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ANN-Based Failure Modeling of T-56 Engine Turbines

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Abstract

The T-56 turboprop engine is one of the most widely used in military transportation aircraft. It operates virtually everywhere, from the arctic circle to the Sahara. Operation in desert conditions, however, presents a challenge for maintenance engineers regarding preventive maintenance scheduling. Erosion caused by sand particles drastically decreases turbine blades life. Recent studies showed that Artificial Neural Network ANN algorithms have much better capability at modeling reliability and predicting failure than conventional algorithms. In this study, more than thirty years of local operational field data were used for failure rate prediction and validation using several algorithms. These include Weibull regression modeling to establish a reference, feed-forward back-propagation ANN, and radial basis neural network algorithm. Comparison between the three methods is carried out. Results show that the failure rate predicted by both the feed-forward back-propagation artificial neural network model and radial basis neural network model are closer to actual failure data than the failure rate predicted by the Weibull model. The results also give an insight into the reliability of the engine turbine under actual operating conditions, which can be used by aircraft operators for assessing system and component failures and customizing the maintenance programs recommended by the manufacturer.

Keywords: Reliability; Neural Network; Back Propagation Algorithms; Turbine Blades.

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1. Introduction

Modern aircraft engines are complex machines. They provide the necessary thrust for the aircraft to fly. Therefore, the safety of an aircraft greatly depends on the reliability of its engines. The extreme hi temperature, pressure, and velocity of the intake air mass may contain sand and dust which will cause a catastrophic damage to aircraft turbine and engine. So preventive maintenance and continuous monitoring of engines are essential measures to increase both reliability and aircraft safety.

The Turbine system is a 4-stage turbine designed to extract the air energy directed from the combustion chamber at extreme hi pressure and temperature - maximum Turbine inlet temperature (TIT) of 1077ºC at Take-off power limited to 5 minutes, 1010ºc maximum continuous operation and, 932ºc recommended cruise power - develop 11000 Hp of mechanical energy to drive the compressor, propeller, and engine accessories. As we mentioned in the introduction part, the turbine section is the most effected by thermal distress, sulfidation and sand ingestion. The Turbine system consists of many components, some of the man turbine components: Turbine inlet casing, vane and seal support, Turbine vane casing, four stages of turbine stator, four stages of turbine rotor, Thermocouples, and rear bearing support, as presented in Figure 1. To simplify our modeling, we will deal with the engine turbine as a single unit.

