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ANN-BASED FAILURE MODELING OF CLASSES OF AIRCRAFT ENGINE COMPONENTS USING RADIAL BASIS FUNCTIONS

MODELOWANIE USZKODZEŃ ELEMENTÓW SILNIKA SAMOLOTOWEGO W OPARCIU O SZTUCZNE SIECI NEURONOWE O RADIALNYCH FUNKCJACH BAZOWYCH

The objective of this research is to present a model to predict failure of two categories of critical aircraft engine components; non-rotating components such as valves and gearboxes, and rotating components such as engine turbines. The work utilizes Weibull regression and artificial neural networks employing Back Propagation (BP) as well as Radial Basis Functions (RBF). The model utilizes training failure data collected from operators of turboprop aircraft working in harsh desert conditions, where sand erosion is a detrimental factor in reducing turbine life. Accordingly, the model is more suited for accurate prediction of life of critical components of such engines. The algorithm, which uses Radial Basis Function (RBF) NN, uses a closest point specifier. The activation is based on the deviation of the earlier prototype from the input vector. Two earlier models are used for comparison purposes; namely Weibull regression modeling and Feed-Forward BP network. Comparison results show that the failure times represented by RBF are in better compromise with actual failure data than both earlier modeling methods. Moreover, the technique has comparatively higher efficiency as the neuron's number in each layer of ANN is reduced, to decrease computation time, with minimum effect on the accuracy of results.

Keywords: *neural network, radial basis function, Reliability, engine components.*

Celem pracy jest przedstawienie modelu służącego do predykcji uszkodzeń dwóch kategorii krytycznych elementów silnika samolotowego: elementów nieobrotowych, takich jak zawory i skrzynie biegów oraz elementów obrotowych, takich jak turbiny silnika. W pracy wykorzystano regresję Weibulla i sztuczne sieci neuronowe oparte na propagacji wstecznej oraz radialnych funkcjach bazowych (RBF). Model wykorzystuje dane o błędach zebrane od operatorów samolotów turbośmigłowych pracujących w trudnych warunkach pustynnych, gdzie erozja powodowana przez piasek stanowi szkodliwy czynnik ograniczający żywotność turbin. Prezentowany model jest więc szczególnie przydatny do trafnego prognozowania żywotności krytycznych elementów takich silników. Algorytm, który wykorzystuje sieci neuronowe o radialnych funkcjach bazowych, używa specyfikatora najbliższego punktu. Aktywacja bazuje na odchyleniu wcześniejszego prototypu od wektora wejściowego. Dwa wcześniejsze modele oparte na regresji Weibulla (Weibull regression modeling) oraz sieciach typu Feed-Forward Backpropagation wykorzystano do badań porównawczych. Wyniki porównania pokazują, że czasy uszkodzeń odwzorowane przez RBF pozostają w większej zgodzie z rzeczywistymi danymi o uszkodzeniach niż w przypadku obu wcześniejszych metod modelowania. Co więcej, technika ta ma porównywalnie większą efektywność, ponieważ liczba neuronów w każdej warstwie sieci neuronowej została zredukowana tak aby zmniejszyć czas obliczeń, przy minimalnym wpływie na dokładność wyników.

Słowa kluczowe: *sieć neuronowa, radialna funkcja bazowa, niezawodność, elementy silnika.*

1. Introduction

Reliability of modern aircraft engines is highly affected by failure prediction methods of their critical parts. When these engines are operated in severe desert conditions, the high temperature, pressure, and velocity of the intake air may increase the effect of sand erosion on the rotating engine critical components, such as high-pressure turbine blades, and gearboxes. Sand also contributes to blockage of failure of nonrotating parts like engine valves that get blocked by sand particles. To better schedule cost-effective preventive maintenance, more accurate modeling and prediction of component life is important. This also helps to enhance both aircraft safety and reliability.

