RELIABILITY ANALYSIS OF C-130 TURBOPROP ENGINE COMPONENTS USING ARTIFICIAL NEURAL NETWORK

BY

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Dedication

To my parents who taught us how to give…..

To my wife who supported me morally wholeheartedly…..

To my children Ibrahim, Muhammad and Lama who taught us patience and love…..

To my brothers who spared no effort in encouragement….

To all researchers who are working to improve the quality of life of humans…..

To all of them I dedicate this work

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"In the name of Allah, The Most Gracious and The Most Merciful"

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LIST OF ABBREVIATIONS

ADALINE	**:**	Adaptive Linear Neuron
ANN	**:**	Artificial Neural Network
APU	**:**	Auxiliary Power Unit
ART	**:**	Adaptive Resonance Theory network
BP	**:**	Back Propagation algorithm
CDF	**:**	Cumulative Distribution Function
CV	**:**	Critical Value
FAR	**:**	U.S. Federal Aviation Regulations
FOD	**:**	Foreign Object Damage
GA	**:**	Genetic Algorithm
GOF	**:**	Goodness Of Fit
KS	**:**	Kolmogorov-Simirnov goodness of fit
LDA	**:**	Life Data Analysis
LMS	**:**	Least Mean Square rule
LR	**:**	Learning Rate
MAE	**:**	Mean Absolute Error
MAPE	**:**	Mean Absolute Percentage Error
MLP	**:**	Multilayer Perceptron Neural Network
MOM	**:**	Moment
MPD	**:**	Maintenance Planning Document
MRO	**:**	Maintenance Repair and Overhaul
MSE	**:**	Mean Square Error
MTBF	**:**	Mean Time Between Failures
MTTF	**:**	Mean Time To Failure
MTTF	**:**	Mean Time Between Failures
OEM	**:**	Original Equipment Manufacturer Manual
PDF	**:**	Probability Distribution Function
RAM	**:**	Reliability, Availability and Maintainability
RBF	**:**	Radial Based Function
RUL	**:**	Remaining Useful Life
T.O	**:**	Technical Order Book
T.T	**:**	Total Operational Time
TiN	**:**	Titanium Nitride
TIT	**:**	Turbine Inlet Temperature
TSO	**:**	Time Since Overhaul
$\mathbf{T_{0.5}}$	**:**	Life by which half of the units will survive

ABSTRACT

Full Name	:	Nizar Awadallah H Qattan
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In this study, we predict the failure rate of Lockheed C-130 Engine Turbine. More than thirty years of local operational field data were used for failure rate prediction and validation. The Weibull regression model and the Artificial Neural Network model including (feed-forward back-propagation, radial basis neural network, and multilayer perceptron neural network model); will be utilized to perform this study. For this purpose, the thesis will be divided into five major parts. First part deals with Weibull regression model to predict the turbine general failure rate, and the rate of failures that require overhaul maintenance. The second part will cover the Artificial Neural Network (ANN) model utilizing the feed-forward back-propagation algorithm as a learning rule. The MATLAB package will be used in order to build and design a code to simulate the given data, the inputs to the neural network are the independent variables, the output is the general failure rate of the turbine, and the failures which required overhaul maintenance. In the third part we predict the general failure rate of the turbine and the failures which require overhaul maintenance, using radial basis neural network model on MATLAB tool box. In the fourth part we compare the predictions of the feed-forward back-propagation model, with that of Weibull regression model, and radial basis neural network model. The results show that the failure rate predicted by the feed-forward

back-propagation artificial neural network model is closer in agreement with radial basis neural network model compared with the actual field-data, than the failure rate predicted by the Weibull model. By the end of the study, we forecast the general failure rate of the Lockheed C-130 Engine Turbine, the failures which required overhaul maintenance and six categorical failures using multilayer perceptron neural network (MLP) model on DTREG commercial software. 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.

ملخص الرسالة

الاسم الكامل: نزار بن عوض الله حسين قطان

عنوان الرسالة: ' تحليل الموثوقية في مكونات المحرك المروحي التربيني لطائرة السي-١٣٠ باستخدام الشبكات العصبيه الإصطناعية '

التخصص: هندسة الطيران والفضاء

تاريخ الدرجة العلمية: ١٤٣٤هـ - ٢٠١٣م.

في هذه الدراسة، تم تحليل وتنبؤ الأعطال في تربينات محرك طائرة السي-١٣٠ من صنع شركة لوكهيد مارتن. ولإتمام هذه العملية والتحقق من صحة التحليل, فقد تم استخدام بيانات تشغيليه ميدانيه لأكثر من ثلاثين عاماً. وتم استخدام عدة نماذج علمية وهي: نموذج الإنحدار باستخدام التحليل الوابلي, ونموذج الشبكات العصبية الإصطناعية باستعمال العديد من الخوارزميات بما في ذلك (شبكات التغذية الأمامية ذات الانتشار الإرتدادي Feed-forward back-propagation , الشبكة العصبية الإصطناعية بدالة الأساس الشعاعي Radial basis neural network , المستشعر المتعدد الطبقات Multilayer perceptron). و لهذا الغرض, فقد تم تقسيم الأطروحة إلى خمسة أجزاء رئيسية . يتناول الجزء الأول تحليل الإنحدار باستخدام نموذج وايبل للتنبؤ بنسبة أعطال التوربينات في حالة الأعطال التي تتطلب صيانة عامه, و الأعطال اللتي تتطلب عمرة شاملة. وفي الجزء الثاني تم بحث استخدام نماذج الشبكة العصبية الصناعية (ANN) بطريقة خوارزميات التغذية الأمامية ذات الإنتشار الإرتدادي كقاعدة للتعلم. وتم استخدام حزمة MATLAB من أجل بناء وتصميم برنامج لمحاكاة البيانات الميدانية، حيث أن المدخلات إلى الشبكة العصبية تمثل المتغيرات المستقلة ، والنواتج تمثل معدل للأعطال العامة في التوربينات ، و الأعطال التي تتطلب عمرة شاملة. في الجزء الثالث تم استخدام خوارزميات الشبكة العصبية الإصطناعية بدالة الأساس الشعاعي لتوقع المعدل العام لأعطال التوربينات, والأعطال التي تتطلب عمرة شاملة, بالإستعانة بنموذج الشبكة العصبية المبرمجه ضمن حزمة MATLAB. وللتحقق من صحة النتائج, تم في الجزء الرابع عمل مقارنة علمية بين مخرجات خوارزميات شبكات التغذية

الأمامية ذات الإنتشار الإرتدادي, و خوارزميات طريقة الشبكة العصبية الإصطناعية بدالة الأساس الشعاعي, مع نموذج الإنحدار باستخدام التحليل الوابلي. وبناءً عليه, فقد إتضح من خلال هذه المقارنة أن الشبكات العصبية اللإصطناعية لديها القدرة الفائقة لمحاكاة النتائج الفعلية لعدد مرات اللأعطال. مقارنة بنموذج التحليل الوابلي.