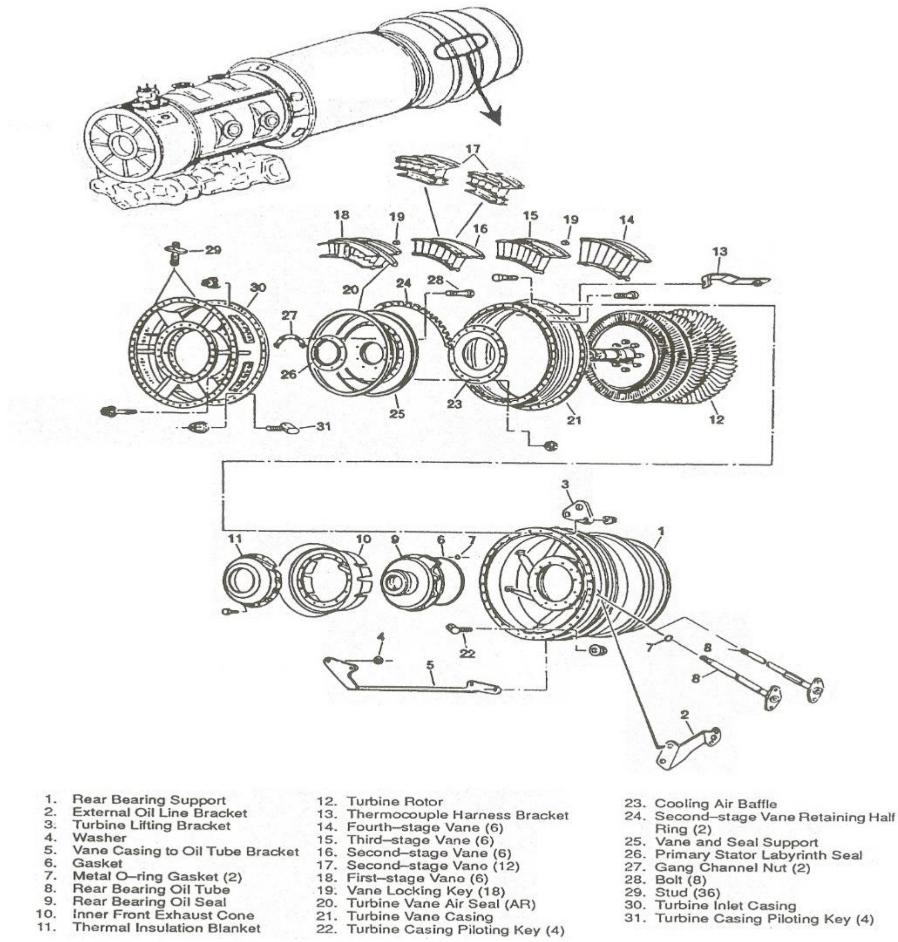

Figure 1: T-56 Turbine Unit Assemblies

2. Literature Review

Zaretsky proposed a generalized Weibull-based methodology for structural life prediction that uses a discrete-stressed volume approach. They applied this methodology to qualitatively predict the life of a rotating generic disk with circumferentially placed holes as a function of the various Weibull parameters [1]. Al-Garni studied the failure rate in many aviation industries fields with a focus on aircraft components and systems by using both two and three parameters Weibull [2,3]. His novel approach was to study and calculate the reliability analysis not only on the component level, but also at the system level. Through his study, he focused on a lot of maintenance issues and procedures that would promote and enhance the reliability of studied system by concluding his research with some practical recommendation related to the maintenance practices and customizing the maintenance programs recommended by the manufacturer.

Artificial Neural Networks were introduced several decades ago as a means of modeling. There have been numerous publications explaining these methods, see for example [4-7]. The convergence criteria in all of them is case are the reduction of mean square error to a minimum value. This delta rule for a single layer can be called a precursor of the back propagation net used for multi-layer nets. The multi-layer extension of Adaline formed the Madaline. In 1982, John Hopfield’s introduced new concept networks, Hopfield showed how to use “Using spin glass “type of model to store the information in dynamically stable networks [8]. His work paved the way for physicists to enter neural modeling, thereby transforming the field of neural networks. Three years later, Parker back propagation net paved its way into neural networks [9]. This method propagates the error information at the output units back to the hidden units using generalized delta rule. This net is basically a multilayer, feed foreword net trained by means of back propagation. Back propagation net emerged as the most popular learning algorithm for the training for multilayer perceptions and has been the workhouse for many neural network applications. This approach is what we are going to utilize in this study since it has proven its power in many fields especially in engineering and it's one of the approaches that is widely used in industry. As a result, Broomhead and Lowe developed Radial Based Functions (RBF). This is also a multilayer net that is quite similar to the back propagation net. Al-Garni utilized the back propagation approaches to predict the failure of some equipment [2,3]. The number of input and output layers and neurons played a significant role in the accuracy of the prediction. Selecting the right structure of the network was one the challenges in the study in order to come up with an optimum model with good parameters that would lead to a reliable prediction of the failure. Kutsurelis utilized ANNs as a forecasting tool to study their ability in predicting the trend of some stock markets indices [10]. Meanwhile, Broomhead and Lowe developed Radial Based Functions (RBF). This is also a multilayer net that is quite similar to the back propagation net.

3. Weibull Modeling

The general Turbine failure data (T.T) of 30years of data from a major local operator of the T-56 aircraft engine in the Gulf Area is analyzed using Weibull Analysis on (MS Excel). The result index of fit, R =0.989 (almost 99%), indicating a strong linear fit to data, thus supporting the hypothesis that the data came from a Weibull distribution. For this hi index for the goodness of fit, the two parameters Weibull will be adequate to give us a trend of the failure with a good fit. Results were validated using comparison with "Windchill Quality Solution" software. Table 1 shows such a comparison and indicates high quality results.

Table 1: comparison between (MS Excel) Weibull program and "Windchill Quality Solution" software for T-56 general Turbine failure data (T.T)

(MS Excel) Weibull output		"Windchill Quality Solution" output	
Multiple R (index of fit)	0.989338178	Multiple R (index of fit)	0.989360
R Square	0.97879003	R Square	0.978834
Beta (Shape Parameter)	1.922759422	Beta (Shape Parameter)	1.967766
Alpha (Characteristic Life)	7465.32048	Alpha (Characteristic Life)	7417.277301

Figures 2 and 3 show the Weibull analysis for the T-56 general Turbine failure data using "Windchill Quality Solution" software as well as the variation of β vs. η.

