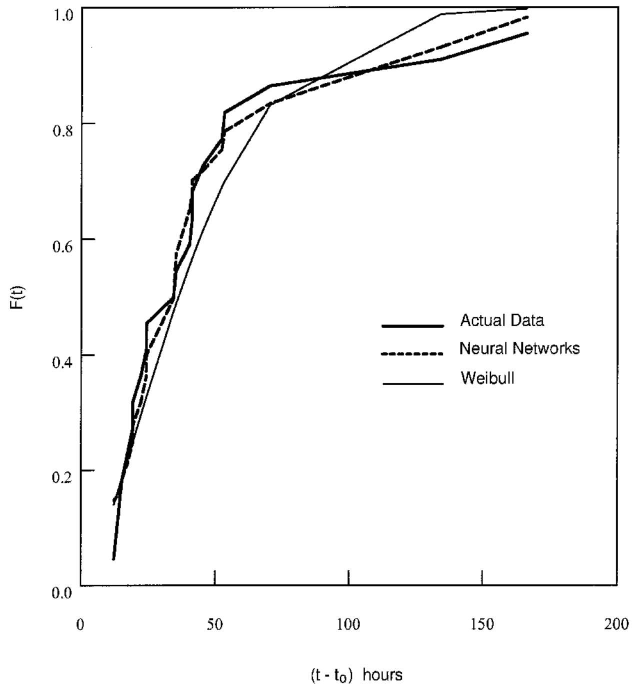

Fig. 9 $F(t)$ for Boeing tire p_{11} vs failure data (hours).

rates predicted by them are presented in Fig. 4. It can be observed from Fig. 4 that the neural model with three inputs is closer to the actual data than other cases, i.e., 1 or 2 inputs. Therefore, we have adopted three input neural models in our study. In the visual technique, the actual and the predicted failure rates of the tires are compared. Figure 5 shows a comparison between the actual and the predicted failure rate for the p_{53}, using a neural network and the Weibull model. For the performance evaluation of the neural network model and the expression model, we have compared the predictive accuracy of the two models for the given tire data. Figure 5 shows that the neural model is in closer agreement with the real data than is the Weibull model. Figures 5–8 show the actual failure rate, the predicted failure rate from the neural network model, and the predicted failure rate from the regression model for the four tires of the fifth airplane. In general, it is observed from the result in Figs. 5–12 that the neural network model predicts the failure rate better than the regression model, and the result can be considered in two groups (groups A and B). Group A is when the rate of $F(t)$, with respect to $(t - t_0)$, 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. 5 for the third tire of the fifth airplane, p_{35}. Group B is when the rate of $F(t)$ 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. 6 for the second tire of the fifth airplane, p_{25}.