وفي نهاية هذا الجزء قمنا بتصنيف الأعطال الشائعة لتوربينات محركات طائرة السي-١٣٠ لستة أقسام رئيسية. وبإستخدام خوارزميات الشبكات العصبية بطريقة المستشعر المتعدد الطبقات على حزمة البرنامج التجاري DTREG, تم توقع معدل الأعطال التي تتطلب صيانة عامة, و الأعطال اللتي تتطلب عمرة شاملة, بالإضافة للأعطال الست الشائعة.

وأخيرا, ومن خلال نتائج هذه الدراسة, يمكن إعطاء نظرة ثاقبة في مدى الإعتمادية لتوربينات محركات طائرة السي-١٣٠ تحت ظروف التشغيل الفعلية ، واستخدامها كأداه لتخطيط الصيانة , من خلال معرفة عدد الوحدات المطلوب توفرها كبديل في حالة الأعطال, و تخصيص برامج الصيانة الموصى بها من قبل الشركة المصنعة.

CHAPTER 1

INTRODUCTION

Modern aircraft engines are very 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 engine. Engine turbine extracts energy from a flow of expanding combustion gas, and converts the gaseous energy to mechanical energy in the form of shaft power to drive the propeller, compressor, and all engine accessories. A large mass of air must be supplied to the turbine in order to produce the necessary power. This extreme high temperature, pressure, and velocity 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.

There are various conventional regression models that can be applied to predict the failure of equipment and systems; however, there has been a growing interest lately in the application of artificial neural networks (ANN), which have outperformed regression models. The ability of neural networks to model multivariate problems without making complex dependency assumptions among the input variables is an advantage over statistical method. Moreover, neural networks extract the implicit nonlinear relationships among the complex input data gathered from many maintenance records through a learning process from the training data. The objective of this research is to build a neural network model to predict the general Lockheed C-130 engine turbine failure rate and the failures which required overhaul maintenance, based on local environment. The results of the ANN model are also compared by the predictions of the Weibull regression model, and radial basis neural network model. Also to enhance maintenance planning, we will model all engine turbine failures including general failure, failure which required overhaul maintenance and, six categorical failures classified by reasons of failure using Multilayer Perceptron Neural Network (MLP) model on DTREG commercial software.

The rest of this paper is organized as follows. Section II reviews the literature on Weibull distribution and artificial neural network. Following a description of the failure data, and its mortality characteristics, Weibull distribution analysis was modeled, and validated by Windchill quality solution software as discussed in Section III. Section IV describes the ANN approach including BP neural network analysis, which compared with Weibull regression and RB NN model. Finally to enhance maintenance planning, we modeled most frequent turbine failures, using Multilayer Perceptron Neural Network (MLP) on DTREG software. The conclusions and future work are discussed in section V.

1.1 Lockheed C-130 Engine

Since the Lockheed C-130 Engine turbine are used as a test model for the analysis, it would be appropriate to introduce the function and layout of the system before proceeding with a description of our work. The airplane is powered by four constant speeds T-56 Turboprop engines. Complete engine consists of a gas turbine power unit connected by an extension shaft and supporting structure to reduction gear assembly to the engine propeller which creates the required thrust. The power section has a single-entry 14 stages axial-flow compressor, a set of 6 combustion chambers of through-flow type, and a 4-stage turbine. Mounted on the power section is an accessories drive assembly and components of the engine fuel, ignition, and control systems as shown in Figure 1-1. [1,2,3,4].

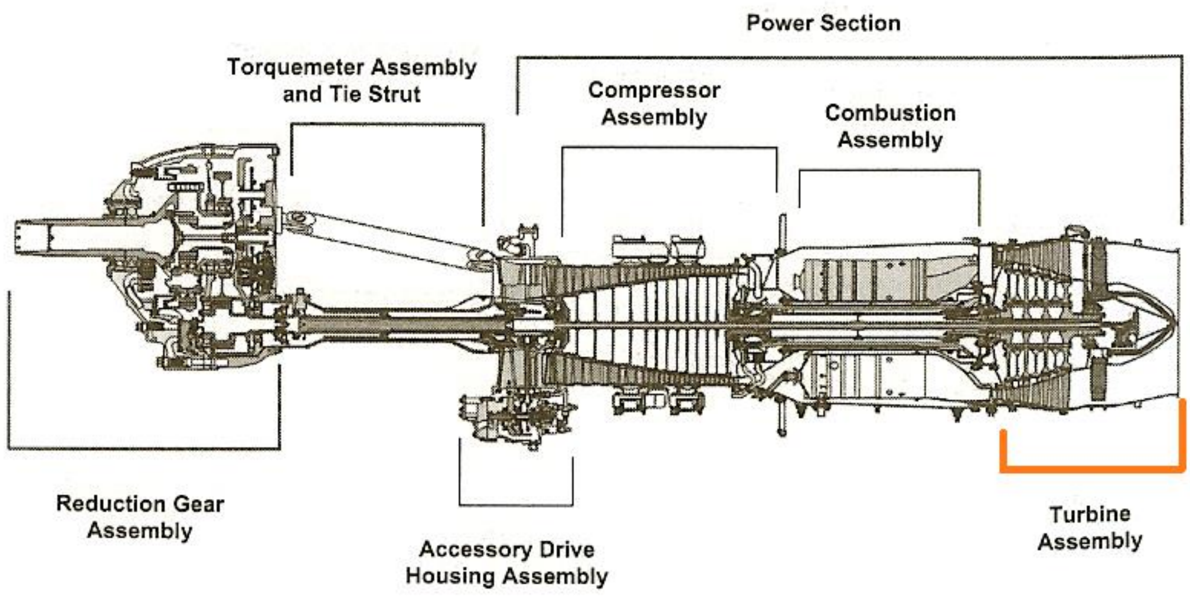


Figure 1-1 T-56 Turboprop engines

Inlet air enters the compressor and progressively compressed through the 14 stages compressors. The compressed air - at approximately 125PSI, 315ºC (600ºF) - flows through a diffuser into the combustion section. Fuel is injected into the combustion chambers, mixed with air and burned, increasing the temperature and thereby the energy of gases. The hot gases pass through the turbine causing it to rotate and drive the compressor, propeller, and engine accessories. The gases after expanding through the turbine flow out a tailpipe as presented in Figure 1-2. The reduction gear assembly contains a reduction gear train, engine starter, an A.C generator, a hydraulic pump, and oil pump. The reduction gear train is in two stages providing an overall reduction of 13.54 to 1 between engine speed of 13,820 RPM and propeller shaft speed of 1,021 RPM.