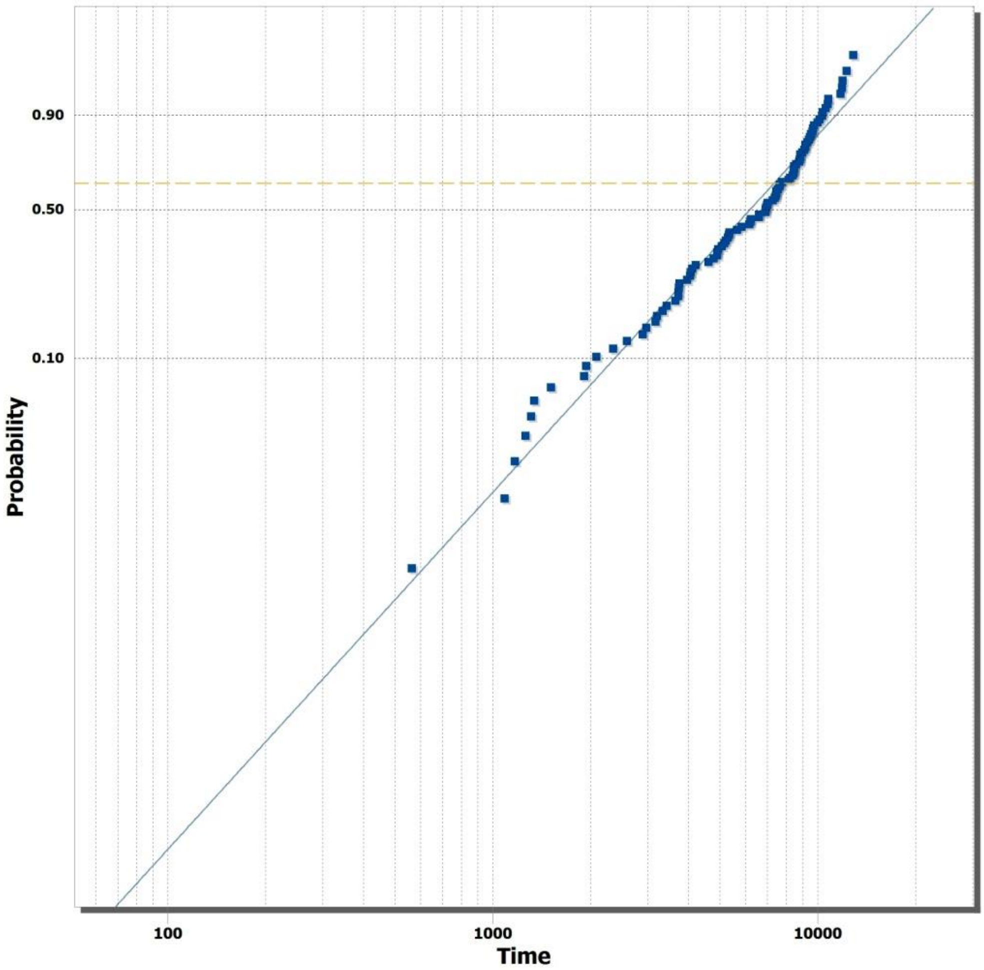

Figure 2: Probability of T-65 general Turbine failure

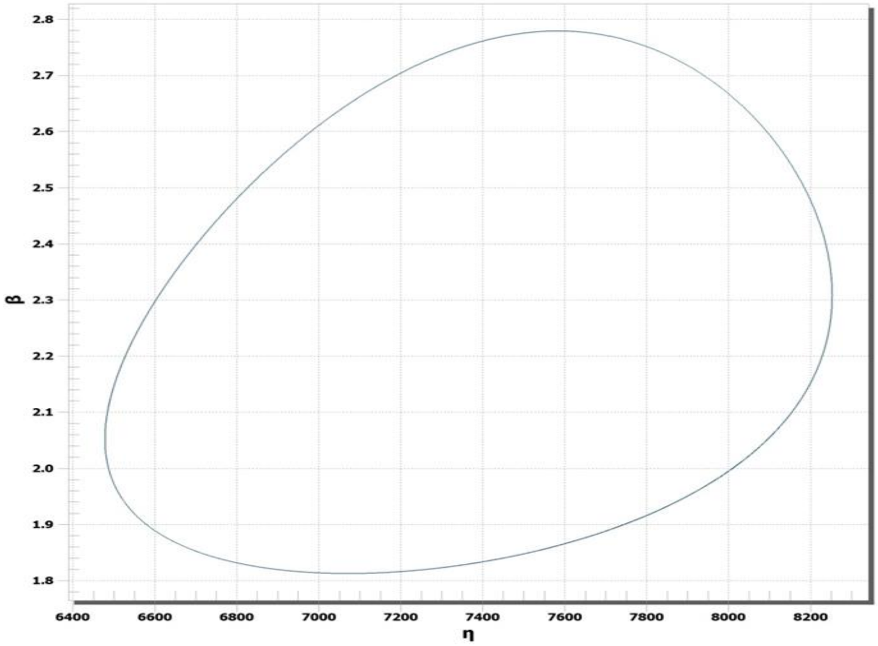

Figure 3: β vs. η contour plot of T-56 general Turbine failure

4. The Back Propagation Model

The back propagation ANN concept is based on a gradient descent algorithm that is used to continually adjust the network weights to maximize performance, using some criterion function. The aim of the network is to train the network to achieve a balance between the ability to respond correctly to the input patterns that are used for training and the ability to provide a good response to the input that are similar.The network has two main segments: the forward-feed and the backpropagation. The former segment simply starts by sending weighted input signals thorough the perceptions of each layer in the network, as illustrated in Fig. 4. The back-propagation segment calculates the error by referring to the stopping criteria that was set for the network. Commonly, neural networks are adjusted, or trained, so that a particular input leads to a specific target output. Here the network is adjusted, based on a comparison of the output and the target, until the network output matches the desired target. The stopping criterion is basically a preset value for the difference between the input and the desired output of the network. It is referred to as the error function or the mean square error (MSE).