The type of engine system which is currently under consideration comprises a 4-stage turbine subjected to extreme high pressure and temperature as it draws air energy from the combustion chamber. The maximum Turbine Inlet Temperature (TIT) can reach up to 1077ºC while it has a maximum generated power of 11,000 hp. Both turboprop and turbofan engines contain also no rotating parts that are critical to engine operations. These include turbine bleed air valves, high pressure valves, stator vanes, casing and support, support for rear bearing, and thermocouples. The failure of any of these components can lead to the failure of the entire turbine system. Hence, it is important to address this type of failure for aircraft safety and this research present a failure model for the parts that were found to fail the most in engines operated in the desert climate of Saudi Arabia. The work will proceed to compare predictions made by Weibull regression and Artificial neural networks algorithms that utilize either Back Propagation or Radial Basis Functions with the actual failure data from available data from the aviation industry.

2. Literature Review

There is a large body of research on modeling of reliability of aircraft system components for different types of failure. Most of this research was based on a Weibull distribution to predict the component life, utilizing discrete-stressed volume approach [21]. Later, Sheikh et al. [16] and Al-Garni et al. [2] used Feed-Forward, Back-Propagation ANN to better model failure, as compared to the more common two-parameter and three-parameter This advantage of FF-BP models was extended to both component and system levels [3, 4, 5, 18]. The work enabled customizing maintenance plans to suit different operator conditions. Later, Qattan [15] used also Radial Basis Functions for modeling of failure time of rotating components.

Artificial Neural Networks were introduced as a means of modeling. A great body of literature was dedicated to explaining these methods, see for example Kutusurelis [10] and Paul et al. [14]. The basic convergence criterion, known as the delta rule, in all of these algorithms is based on reducing some mean square error to its least value. The convergence criterion is generally utilized for single layer networks and also forms the foundation for a back propagation used for multi-layer networks. Additionally, Hopfield [9] used a "spin glass" model for storing data in dynamically stable type of networks. By that time, the well-established back propagation network used a basic delta rule to propagate the output error back to the hidden units, see for example Parker [13]. In his work, he used BP to train a multilayer feed forward network.

Another type of net, known as Radial Based Functions (RBF), was formulated by Broomhead and Lowe [8]. In RBF networks, the accuracy of modeling depends mainly on the number of neurons in the input and output layers. Most of the research work aimed at selecting the most suitable structure and parameter values of the network that increase the failure prediction reliability. Several variations of PB and RBF networks were used to study failure of aircraft components with different training methods, including deep belief networks of Lin et al. [11].

In a more recent work, Abdelrahman et al. [1] investigated the training of BP ANN to model failure of engine components. The work, which was expanded by Al-Wadiee [6], showed significant improvement over the traditional Weibull model results. Both work, however, did not deal with utilization of the predicted results.

Later, Tian [17] used ANN based method to predict the remaining life of equipment that are fitted with health monitoring. The monitoring of age and multiple condition was used to train the NN. Also, Bin et al. [7] utilized two decomposition methods to obtain the fault feature frequency in rotating machinery. Then, they used an artificial neural network for the early fault diagnosis of these components. The fault pattern of the machinery was identified using a three layers BP NN model taking the fault feature frequency as the target input. The spectral bandwidth energy of vibration signal spectrum was taken as a characteristic parameter, whereas 10 types of representative rotor fault were considered the output.

Wang and Wang [20] used a nested extreme response surface to tackle time dependency issues in reliability analysis. In their work, Nieto et al. [12] combined support vector machines with particle swarm optimization technique. This significantly improved regression accuracy. Vanini et al. [19] also used multiple dynamic neural networks to learn the nonlinear dynamics of jet engines. Residuals obtained by comparing operating modes of healthy and faulty conditions of engines were used to develop a reliable criterion for detecting and isolating faults.

3. Modeling of component failure

As this work aims at failure modeling of aircraft critical components using Weibull and ANN (Back propagation/Radial Basis Function). Since the Weibull regression method is well documented in literature [21], more emphasis is given in the present work to the back propagation and Radial Basis Function ANN modeling.