Power Planet General Characteristics

- Type: Turboprop.
- Compressor: 14 stages axial flow.
- Combustors: 6 cylindrical flow-through.
- Turbine: 4 stages.
- Fuel type: JP8, 2412 pounds per hour per engine.
- Oil system: 2 systems (1 each for power section and reduction gearbox).
- Maximum power output: 4,300 SHP per engine.
- Overall pressure ratio: 14.5:1.
- Power-to-Weight ratio: 2.75:1 (SHP/lb).

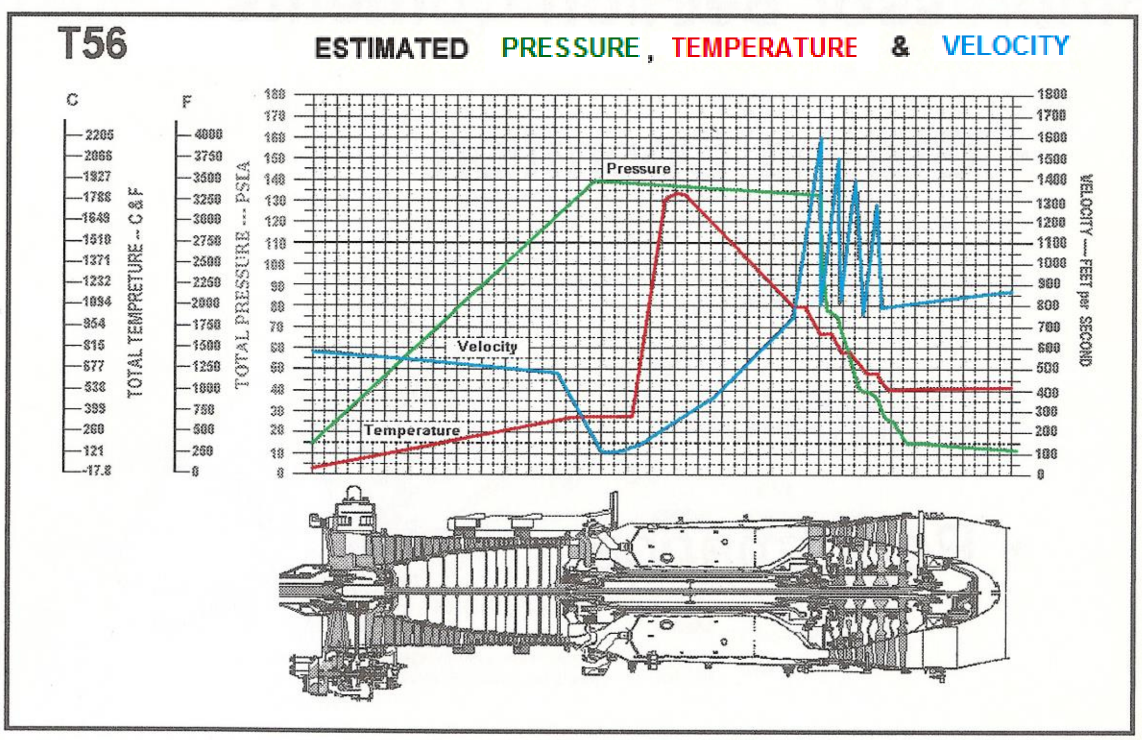
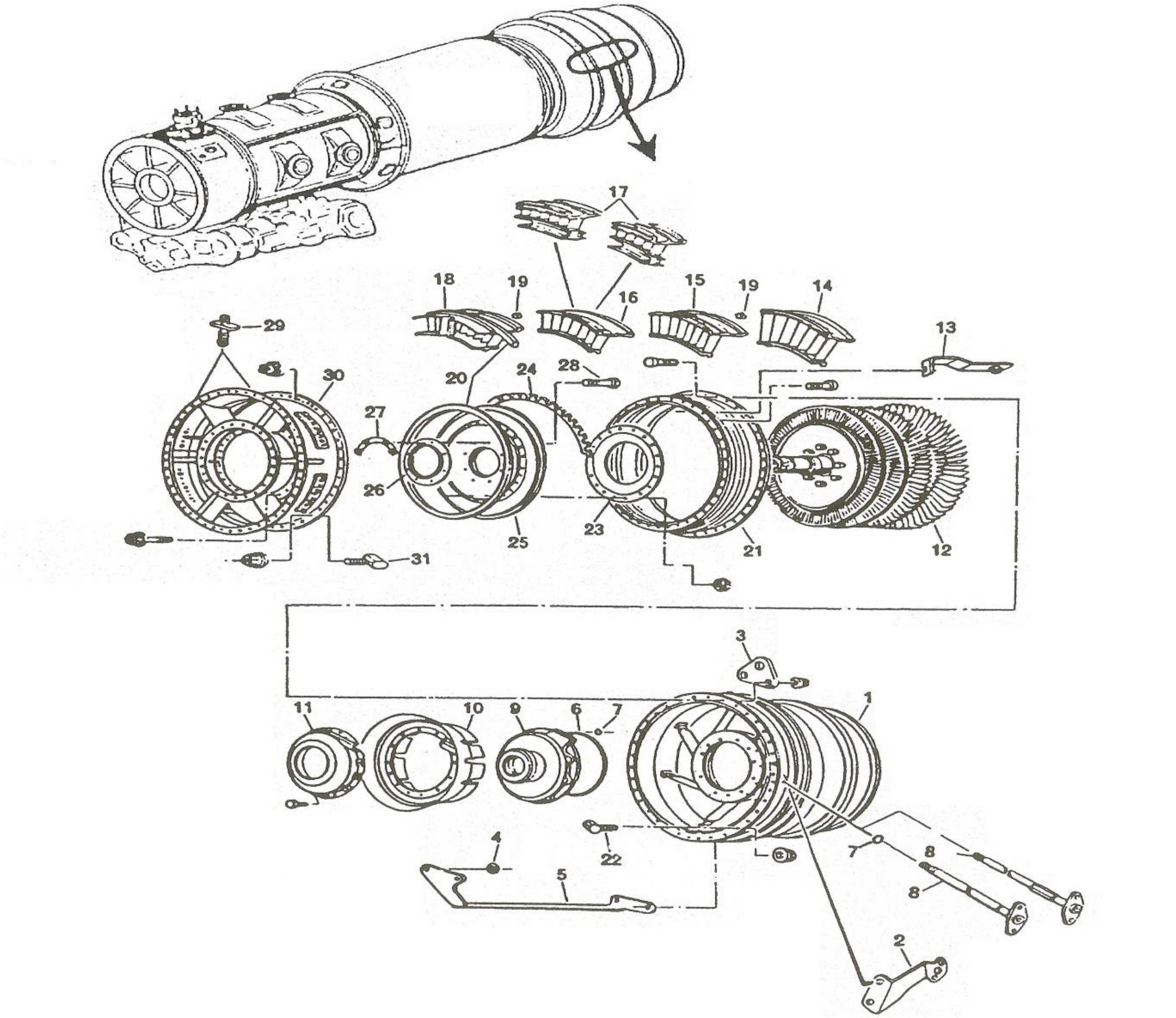


Figure 1-2 Schematic of power section air flow

1.2 Lockheed C-130 Engine Turbine

The turbine system is a 4-stages turbine, designed to extract the gas energy directed from the combustion chamber at extreme high 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 - developing 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 affected area 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 1-3. [5]. To simplify our modeling we will deal with the engine turbine as a single unit.