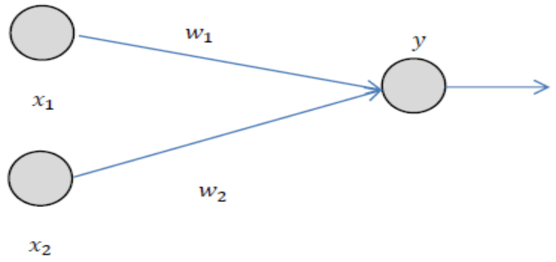

Figure 4: Forward feed of Inputs to a perceptron

Transforming the input signals into output signals is accomplished by an activation function which depends on the structure and the nature of the network. Here, a log-sigmoid function will be utilized for activation. Taking the input and adjusting it into an output range of 0 to 1, this function is suited for problems involving reliability and failure rates.

The logic of the algorithm is detailed in [4] and is summarized in the following set of equations.

$$x_j = normalized\ Xd \quad 1 < d \leq m \tag{1}$$

$$netk = \sum_{j=1}^{k-1} W_{kj} x_j \qquad m \leq k \leq N + n, \tag{2}$$

$$x_k = f(netk) \qquad m < k \leq N + n, \tag{3}$$

$$O_s = X_{N+s} \quad 1 \leq s \leq n, \tag{4}$$

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

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. The non-linear activation function $f\,(net_k)$ in Equations. 5 is a 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 and its size depends on the number of neurons in the corresponding adjacent layers of ANN. W_{kj} are the elements of this weight matrix. The term x_k is called the "activation level" of the neuron, and O_s is the output from the network. Fig. 5 shows a typical ANN model with 3 layers.

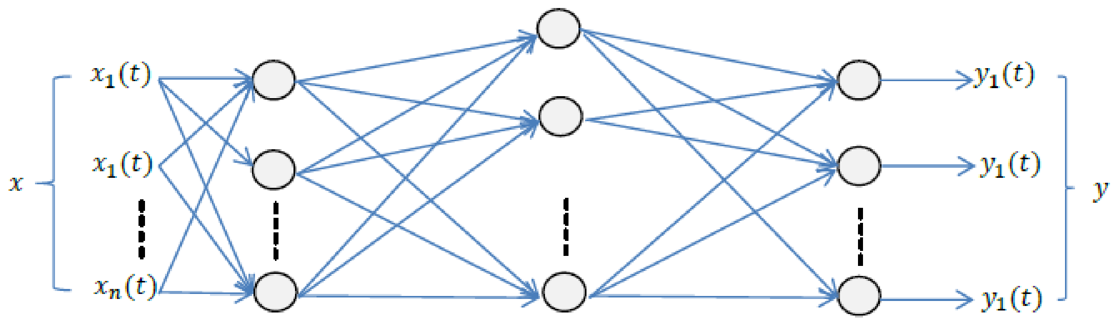

Figure 5: A three-layer Artificial Neural Network

5. Radial basis function modeling

Radial Basis Function (RBF) neural network model on MATLAB toolbox will be used to evaluate our BP ANN model. RBF is essentially a nearest neighbor type of classifier, where the activation of a hidden unit is determined by the distance between the input vector and the prototype vector. The basic idea of RBF is that a predicted target value of an item is likely to be about the same as other items that have close values of the predictor variables, as seen in Figure 6.