3.1. Back propagation artificial neural network

The back propagation ANN modeling utilizes some criterion function to maximize the performance by continuously varying the network weights through gradient descent algorithm. The goal of this model is to train the network in such a manner that a compromise can be achieved between the ability to respond accurately after receiving training input patterns and the capability to produce accurate responses for similar inputs. The network has two main segments; the forward-feed and the back-propagation. The input signals are transformed into output signals using a suitable activation function. Log-sigmoid function is an activation function that proved to give good results for component failure time modeling. The algorithm is detailed in works of [8] and [1], and is only summarized here.

Let m and n be the number of inputs and outputs of the network; respectively, and let X_d be the input signal to the ANN, whereas f (net_k) is the activation function. This function is normally a non-linear log-sigmoid function, whose parameter values depend on the preferred output data range. Let N be the number of intermediate neurons. In this case, we can define a normalized set of inputs as follows:

$$x_j = \text{normalized values of } X_d \;, 1 < d \leq m \tag{1}$$

Here the rank of neuron activation is defined as:

$$x_k = f(\text{net}_k), \quad m < k \leq N + n \tag{2}$$

where:

$$\text{net}_k = \sum_{j=1}^{k-1} W_{kj} x_j \;, \quad m \leq k \leq N + n \tag{3}$$

Here, W_{kj} are the elements of the weight matrix. The number of neurons in the corresponding neighboring layers determines the size of this weight matrix W.

The activation log-sigmoid function is given by:

$$f\ (net_k) = \frac{1}{1+e^{-netk}} \tag{4}$$

The network output is calculated from the output layer neuron signals as:

$$O_s = X_{N+s} \quad 1 \leq s \leq n \tag{5}$$

In the above equations, N is always less than the number of inputs of the ANN. Moreover, If we consider the inputs as neurons of the input layer, then the sum $(N + m)$ is the total number of neurons in the network. Figure 1 shows a typical 3 layer ANN model with inputs p_R and weights $w_{s,R}^{1}$.

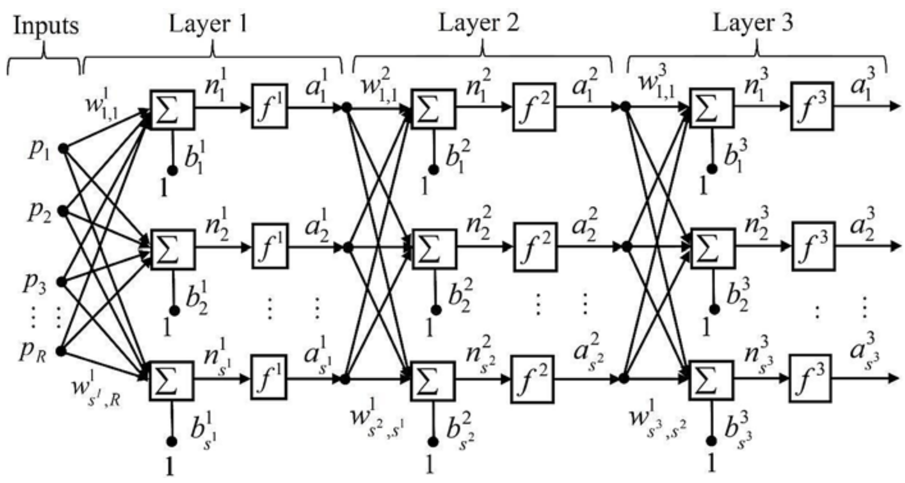

Fig. 1. A schematic of multilayer ANN with a general activation function

3.2. Radial basis function artificial neural network

In RBF neural network modeling, the hidden unit activation is based upon the spacing between the input prototype and the input vector. This RBF model employs a closest point classifier type to detect anomalies. An extended version of the model utilizes nominal data. Here, as soon as the data is added to the system, it is compared to the RBF model, and is classified as nominal if it falls within the boundaries of the model. If it does not fall within these boundaries, then it is classified as anomalous. This approach has many applications in complex systems and subsystems, including those of military aircraft. The accuracy of the model in this case depends on the number of elements in each layer, as well as the appropriate choice of the radial basis function. The selection of the radial basis function for the detection of an anomaly is done considering the condition:

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

where $\alpha \in (0,\infty)$ θ_α is the α central moment, given by:

$$\theta_\alpha = \sum_{k=1}^{N} |x_k-\mu|^\alpha$$

and μ is the center of the data set defined as:

$$\mu = \frac{1}{N}\sum_{k=1}^{N} x_k . \quad (7\text{-b})$$

The mean μ and the central moment θ_α as given by equations (7), are evaluated for the nominal condition from the data of a sampled time series. In this case, the distance from the center μ to any vector x is given by:

$$x-\mu_{l_\alpha} = \left(\sum_{k=1}^{N} |x_k-\mu|^\alpha\right)^{1/\alpha}. \quad (8)$$

Therefore, the radial basis function is defined by $f_{nom} = f(x)$ at the nominal condition. The mean and central moment are not changed for the anomalous conditions, whereas the radial basis function is calculated using the possibly anomalous data set under the condition at a slow time scale. Anomaly can be measured at the k epoch by the distance from the neuron's center, given by:

$$M_k \equiv d(f_{nom}, fk) \quad (9)$$

This distance is inversely proportional to the outputs of the Gaussian transfer functions of the hidden layer. Fig. 2 depicts the general architecture of a RBF network. The network consists of three layers. The first layer has one neuron for each predictor variable. It is pivotal to normalize the range of the input values prior to the input layer. The second layer, the hidden layers, receive the resulting values from the first input layer. Since the neuron's number in this layer varies, an optimum value is obtained through the process of training. In this layer, every neuron is modeled as RBF which is centered on a point whose dimensions are the same as the number of the predictor variables. The RBF function's radius represents the spread which may vary for each dimension. The spreads and the centers are optimally evaluated again in this process of training.

The Euclidean distance is evaluated from the neuron's center point after a hidden neuron is given some input values in the form of vector x from the input layer. Next, for this distance, the model uses RBF type kernel function by utilizing the spread values that were calculated in the previous step. The output of the value is then transferred to the summation layer which is also the last layer. In the summation layer, first the neuron value produced by the hidden layer is multiplied by a weight (W_i) which is related to the neuron and afterwards the output of the network is obtained by summation of all the weighted values. Accordingly, training is carried out to determine the neuron's number in the hidden layer, the RBF function's radius in each dimension, the center's coordinates for each hidden-layer RBF function, and the weights that are applied to the outputs of the RBF function as they are transferred to the last layer (summation layer).

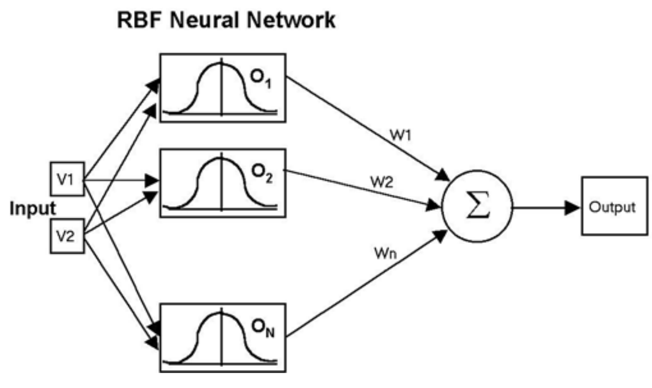

Fig. 2. Model for the RBF Network

The error function is calculated as:

$$\text{error} = \sum\left[F(t)-O(t)\right]^2 \quad (10)$$

4. Results and discussion

Actual failure data over a period of thirty years was provided by local aviation operator working within the Arabian Gulf Area contained both the Time Since Overhaul (T.S.O.). A subset of this data is used to train the ANN network with 2, 4, and 1 neurons in the input, hidden, and output layers; respectively. The prediction results are compared to Weibull predictions, and to the actual data in Fig.3. Fig. 4 presents a similar comparison when the ANN model utilizes 4, 20, and 1 neurons in the three layers.