1. Rear Bearing Support
2. External Oil Line Bracket
3. Turbine Lifting Bracket
4. Washer
5. Vane Casing to Oil Tube Bracket
6. Gasket
7. Metal O–ring Gasket (2)
8. Rear Bearing Oil Tube
9. Rear Bearing Oil Seal
10. Inner Front Exhaust Cone
11. Thermal Insulation Blanket
12. Turbine Rotor
13. Thermocouple Harness Bracket
14. Fourth–stage Vane (6)
15. Third–stage Vane (6)
16. Second–stage Vane (6)
17. Second–stage Vane (12)
18. First–stage Vane (6)
19. Vane Locking Key (18)
20. Turbine Vane Air Seal (AR)
21. Turbine Vane Casing
22. Turbine Casing Piloting Key (4)
23. Cooling Air Baffle
24. Second–stage Vane Retaining Half Ring (2)
25. Vane and Seal Support
26. Primary Stator Labyrinth Seal
27. Gang Channel Nut (2)
28. Bolt (8)
29. Stud (36)
30. Turbine Inlet Casing
31. Turbine Casing Piloting Key (4)

Figure 1-3 Turbine Unit Assemblies

1.3 Statement Problem

Lockheed C-130 is widely operated in desert environments in our region, and often encounters sand and dust erosion, which have been known to create a number of operating problems for the power plant. The engine turbine is most affected by sand and dust ingestion, as it works under extreme temperate and pressure conditions. Operating in such erosive – ingestion of sand, dust or dirt - and corrosive – salt laden environments - will result in wearing of the blade leading edges and trailing edge root, causing airfoils changing shape, and may lead to structural failure Figure 1-4.

Engine turbines operating in such harsh environments are known to suffer from the following:

- Reduction in air mass flow.
- A clog or block cooling air passages, turbine wheels, and the thermocouples.
- Reduction in stall margin.
- Increased probability of unscheduled engine rundown.
- Loss of turbine efficiency.
- Turbine vane burn-through.
- Increased turbine materials temperature causing shorter service life Figure 1-5. [6].
- Intensive increase in turbine temperature during engine startup.
- Turbine sulfidation. Figure 1-6. [6].

Preventive maintenance and continuous monitoring of engines are essential measures to increase both reliability and aircraft safety. Maintenance Planning Document (MPD) prepared by the manufacturer is the main document that is used by aircraft operators in developing their maintenance programs for a particular type of aircraft. MPD sets minimum maintenance requirements for the aircraft. Each operator should customize MPD based upon its own operating conditions, environment, maintenance capabilities, practices, and rules of the local regulatory authority. Most of the operators usually use the inspection or replacement intervals mean time between failures as recommended by the manufacturer in their maintenance program as long as they do not conflict with local regulations. Once an engine reaches the serviceability limit for overhaul, according to U.S. Federal Aviation Regulations (FAR), the engine must be removed from the aircraft for overhaul. Reference to maintenance Technical Order book (T.O) the life time limit for Lockheed C-130 Engine turbine overhaul maintenance is (6000) operational hours, but unfortunately the actual overhaul maintenance is way much than this limit (2500) hours due to local environment mentioned above. The time taken to reach this failure is measured by the associated total operational time (T.T), and the time since overhauled (TSO). Manufacturer recommendations are based on the test data. Even the most faithful and rigorous testing will fail to precisely simulate all field conditions. On the other hand, field data capture the operating and environmental stresses associated with the actual usage conditions. It is quite likely that there would be variations between the field reliability data and manufacturer reliability test results. Usage of field data allows for more accurate predictions of reliability performance of the components. This enables the operators to develop appropriate inspection or replacement programs, and spare part plans based on their own operating and environmental conditions, which will results in decreasing maintenance cost and minimizing flight delays and cancellations due to unexpected failures. Analysis of failure data for the fielded systems is also very important to manufacturers because the information received from the field gives a true measure of product performance and it points out the areas of improvements to refine the product by design changes.

However there is a limited number of studies on the fielded systems because of in-service failure data may be incomplete due to lost information, and often more difficult to obtain. However this problem is less problematic in large aviation organizations, which usually operate with strict data reporting requirements.

Hence methods presented in this study can be used to assess the failure characteristics of any system or component and to customize the manufacturer recommended maintenance program; it will prove the way for further discussions and investigations, especially in our unique operating and environmental conditions.