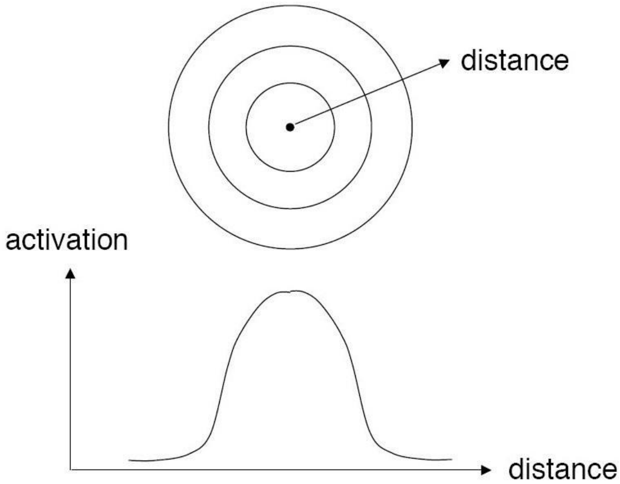

Figure 6: Radial Basis Function (RBF) neural networks

The RBF technique used herein for the anomaly detection is an extension of the standard RBF to form a statistical model of nominal data. As new data enters into the anomaly detection system, it is compared with the RBF model. If it falls within the boundaries defined by the model, then it is considered as a nominal data; otherwise, the data is considered as anomalous. The approach is generic and has been applied to a variety of problems, including advanced military aircraft subsystems. A key requirement for RBF is appropriate selection of the radial basis function and the order of the statistics of the model. From this perspective, a radial basis function for anomaly detection is chosen as:

$$f(x) = exp\left(-\frac{1}{\theta_\alpha}\sum_k |x_k - \mu|^\alpha)\right) \tag{6}$$

Where the parameter $\alpha \epsilon (0, \infty)$; and μ and θ_α are the center, and α th central moment of the data set, respectively. From a sampled time, series data under the nominal condition, the mean μ and the central moment θ_α are calculated as:

$$\mu = \frac{1}{N}\sum_{k=1}^{N} x_k \quad and \quad \theta_\alpha = \sum_{k=1}^{N}|x_k - \mu|^\alpha \tag{7}$$

The distance between any vector x and the center μ is obtained as:

$$\|x - \mu\|_{\ell\alpha} = (\sum_k |x_k - \mu|^\alpha)^{1/\alpha} \tag{8}$$

Hence, at the nominal condition, the radial basis functions $f_{nom} = f(x)$. For different anomalous conditions, the parameters, μ and θ, are kept fixed; and the radial basis function f_k is evaluated from the data set under the (possibly anomalous) condition at the slow time scale. Then, the anomaly measure at the kth epoch is defined as a distance function.

$$M_k \equiv d(f_{nom}, f_k) \tag{9}$$

The neurons in the hidden layer contain Gaussian transfer functions whose outputs are inversely proportional to the distance from the center of the neuron.

Figure 7 shows that RBF have three layers: Input layer – There is one neuron in the input layer for each predictor variable. In the case of categorical variables, *N-1* neurons are used where *N* is the number of categories. The input neuron (or processing before the input layer) standardizes the range of the values by subtracting the median and dividing by the interquartile range. The input neurons then feed the values to each of the neurons in the hidden layer. Hidden layer – This layer has a variable number of neurons (the optimal number is determined by the training process). Each neuron consists of a radial basis function centered on a point with as many dimensions as there are predictor variables. The spread (radius) of the RBF function may be different for each dimension. The centers and spreads are determined by the training process. When presented with the x vector of input values from the input layer, a hidden neuron computes the Euclidean distance of the test case from the neurons center point and then applies the RBF kernel function to this distance using the spread values. The resulting value is passed to the summation layer. Summation layer – The value coming out of a neuron in the hidden layer is multiplied by a weight associated with the neuron ($W_1, W_2, \ldots. W_n$ in this figure) and passed to the summation which adds up the weighted values and presents this sum as the output of the network.

The following parameters are determined by the training process:

1. The number of neurons in the hidden layer.
2. The coordinates of the center of each hidden-layer RBF function.
3. The radius (spread) of each RBF function in each dimension.
4. The weights applied to the RBF function outputs as they are passed to the summation layer.

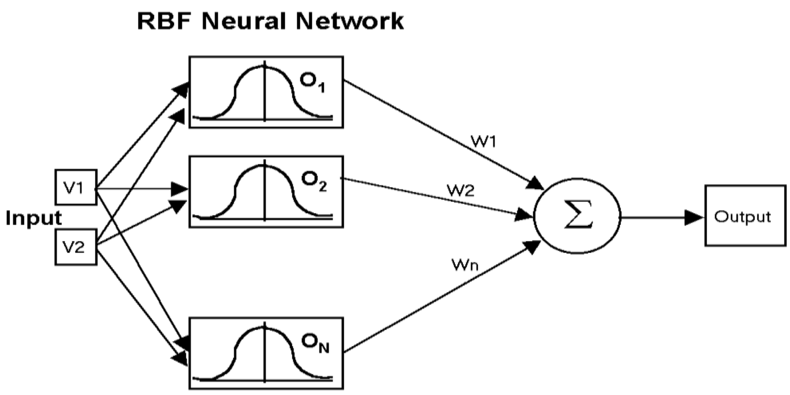

Figure 7: RBF Network Architecture

6. Results and Discussion

The core of the above model is implemented using MATLAB for several network configurations. In the present work the (4,20,1) structure, which is basically having four neurons for the input layer, twenty neurons for the hidden layer, and a single output layer with one neuron, is the optimum for minimizing the sum squared error Equations. 7 The sizes of the weight matrices W_1, and W_2 are 20x4 and 1x20 respectively.