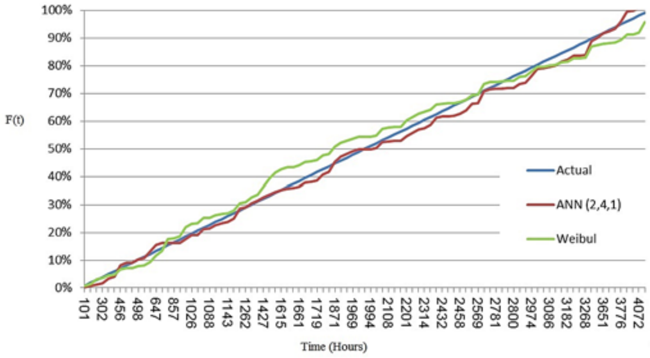

Fig. 3. Comparison of results of ann (2, 4, 1), Weibull model, and actual failure rate for turbine requiring overhaul maintenance (T.S.O)

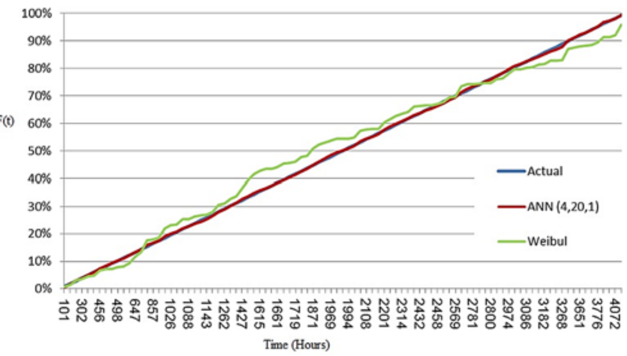

Fig. 4. Comparison of results of ANN (4, 20, 1), Weibull model, and actual failure rate for turbine requiring overhaul maintenance (T.S.O)

It can be noted from Figures 3 and 4 that the network training significantly improves with this change in the network configuration. It was also found that there is only negligible effect of changing other parameters such as learning rate and momentum constant.

A comparison was carried out between the maximum error percent in predictions using several ANN-BP configurations and the results of these configurations are summarized below in Table 1. The error in this table is calculated based on comparison with the actual collected field data. Again, it is clear from the table that ANN (4,20,1) configuration has the least mean error among all the other ANN-BP configurations and hence this configuration most closely matches with the actual data. Further increase in neuron numbers in any of the layers does not significantly reduce error, but increases run-time considerably.

Table 1. Percentage error for failure of Turbine requiring overhaul maintenance (T.S.O.)

Network Configuration	Mean Error (%)
BP - ANN (4, 20, 1)	0.84
BP - ANN (4, 10, 1)	1.00
BP - ANN (4, 8, 1)	1.51
BP - ANN (3, 6, 1)	4.51
BP - ANN (2, 4, 1)	6.85

Table 2. Mean percentage error for failure rate of turbine requiring overhaul maintenance (T.S.O) for Weibull, BP ANN (4, 20, 1), RBF ANN

Method	Mean Error (%)
Weibull	16.55
ANN- BP (4,20,1)	0.84
ANN-RBF (best config.)	1.09E-15

It is worth noting that a similar approach can be implemented for predicting turbine failure requiring overhaul maintenance (T.S.O), which is sometimes used in the aviation industry. Table 2 presents the MATLAB results for comparison between BP ANN (4, 20, 1), Weibull regression model, and RBF neural network model for this case. It is clear from the table that there is negligible mean percentage error of around 1.09E-15 % when Radial based function neural network was used for prediction of failure rate for turbines that requires overhaul maintenance. Hence, the comparison in Table 2 clearly establishes that ANN-RBF model presents more accurate modeling of turbine failure rate than both Weibull regression and ANN-BP models.