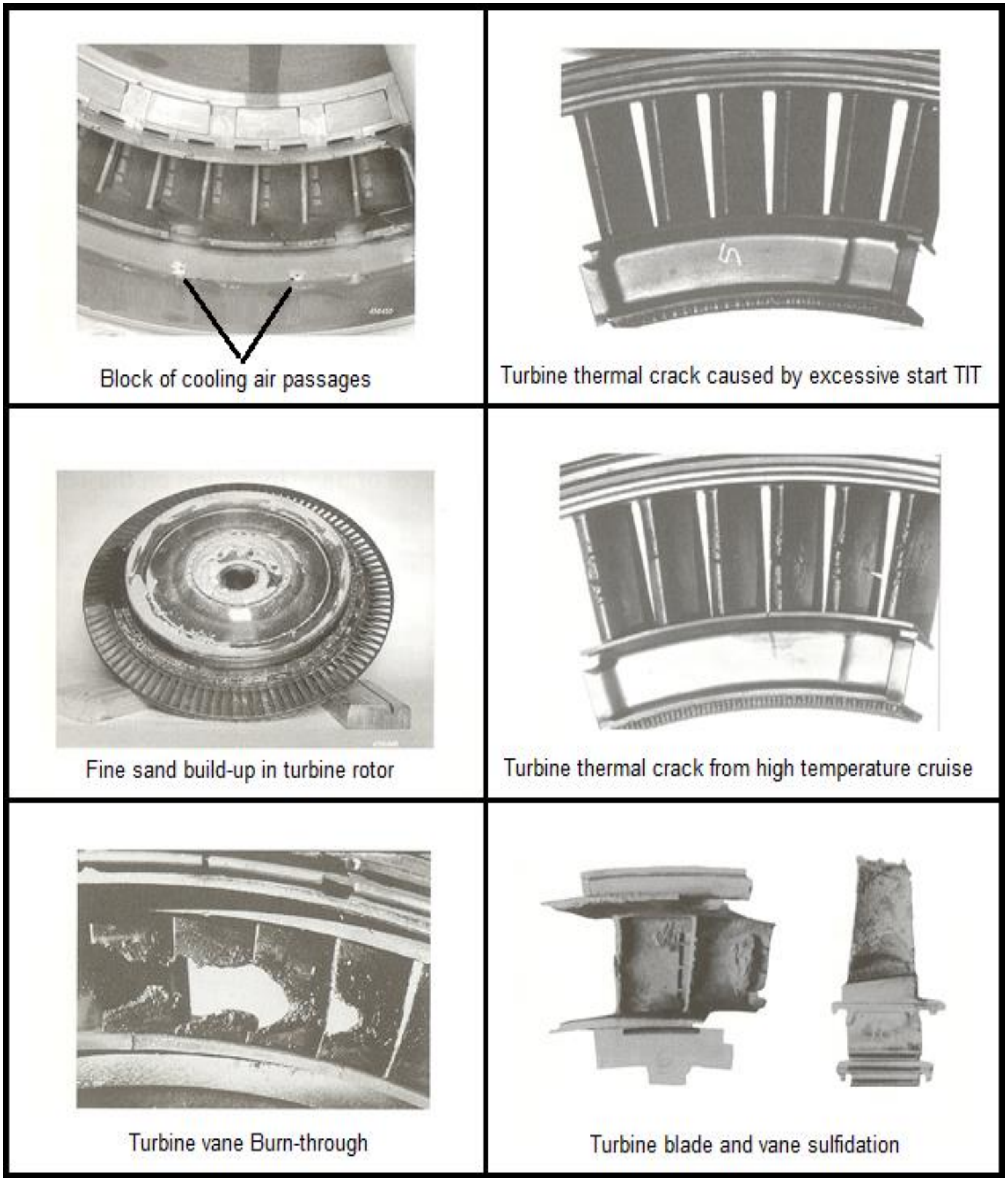


Figure 1-4 Effects of sand ingestion and sulfidation on the T-56 Turbine

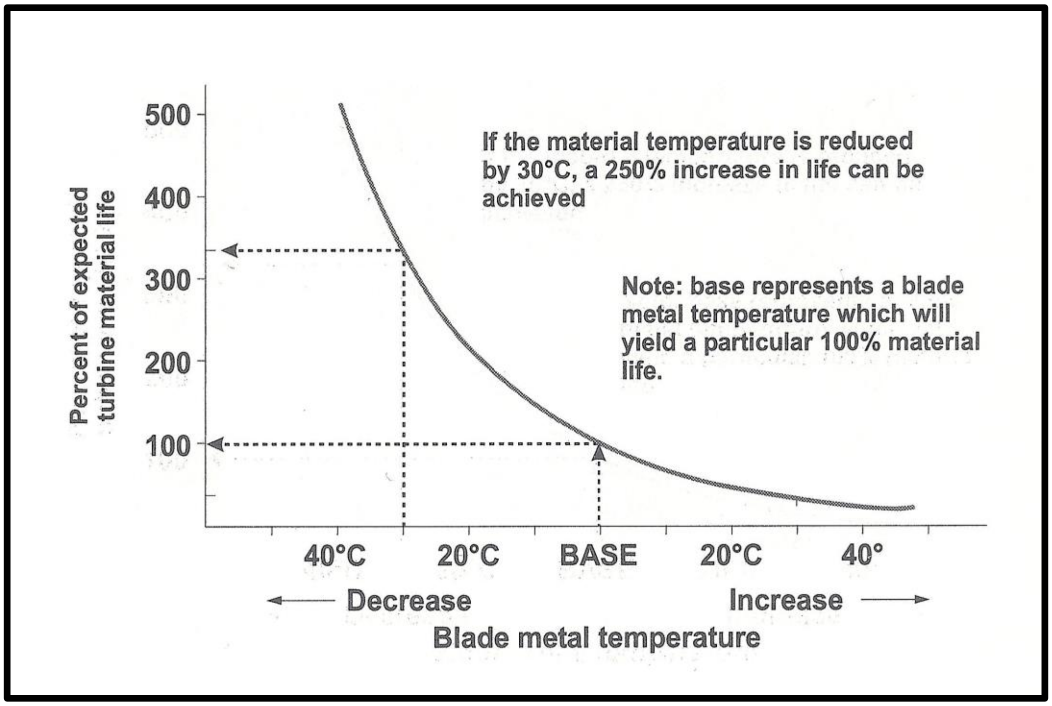


Figure 1-5 Effect of temperature on T-56 turbine blade materials

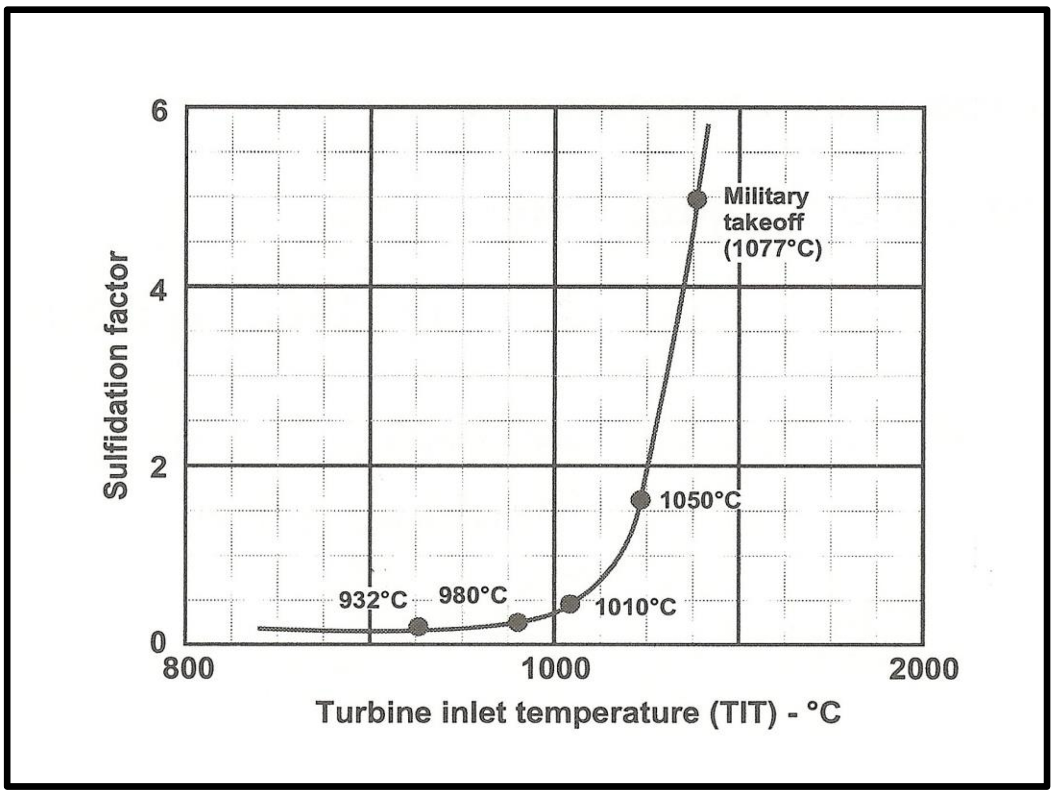


Figure 1-6 Effect of temperature on sulfidation

1.4 Objectives

The main objective of this study is to accurately model the failure rate of Lockheed C-130 engine turbine system, based on a history of data collected from a local maintenance facility by feed-forward back-propagation MATLAB code, and to compare it with that of Weibull regression model, and radial basis neural network on MATLAB tool box, to ensure a reliable data which can be utilized for maintenance planning based on the local environment. The Three models are constructed for two cases. The first case is for general turbine failure. The second case is for turbine failures that required overhaul maintenance.

Finally, to give an insight into the reliability of the engine turbine in our desert environment, which can be used by aircraft operators for assessing system and component failures and customizing the maintenance programs recommended by the manufacturer, all engine turbine failures including general failure, turbine failures that required overhaul maintenance, and six categorical classified reasons of failure are forecasted by Multilayer Perceptron neural network (MLP) model on DTREG program.

CHAPTER 2

LITERATURE REVIEW

2.1 Weibull Distribution

Weibull distribution was originally derived in 1928 by R. A. Fisher and L. H. C. Tippett [7]. Their, derivation became known to researchers who were familiar with extreme-value theory. In 1939 a Swedish scientist, Waloddi Weibull, derived the same distribution with which his name has been associated in recent years. This derivation came about as the result of an analysis of breaking-strength data and can be found in [8], Weibull also related published papers [9], and [10], illustrates several examples of the distribution's practical value in analyzing various types of data. Further [11] Weibull explained the reasoning of the Weibull distribution through the phenomenon of the weakest link in the chain, [12].

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 [13]. Al-Garni studied the failure rate in many aviation industry fields with a focus on aircraft components and systems by using both two and three parameters Weibull [14]. His new 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 researches with some practical recommendation related to the maintenance practices, and customizing the maintenance programs recommended by the manufacturer. He also used the Weibull model, Mixture model, and phased bi-Weibull model for modeling the failure of the aircraft air-conditioning/cooling pack under a customer-use environment at the component level. The results indicate that the water separator is the component with the most observed failures. Dirt contamination is identified as the most frequently occurring failure type for the water separator. The rate of occurrence of failures for the system indicates no trend and is almost constant. This is likely due to weather conditions in the region. Results also point out that the failures occur at a higher rate than that estimated by the manufacturer [15]. Tozan et al. [16,17] Used simple and mixture Weibull methods for forecasting the failure rate distribution of Boeing 737 aircraft Auxiliary Power Unit (APU) oil pumps. He found that the method can make quantitative trades between scheduled and unscheduled maintenance or non-destructive inspection and replacement, The method also help in determining the age at which an operating part in an aircraft system should be replaced with a new one for various cost ratio. The results were in close agreement with the real data indicating the validity of the Weibull model, and it is demonstrated that the mixture Weibull model is more accurate in predicting the failure rate of APU oil pumps than simple Weibull model. Anwar. K. Shaikh et al. [18] studied the reliability of some rotating equipment that is used in oil and gas field, two parameters Weibull was utilized in his study. Further in [19] He studied the reliability analysis of airplane tires using the Weibull analysis method to determine reliability of a variety of machine elements and systems. The data of time to failures of aircraft tires have been used. Also he has demonstrated that Weibull could be utilized