Tables 2 and 3 show a comparison between Weibull regression, (4,20,1) BP ANN MATLAB output, and radial basis neural network model on MATLAB toolbox - which gives negligible average error of (7.54E-16 %) - in relation to actual data. Figure 8 shows that the BP ANN MATLAB code with (4, 20, 1) structure, comes in close agreement with radial based ANN toolbox in relation to the actual data. In other hand, Weibull regression showed a significant error when compared to the neural network method, and has proven, that ANN is more responsive to changes in the failure rate and predicts the failure rate better than the Weibull regression.

Table 2: Comparison between General Turbine failure (T.T) rate predicted by Weibull, (4, 20, 1) BP ANN, RB ANN with actual failure

Curve	**Mean Percentage Error (compared to F(t))**
Weibull	18.20 %
BP ANN (4,20,1)	0.96%
Radial based ANN	7.54E-16

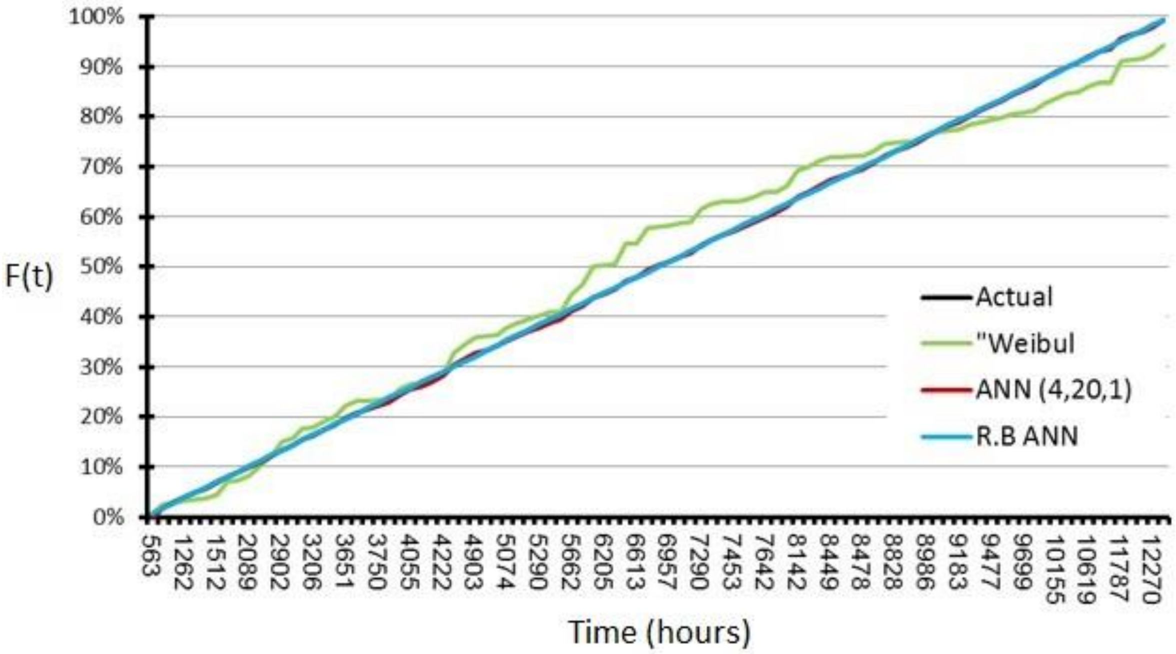

Figure 8: Comparison between General Turbine failure data (T.T) predicted by using Weibull, (4, 20, 1) ANN structure, RB ANN and actual failure rate against time

Finally, increasing dependence on artificial neural network (ANN) model leads to a key question – will the ANN models provide accurate and reliable predictions in relation to the observe data. For that owing to space limitation, a representative set of general Turbine failures and failures which required overhaul maintenance data (T.T) will be presented to construct the model validation. From the collected data a set of (66 series) 70% was used for training of the BP ANN model and the remaining 30% used for testing the model. Train and test sets selected randomly, as the optimum structure of the model (4, 20, 10) is determined by default conditions in MATLAB software and trial and error procedure. Table 3 shows the twenty nine points (30%) tested data and the related error of each point in relation to actual data.