Figure 5 presents a comparison of the three methods' results over a range of more than 4,000 hours. From this figure, it can be deduced from figure that it is more advantageous to use RBF neural network for predicting failure rate as compared to Weibull or BP ANN model. Moreover, the BP ANN (4, 20, 1) configuration also depicts far better results than Weibull regression model.

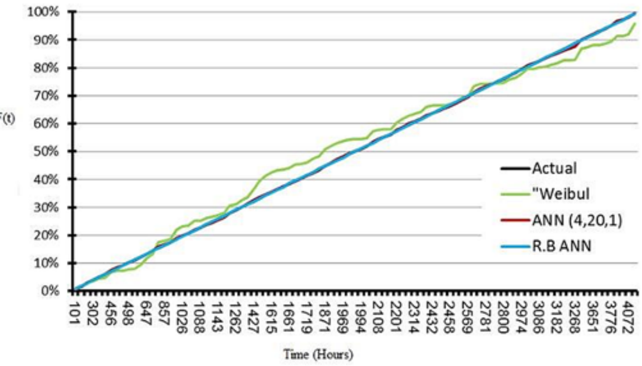

Fig. 5. Comparison of BP ANN model, RBF ANN and Weibull regression with actual failure rate for turbine requiring overhaul maintenance (T.S.O)

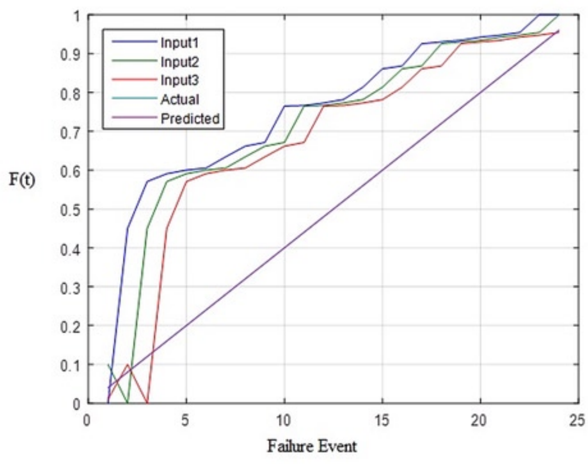

Fig. 6. RBF ANN analysis of Gear boxes failure training data without denormalization