in calculating the reliability of an assembly of rotating parts subjected to fatigue failure. The fatigue life distribution of each individual component in the assembly is considered to be Weibull distributed. They found that this method is quite an accurate method of determining mean time between failures (MTBF), and also provide fairly accurate reliability characterization [20]. Samaha et al [21]. Studied the utilization of Weibull to predict the failure of some equipment based on history of data to give an indication of the component failure mechanism. He has also demonstrated that Weibull could be utilized in calculating the number of future failures according to the mean time between failures (MTTF). Erwin with assistance from NASA used Weibull model in aging and predicting the life of aircraft engine structures including critical rotating components like high pressure turbine blades, fan, and compressors, [22]. Lewis et al [23,24]. Used regression based analysis which will be basically used in this study.

2.2 Artificial Neural Network (ANN)

Earlier, in 1943, McCulloch and Pitts presented a neural computing model called the MCP neuron [25]. In the paper they tried to explain how the brain could produce complex patterns from a connection of basic neurons. They formed a logical calculus of neural network. A network consists of number of neurons and properly set synaptic connections that can compute any computable function. They gave a simple model of such a neuron that consisted of a collection of inputs and a single output. The inputs were either excitatory (+1) or inhibitory (-1). The function for the neuron weights and sums the results to produce either a +1 or a -1. The arrangement of neuron in his case maybe represented as a combination of a logic function. The most important type feature of this type of neuron is the concept of the threshold. If the net input to a particular neuron is greater than the specified threshold by the user, then the neuron fires. Logic circuits are found to use this type of neuron extensively. Later, D.O. Hebb in 1949 theorized that learning occurred in brains when synapses and neurons fire repeatedly which in a way 'trains' the network to recognize the same stimulus when it occurs again [26]. Hebb proposed that the connectivity of the brain is continually changing as an organism learns different functional tasks, and that neural assemblies are created a change. The concept behind the Hebb theory is that if two neurons are found to be active simultaneously the strength of connection between the two neurons should be increased. The concept is similar to that of correlation matrix learning. Moreover, Rosenblatt introduced perceptions. In perceptions network the weights on the connection paths can be adjusted. A method of iterative weight adjustment can be used in perception net [27]. The perception net is found to converge if the weights obtained allow the net to produce exactly all the training inputs and target output vector pairs. Later, Widrow and Hoff introduced (ADALINE), abbreviated from Adaptive Linear Neuron uses a learning rule called as Least Mean Square (LMS) rule or Delta rule [28]. This rule is found to adjust the weights so as to reduce the difference between the net input to the output and the desired output. The convergence criteria in this 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, [29]. 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, [30]. 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 (MLP) networks 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 is one of the approaches that is widely used in industry. As a result Broomhead and Lowe developed Radial Based Functions (RBF) neural network [31] and [32], This is also a multilayer net that is quiet similar to the back propagation net, which was developed from an exact multivariate interpolation [33], and has attracted a lot of interest since its conception. There are a number of significant differences between RBF and MLP networks. That the RBF network has one hidden layer while MLP network has one or more hidden layers, the hidden and output layer nodes of the RBF network are different while the MLP network nodes are usually the same throughout, and RBF networks are locally tuned while MLP networks construct a global function approximation. This thesis also looks at RBF neural network for back propagation ANN validation, and MLP neural network for multiple categorical failures analysis.