Table 3: General turbine failure (T.T) Tested Data

No	Target	Calculation	Error (%)
1.0	0.00734	-0.00301	141.047
2.0	0.03878	0.03916	0.959
3.0	0.10168	0.09868	2.950
4.0	0.16457	0.16260	1.197
5.0	0.19602	0.19769	0.854
6.0	0.27987	0.27041	3.380
7.0	0.29036	0.28116	3.168
8.0	0.32180	0.32695	1.599
9.0	0.34277	0.34149	0.373
10.0	0.37421	0.37034	1.035
11.0	0.38470	0.37928	1.409
12.0	0.39518	0.38764	1.909
13.0	0.40566	0.39476	2.687
14.0	0.52096	0.51918	0.343
15.0	0.54193	0.54295	0.188
16.0	0.56289	0.56323	0.060
17.0	0.57338	0.57113	0.391
18.0	0.63627	0.63924	0.467
19.0	0.65723	0.66207	0.736
20.0	0.66771	0.67237	0.697
21.0	0.68868	0.68827	0.059
22.0	0.72013	0.72206	0.268
23.0	0.76205	0.75941	0.347
24.0	0.79350	0.78958	0.494
25.0	0.80398	0.80178	0.275
26.0	0.85639	0.85327	0.365
27.0	0.87736	0.87723	0.014
28.0	0.96122	0.96300	0.185
29.0	0.98218	0.97888	0.336

With an average Error of 0.9603 %

Figure.9 shows the BP ANN model results of the 60% trained general turbine failure training data, and Figure.10 shows the 30% general turbine failure tested data.

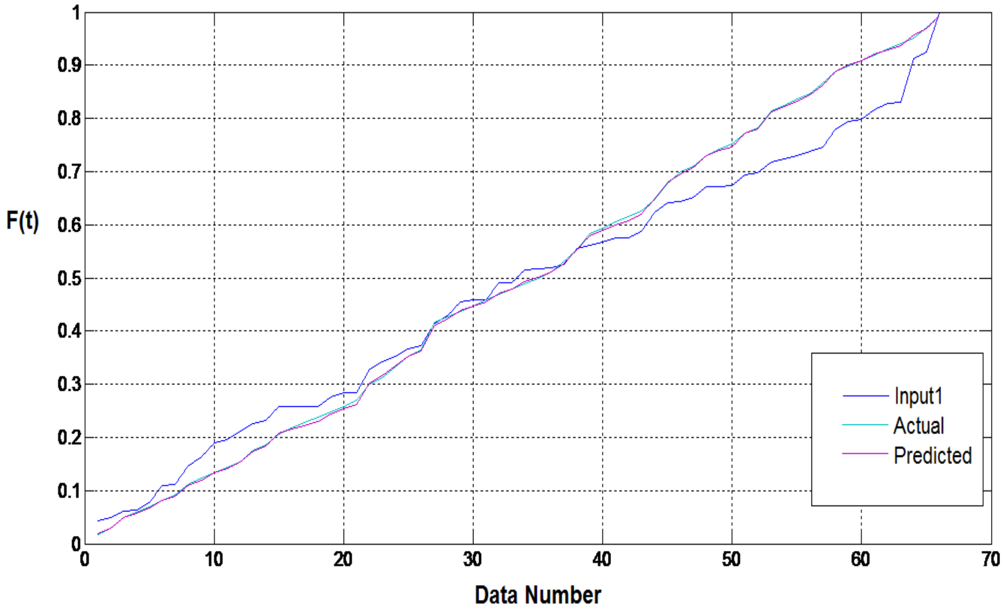

Figure 9: The BP ANN model results of general turbine failure (T.T) training data