Table 3. General failure data for gear boxes using Weibull analysis- Part I

t_i	t_i - t_0 t_0 =506.6	i	F = i/N + 1 N = 44	R = 1- F	ln (t_i - t_0) = x_i	ln[ln(1/R)] = y_i
4838.6	4332.00	1	0.022222	0.977778	8.373785	-3.795447
5183.7	4677.10	2	0.044444	0.955556	8.450434	-3.090870
5246.5	4739.90	3	0.066667	0.933333	8.463771	-2.673752
5345.2	4838.60	4	0.088889	0.911111	8.484381	-2.374184
5437.9	4931.30	5	0.111111	0.888889	8.503358	-2.138911
5663	5156.40	6	0.133333	0.866667	8.547994	-1.944206
5680.6	5174.00	7	0.155556	0.844444	8.551401	-1.777405
5753.2	5246.60	8	0.177778	0.822222	8.565336	-1.630945
5773.3	5266.70	9	0.200000	0.800000	8.569159	-1.499940
5868	5361.40	10	0.222222	0.777778	8.586980	-1.381050
5900	5393.40	11	0.244444	0.755556	8.592931	-1.271888
5926.2	5419.60	12	0.266667	0.733333	8.597777	-1.170683
6031.5	5524.90	13	0.288889	0.711111	8.617020	-1.076088
6752.5	6245.90	14	0.311111	0.688889	8.739681	-0.987048
6915	6408.40	15	0.333333	0.666667	8.765365	-0.902720
7385.9	6879.30	16	0.355556	0.644444	8.836272	-0.822421
7395	6888.40	17	0.377778	0.622222	8.837594	-0.745582
7555	7048.40	18	0.400000	0.600000	8.860556	-0.671727
8173.2	7666.60	19	0.422222	0.577778	8.944629	-0.600448
8293	7786.40	20	0.444444	0.555556	8.960134	-0.531391
8540.9	8034.30	21	0.466667	0.533333	8.991475	-0.464246
8586.3	8079.70	22	0.488889	0.511111	8.997110	-0.398735
8953	8446.40	23	0.511111	0.488889	9.041496	-0.334606
9046.1	8539.50	24	0.533333	0.466667	9.052458	-0.271625
9523	9016.40	25	0.555556	0.444444	9.106800	-0.209573
9542.9	9036.30	26	0.577778	0.422222	9.109005	-0.148241
9542.9	9036.30	27	0.600000	0.400000	9.109005	-0.087422
9684.41	9177.80	28	0.622222	0.377778	9.124543	-0.026910
9777.5	9270.90	29	0.644444	0.355556	9.134636	0.033506
9786.3	9279.70	30	0.666667	0.333333	9.135584	0.094048
9848	9341.40	31	0.688889	0.311111	9.142211	0.154955
9925	9418.40	32	0.711111	0.288889	9.150421	0.216492
9946.7	9440.10	33	0.733333	0.266667	9.152722	0.278961
10249	9742.60	34	0.755556	0.244444	9.184263	0.342715
10563	10056.20	36	0.800000	0.200000	9.215945	0.475885
11044	10537.40	37	0.822222	0.177778	9.262686	0.546514
11462	10954.90	38	0.844444	0.155556	9.301542	0.620981
11545.8	11039.20	39	0.866667	0.133333	9.309208	0.700571
11674	11167.00	40	0.888889	0.111111	9.320718	0.787195
11714	11207.30	41	0.911111	0.088889	9.324321	0.883920
12376	11869.10	42	0.933333	0.066667	9.381694	0.996229

A question that need to be investigated is whether these conclusions can be extended to failure prediction of nonrotating components, or components not directly affected by the airflow. Accordingly, a similar study was carried out for gearbox failure data. The failure data for gear boxes was also collected from local aviation company. Tables 3 and 4 present Weibull analysis for Gear box failure for two sets of Weibull parameters, comprising failure data of 42 gearboxes.

Afterwards, RBF-ANN analysis was carried out, with different neurons numbers, and is compared to Weibull analysis results. This is presented in Figure 6. In this figure Input 1, 2, and 3 refer to the

Table 4. General failure data for gear boxes using Weibull analysis – Part II

(1)	(2)	(3)	(4)	(5)	(6)	(7)
t_i	t_i - t_0	i	F = i/N + 1	R = 1- F	ln (t_i - t_0)	ln[ln(1/R)]
9046.1	8539.50	24	0.533333	0.466667	9.052458	-0.271625
9523	9016.40	25	0.555556	0.444444	9.106800	-0.209573
9542.9	9036.30	26	0.577778	0.422222	9.109005	-0.148241
9542.9	9036.30	27	0.600000	0.400000	9.109005	-0.087422
9684.41	9177.80	28	0.622222	0.377778	9.124543	-0.026910
9777.5	9270.90	29	0.644444	0.355556	9.134636	0.033506
9786.3	9279.70	30	0.666667	0.333333	9.135584	0.094048
9848	9341.40	31	0.688889	0.311111	9.142211	0.154955
9925	9418.40	32	0.711111	0.288889	9.150421	0.216492
9946.7	9440.10	33	0.733333	0.266667	9.152722	0.278961
10249	9742.60	34	0.755556	0.244444	9.184263	0.342715
10331	9824.50	35	0.777778	0.222222	9.192635	0.408180
10563	10056.20	36	0.800000	0.200000	9.215945	0.475885
11044	10537.40	37	0.822222	0.177778	9.262686	0.546514
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11545.8	11039.20	39	0.866667	0.133333	9.309208	0.700571
11674	11167.00	40	0.888889	0.111111	9.320718	0.787195
11714	11207.30	41	0.911111	0.088889	9.324321	0.883920
12376	11869.10	42	0.933333	0.066667	9.381694	0.996229