Al-Garni utilized the back propagation approaches to predict the failure of some equipment, [14,15]. 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 of 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. In [14] He modeled the prediction failure rate for Folkker F-27 tires using neural network utilizing the back propagation algorithm as a learning rule. The comparison between the neural model and the Weibull model shows 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. Furthermore, Al-Garn and Ahmad Jamal et al. [34] used the same method to predicting the failure rate for Boeing 737 tires. 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 same results were obtained by Amro M. et al. [35] in predicting the failure of the Boeing 737 engine for both general and corrosion cases. Kutsurelis utilized ANNs as a forecasting tool to study their ability in predicting the trend of some stock markets indices, [36]. Accuracy of the back propagation algorithm which used to train the network was compared against a traditional forecasting method and multiple linear regression analysis. From his study, it was concluded that neural networks do have the capability to forecast financial markets, and if properly trained, the individual investor could benefit from the use of this forecasting tool. Soumitra proposed a model that could be implemented at aircraft maintenance, repair, and overhaul (MRO), [37]. He focused on many applications that could be facilitated by the artificial neural network. His main concept was to feed all aircraft original equipment manufacturer manual (OEM) data to the network. By doing so, he can estimate the probability at the point and the extent of damage caused in an aircraft with a better accuracy. Abd Kadir et al. [38] used ANN to calculate and predict the remaining useful life (RUL) of rotating machinery. He implemented his study on bearings life by utilizing feed-foreword neural network, the study compared results from both ANN and Weibull model with a conclusion of better prediction analysis from the artificial neural network model. Ranjan Ganguli et al. [39] used physics-based model and neural networks of the helicopter rotor in forward flight to analyze the impact of selected faults on rotor system behavior. The results show that the neural network can detect and quantify both single and multiple faults on the blade from noise-contaminated simulated vibration and blade response test data.

CHAPTER 3

WEIBULL METHODOLOGY

3.1 Lockheed C-130 Engine Turbine Failure Time Data

A group of data collected from a local aviation facility, will be analyzed. Data represent time to failure of Lockheed C-130 aircraft engine turbines. Because of the huge fleet, the maintenance facility used to install the turbines randomly to service any required engine. The selected data represents the maintenance tracking history of 14 randomly selected turbines over a period of 37 years regardless of the installed engine or aircraft, and the selected turbines has the largest history of failure record. The data were recorded in two forms, total operation time in hours to a general failure (T.T), and operation time in hours between turbine overhaul maintenance (TSO). The turbine total time is the turbine accumulated operating hours for any newly installed turbine and represents turbine life, while (TSO) is a period of operating hours between each turbine overhaul maintenance, and it reset at every turbine overhaul maintenance action.

The Failure data defined, whenever possible any type of turbine component failure, which required a replacement or turbine overhaul maintenance according to the manufactures standards and recommendation as in the maintenance manual, regardless of failure type, and it does not includes any planned inspection or removals. Also due to the complexity of the turbine system, we will deal with the engine turbine as a single unit.

Finally, the Lockheed C-130 is widely operates in desert, encountering high temperature sandy environments, leading to turbine failure is a major concern. Therefore, to give an insight into the reliability of the engine turbine under actual operating conditions, turbine failures data was divided into six categories, based on reasons of failure and its consequences, to failures which effect structure, performance, failure causing leaks, failure caused by foreign object damage (FOD), failure effecting other maintenance, and failure with reason not mentioned.

In aviation maintenance, there are usually two indices for maintenance tracking program, which are: the operational flight time (the time from starting up the engine till shut down), and cycles (the number of engine starts). In this study we will discuss modeling the failure rate in terms of turbine operating time. However there are limited numbers of study on the fielded systems because in-service failure data are often more difficult to obtain. The objective of this study is to assess the reliability characteristics of Lockheed C-130 aircraft turbine system which is subjected to the effected environment. The way the aviation facility maintains and supports their fleets is rather sensitive information. To respect the sentiments, their names are not disclosed.

3.2 Mortality Characteristics

Determining the age at which an operating part in an aircraft should be replaced with a new part has always been a problem. The age for such a planned replacement should depend on the time-to-failure distribution of the part, the relative costs of an in-service failure, and a planned replacement. There are two conditions required to make planned replacement worthwhile. The first is that the planned replacement of a part must cost less than an unexpected or unscheduled replacement. The second condition is that the failure characteristics of the part must display wear out. This can be better understood by examining the mortality characteristics of parts as shown in Figure 3-1. The descending curve indicates burn-in characteristic in which the failure rate decreases over time; it is what occurs during the early life of a population of units. This first period is known as an infant mortality period. The horizontal curve represents constant random characteristic which indicates that failure rate remains constant over time. Therefore, planned replacement has no advantage in these cases. The rising curve indicates wear out, i.e. increasing failure rate with time. Such units with age-related failure rate may be candidates for planned replacement [15].

Using Weibull models and Artificial Neural Network in forecasting a maintenance planner can make quantitative trades between scheduled and unscheduled maintenance or non-destructive inspection and replacement. The method also helps determining the age at which an operating part should be replaced with a new part. Taking in account the sensitivity of maintenance cost information, in this stage we will only analyzes the time to failure data, leaving the cost of maintenance open for further research.