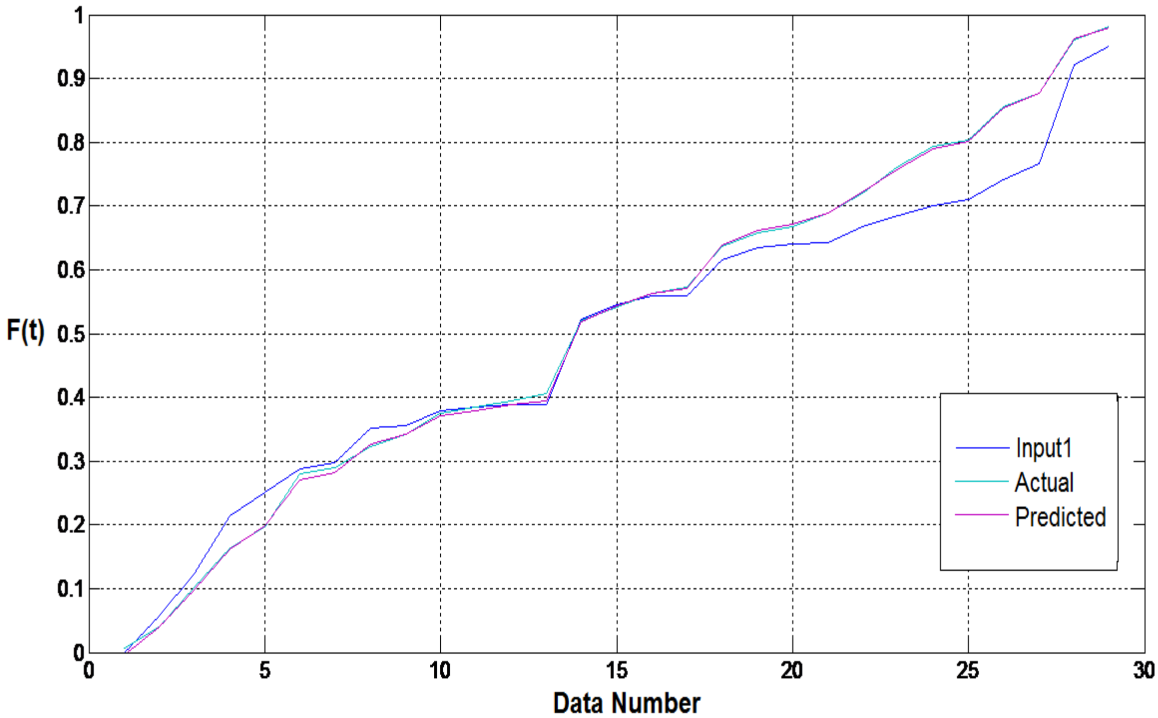

Figure 10: The BP ANN model results of general turbine failure (T.T) testing data

The above two figures show an excellent agreement between the trained values, and the tested sample in relation to the actual failure data. This proves that the model is capable of predicting, with very good accuracy the failure rate of general turbine failures.

7. Conclusion

In this work, more than thirty years of local operational field data were used to predict and validate the failure rate of the T-56 Engine Turbine with respect to time - in hours - of general Turbine failures and failures which required overhaul maintenance, using both Weibull regression and Artificial Neural Network models.

For the Weibull analysis, the data was fitted into the model using two parameters, a good straight line fit to the transformed data support the validity of the Weibull model. The goodness of fit (GOF) test was performed to all data to check the applicability of the Weibull to the data. Results of the Weibull analysis showed a strong level of reliability when compared to the actual failure data. Furthermore, a validation of our MS Excel spreadsheet format of Weibull analysis in comparison to "Windchill Quality Solution" software indicate a very hi quality result and provide quite accurate method of determining mean time between failures, and fairly accurate reliability characterization. The resulting parameters indicate that the engine Turbine has an increasing failure rate over time which makes a planned replacement policy worthwhile. The most common causes of failures in this range are corrosion, erosion, fatigue, and cracking. Since the component exhibits wear out failure pattern, a hard time maintenance action which involves planned replacement and overhaul program is required. The replacements involving such failure rates that increase with time can be scheduled and hence can be modeled to develop the prediction pattern of the failure rates. General Turbine failure rate experiences a failure rate higher than that manufacturer estimated, and overhaul maintenance should be done in 38.5% less Turbine operating hours than what is recommended by the manufacturer, due to the operation in hi erosive, hot desert environment. Thus, a revision in monitoring and inspection program recommended by manufacturer and devising means to decrease the ingestion load acting on the system are likely needed.

For the ANN analysis, the network was designed with different architecture and parameters to ensure reliable results and strong agreement with actual failure data. All parameters were tweaked and adjusted to study the effect of each single element on the behavior of the network; it was evident that the network configuration has a crucial impact on the network performance. A comparative study shows that four input neural network model, performs much better with lesser percentage difference from the actual date than three and two input models, and twenty 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. Finally, ANN outputs showed an excellent level of reliability with respect to minimizing the sum squared error and can be used to schedule a preventive policy for the Turbine failures and overhaul requirements corresponding to an optimal level of turbine reliability. Moreover, it was proven that ANN is more responsive to changes in the failure rate and predicts the failure rate better than the Weibull regression, especially in the erosion failure case, in which the actual data for the failure has a sharper change of slope in respect to time. Radial based ANN analysis was also utilized and gave a negligible average error compared to actual data. A comparison between ANN MATLAB code output, and Radial Basis neural network model on MATLAB toolbox showed that ANN MATLAB code with structure of four neurons input layer, twenty neurons of single hidden layer, and a single output layer with one neuron, comes in close agreement with Radial Based ANN toolbox in relation to the actual data. Moreover, it was proven that ANN is more responsive to changes in the failure rate and predicts the failure rate better than the Weibull regression, especially in the erosion failure case, in which the actual data for the failure has a sharper change of slope in respect to time.Hence turbine is subjected to extreme contaminating loads at almost constant rate which exceed its design strength. Under these conditions, the option to reduce the failure rate may be to curtail the sand ingestion by some devices such as sand separator or Titanium Nitride (TiN) coating blade which extend turbine on wing time by up to 150% in dusty and sandy environments. [11].

Acknowledgements

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