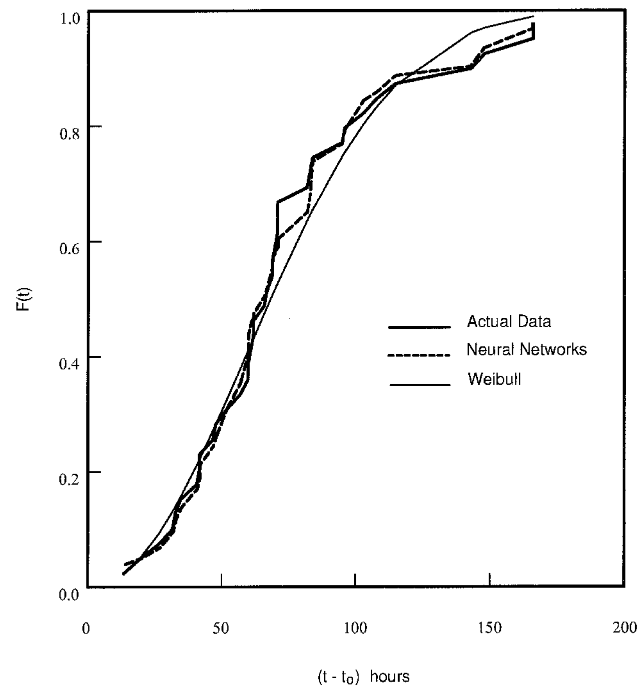

Fig. 10 $F(t)$ **for Boeing tire** p_{33} **vs failure data (hours).**

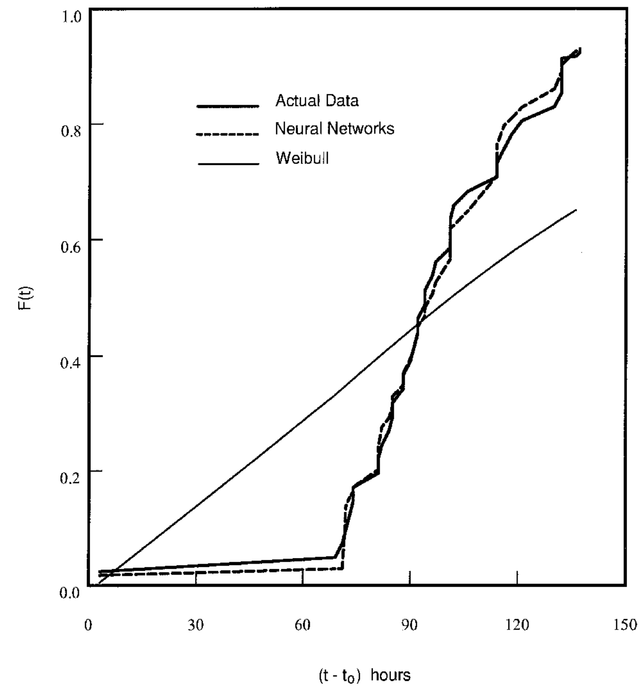

Fig. 11 $F(t)$ **for Boeing tire** p_{22} **vs failure data (hours).**

Group A can be considered as 11 tires, i.e., p_{11}, p_{31}, p_{41}, p_{13}, p_{33}, p_{43}, p_{24}, p_{44}, p_{15}, p_{35}, and p_{45}. Group B can be considered as nine tires, i.e., p_{21}, p_{12}, p_{22}, p_{32}, p_{42}, p_{23}, p_{14}, p_{34}, and p_{25}. In general, the result for all tires in each group is similar, and the values for $F(t)$ and $(t - t_0)$ vary in the range of about 0.90 to 1.0 and 50 to 250 h, respectively.

The fifth airplane is taken as a typical case as shown in Figs. 5–8 for tires p_{35}, p_{25}, p_{15}, and p_{45}, respectively. For the other airplanes, a representative result is shown in Figs. 9–12. For group A, the first tire of the first airplane (p_{11}) and the third tire of the third airplane (p_{33}) are shown in Figs. 9 and 10, respectively. For group B, the second tire of the second airplane (p_{22}) and the third tire of the fourth airplane (p_{34}) are shown in Figs. 11 and 12, respectively.

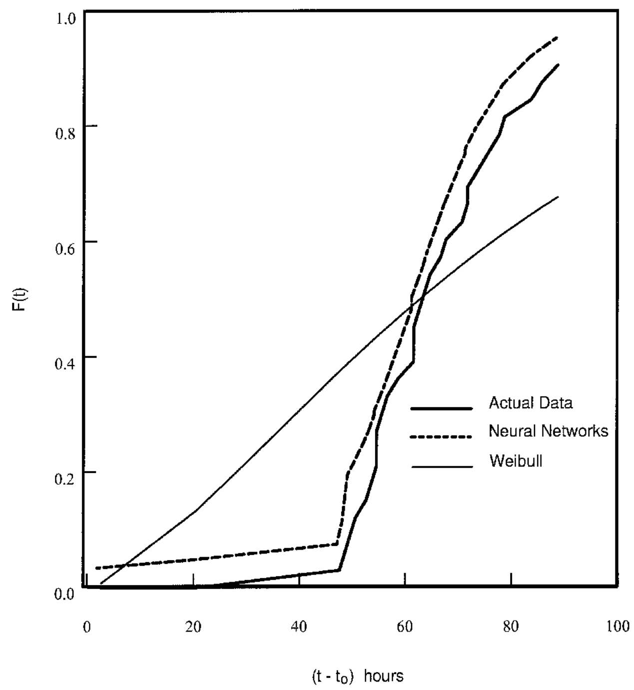

Fig. 12 $F(t)$ **for Boeing tire** p_{34} **vs failure data (hours).**

VII. Conclusions

This study presents a neural network model for the failure rate of tires of five airplanes belonging to the Boeing-737. A two-layered network (including the output layer) was used for modeling the failure rate. A comparative study shows that the three-input neural model with one weight matrix performs much better than the two- and one-input neural models. The three-input neural network model was found to be adequate from visual inspection. A comparison between the neural network model and the regression model shows that the neural network model performs better. It can be concluded that the neural network in general performs better than the regression method, 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.