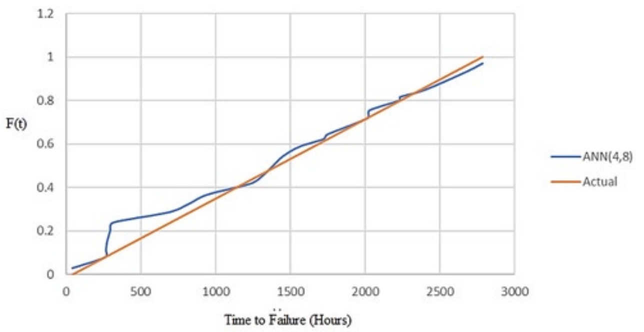

Fig. 7. Comparison of failure prediction results for RBF ANN with the actual data of bleed valves.

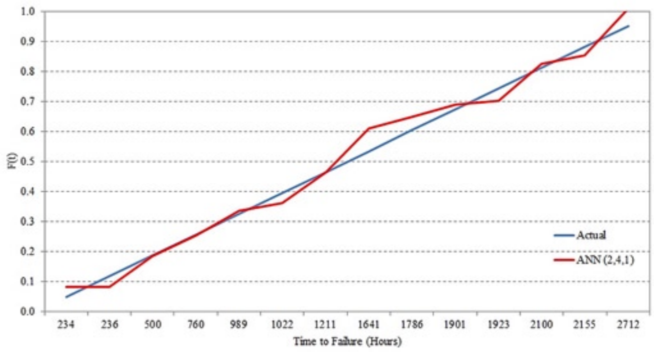

Fig. 8. Comparison of results of ANN (2, 4, 1) for High stage valve with the actual data

different ANN configurations, with increasing number of neurons in the input and hidden layers. It can be seen from the figure that increasing number of neurons results in more accurate predictions, but that prediction accuracy for gearbox failures is less than that of turbine failures. Figure 6: RBF ANN analysis of Gear boxes failure training data without denormalization

Finally, the failure prediction of nonrotating components; namely engine valves was carried out. Collected failure data of high pressure valves and engine bleed valves was used to train the ANN. Calculations of failure prediction of bleed valves are presented in Table 5, whereas calculations for the high pressure valves are presented in Table 6. For the bleed valves, Table 5, a network configuration of 4 neurons in the input layer and 8 in the hidden layer was selected. However, for the case of high pressure valves, Table 6, the results of several network configurations were presented and compared.

Figures 7, 8, and 9 illustrate the comparison between selected network configuration and actual results for bleed valves (Figure 7), and for high pressure valves (Figure 8 and 9). From these figures it is clear that prediction results are better than predictions done for gearboxes, and the accuracy is comparable to predictions done for turbine components.

5. Conclusion

In this work, a RBF NN model is developed for the modeling of critical rotating and nonrotating engine parts operating in desert conditions. The accuracy of the trained model is determined by a comparison to earlier methods of BP NN and Weibull distribution. Testing several values for the number of neurons shows that the percentage deviation from actual failure data is small for networks with 4 or more neurons in the input layer. Further increase in number of neurons does not improve accuracy much and considerably increases run-time. Moreover, it is found that an intermediate neuron number of 20 produces reasonable accuracy for predicting failure of both rotating and nonrotating components, without much increase in run time. The RBF modeling of failure data provided by local operator proved to be superior than the other two methods. RBF NN showed much higher accuracy, as represented by the much smaller value of the sum of error squares. This modeling, therefore, can be utilized to formulate replacement and overhaul guidelines of both rotating and nonrotating engine components that correspond to a certain optimum level of reliability.

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