Appendix: Forward-Pass Calculation

To show the forward-pass calculation, let us choose any value of time $(t - t_0)$, say 97.8 h from the data of tire p_{53} of airplane 720A (the fifth airplane). Because we are considering three inputs to the neural network, we have to normalize three values, and our input vector becomes $\{x\}_{3\times 1}$. We follow the following steps.

Chosen from Table 1, 97.8, 93.8, and 79.8 for $X_{d=1}$, $X_{d=2}$, and $X_{d=3}$, respectively.

Normalized values are

$$x_1 = \frac{(t - t_0)_{\text{chosen}} - (t - t_0)_{\min}}{(t - t_0)_{\max} - (t - t_0)_{\min}}$$

$$= \frac{97.8 - 7.8}{170.8 - 7.8} = 0.5521$$

$$x_2 = \frac{93.8 - 7.8}{170.8 - 7.8} = 0.5276$$

$$x_3 = \frac{79.8 - 7.8}{170.8 - 7.8} = 0.4417$$

Using Eqs. (1–4), with $m = 3$, $N = 4$, and $n = 1$, the weight matrix W^{35} will be 5×5.

The weight matrix for p_{35} is

$$W^{35} = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ -03.41602 & -1.07709 & -1.25859 & 0 & 0 \\ 0.439663 & 1.45472\text{E-}02 & 2.72656 & -13.1454 & 0 \end{bmatrix}$$

From the first equation in this Appendix, the counter k starts from $m + 1$ to $N = n$, i.e., from 4 to 5 (for $m = 3$ and $n = 1$). Therefore, starting the iterations with $k = 4$, we have

$$\text{net}_{k=4} = \sum_{j=1}^{k-1} W_{4j}x_j = W_{41}x_1 + W_{42}x_2 + W_{43}x_3$$

$$= -3.41602 \times 0.5521 + (-1.07709 \times 0.5276) + (-1.25859 \times 0.4417)$$

$$= -3.0093$$

$$x_{x=4} = \frac{1}{1 + \exp^{-\text{net}_4}}$$

$$x_{k=4} = \frac{1}{1 + \exp^{3.0093}} = 0.0470$$

$$k = 5$$

$$\text{net}_{k=5} = \sum_{j=0}^{k-1} W_{5j}x_j = W_{51}x_1 + W_{52}x_2 + W_{53}x_3 + W_{54}x_4$$

$$= 0.439633 \times 0.5521 + (1.45472\text{E-}02 \times 0.5276) + (2.72656 \times 0.4417) + (-13.1454 \times 0.0470)$$

$$= 0.8368$$

$$x_{k=5} = \frac{1}{1 + \exp^{-\text{net}_5}}$$

$$x_{k=5} = \frac{1}{1 + \exp^{-0.8368}} = 0.6978$$

The output from the neural network is 0.6978, which is the failure rate, for $(t - t_0) = 97.8$ (see Fig. 5 for the same result).

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References

[1]Javeed Nizami, S. S. A. K., and Al-Garni, A. Z., "Forecasting Electric Energy Consumption Using Neural Networks," *Energy Policy*, Vol. 23, No. 12, 1995, pp. 1097–1104.

[2]Wu, F. Y., and Yen, K. K., "Application of Neural Network in Regression Analysis," *IEEE Transactions on Power Systems*, Vol. 23, Nos. 1–4, 1992, pp. 93–95.

[3]Meinsky, M. L., and Papert, S. A., *Perceptrons*, MIT Press, Cambridge, MA, 1969.

[4]Hopfield, J. J., "Neural Networks and Physical Systems with Emergent Collective Computational Abilities," *Proceedings of the National Academy of Sciences*, Vol. 79, 1982, pp. 2554–2558.

[5]Werbos, P., "Backpropagation Through Time: What it Does and How to Do It," *Proceedings of the IEEE*, Vol. 78, No. 10, 1990, pp. 1550–1560.

[6]Kapur, K. C., and Lamberson, L. R., *Reliability in Engineering Design*, Wiley, New York, 1977.

[7]Al-Garni, A. Z., Sheikh, A. K., and Badar, M. A., "Failure Statistics of Airplane Tires and a Reliability-Based Forecasting Strategy," *4th Saudi Engineering Conference*, Vol. 4, KAAU, Jeddah, Saudi Arabia, 1995, pp. 463–469.

[8]Sheikh, A. K., Al-Garni, A. Z., and Badar, M. A., "Reliability Analysis of Airplanes Tires," *International Journal of Quality and Reliability Management*, Vol. 13, No. 8, 1996, pp. 28–38.