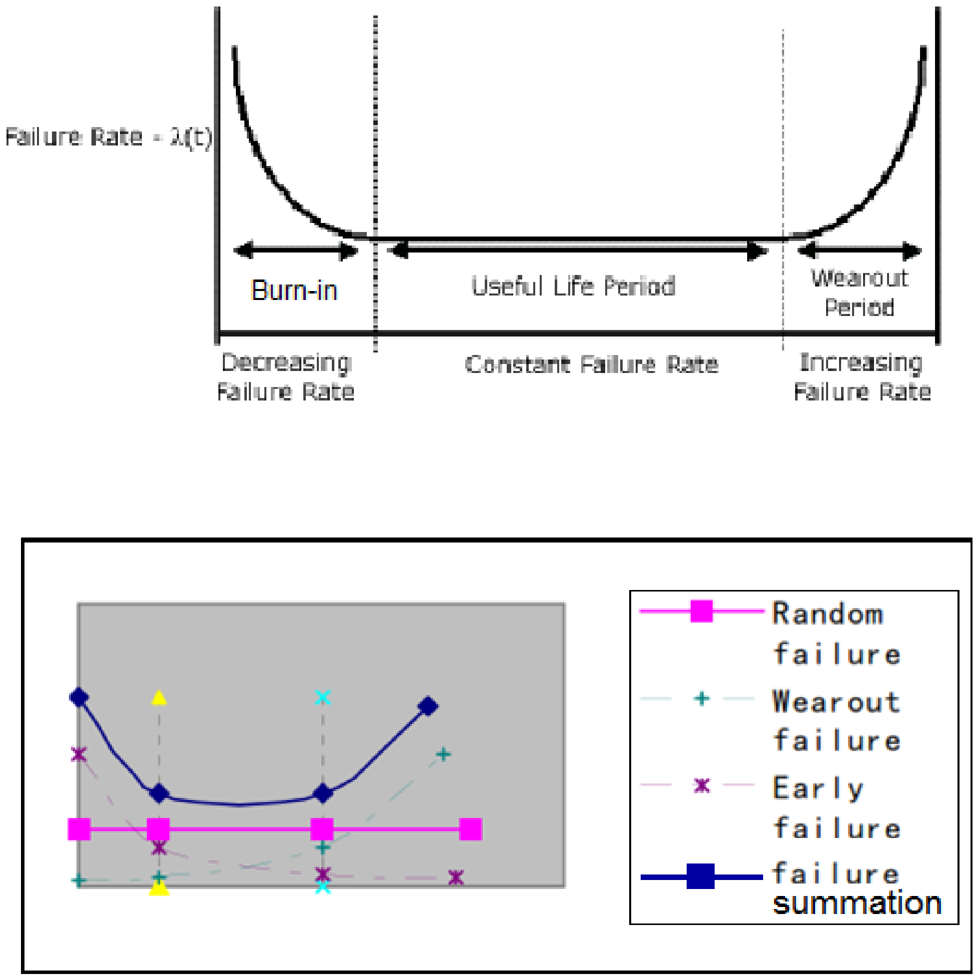


Figure 3-1 Tree types of mortality characteristics

3.3 Weibull Failure Distribution Model

In reliability engineering Weibull probability analysis is widely used in processing and interpreting life data. It can model wide range of life distributions products. It has been used in aerospace engineering as one of the decision making tools to identify and eliminate unexpected part failures to provide an optimal maintenance strategy, particularly in wear out characteristic failure, where an aging mechanism is involved with increasing failure rate [40]. The advantage of the Weibull model is the ability to provide reasonably accurate failure analysis and forecast, with relatively small samples. It can utilize the data as first failure emerges and dictate appropriate action before more failures is generated. In addition, an easy interpretation of the distribution parameters to the failure rates and mortality curve concept.

There are many models for the Weibull distribution like the two-parameter model, three parameters model, mixture model and phase-bi model. In this study we will focus on the two parameters Weibull model. The Weibull distribution can be characterized by a failure rate function λ (t) of the form [18,41,42].

$$\lambda(t) = \frac{\beta}{\eta}\left(\frac{t}{\eta}\right)^{\beta-1} \eta > 0,\ \beta > 0, t \geq 0 \tag{3.1}$$

The reliability function *R(t)* which indicates the probability of surviving beyond a given time *t* can be derived from this failure rate function as follows:

$$R(t) = \exp\left[-\left(\frac{t}{\eta}\right)^{\beta}\right] \tag{3.2}$$

A cumulative function *F(t)* to the reliability function can be defined as:

$$F(t) = 1 - R(t),$$

Thus:

$$F(t) = 1 - \exp\left[-\left(\frac{t}{\eta}\right)^{\beta}\right] \tag{3.3}$$

Equation (3.3) can be rewritten as:

$$\frac{1}{1-F(t)} = \exp\left(\frac{t}{\eta}\right)^{\beta} \tag{3.4}$$

$F(t)$ is known as cumulative distribution function (CDF) and indicates the probability that a failure occurs before time *t*.

Where:

t = time, which is in our case the operating engine hours.

β = Weibull slope (the slop of the failure line on the Weibull chart). Also refer as a shape parameter. It indicates whether the failure rate is increasing, constant, or decreasing. Practically, β<1 indicates that the part has a decreasing failure rate and implies infant mortality. This can be caused by a variety of factors, including design flaws, disassembly, and poor quality control. β=1 indicates a constant failure rate and implies random failures. In this case, one can suspect random events such as maintenance errors, human errors, and foreign object damage (FOD). β >1 indicates an increasing failure rate. The most common causes of failures in this range are corrosion, erosion, fatigue and cracking.

η = scale parameter. The value of η is equal to the number of cycles (operating engine hours) at which 63.2% of the parts have failed. To derive this number, substitute η for the time t into (3.3). And calculate the cumulative failure function [43]:

$$\mathrm{F}(\eta) = 1 - \exp\left[-\left(\frac{\eta}{\eta}\right)^{\beta}\right] = 1 - \exp(-1) = 0.632 \ \ (63.2\%).$$

The function *R(t)* is normally used when reliabilities are being computed, and the function *F(t)* is normally used when probabilities are being computed.

Various approaches are used in fitting the Weibull model to the failure data. In this thesis, the cumulative distribution function *F(t)* is transformed as follows so that it appears in the familiar form of a straight line equation as follows [44,45]:

By taking two natural logarithms Eq (3.4) will take the form:

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

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

$$\ln\left\{\ln\left[\frac{1}{1-F(t)}\right]\right\} = \beta\ln(t) - \beta\ln(\eta) \qquad (3.5)$$

Eq (3.5) has a linear form of $\mathrm{y} = \mathrm{m}'\mathrm{x} + c$ Where:

$$\left.\begin{aligned} \mathrm{y} &= \ln\left[\ln\left(\frac{1}{1-F(t)}\right)\right] \\ \mathrm{x} &= \ln(t) \\ \mathrm{m}' &= \beta \\ \mathrm{c} &= -\beta\ln(\eta) \end{aligned}\right\} \tag{3.6}$$

Eq (3.5) represent a straight line with a slope of β, and intercept c on the Cartesian x, y coordinates Eq (3.6). So the plot of $\ln\left[\ln\left(\frac{1}{1-F(t)}\right)\right]$ against $\ln(t)$ will be straight line with slope of β.

By calculating the slope of the straight line and the y-intercept point on the graph, the parameters β and η can be determined.

3.4 Fitting the Weibull Model to the Data

After arranging the failure data in ascending order, the probability distribution function $F(t)$ can be substituted by its estimate using the median rank formula (the number in the middle of the data set). The most common approximation used for median ranking is that due to Benard. The i^{th} rank value is given by [42,43,46]:

$$F(t_i) = \frac{i-0.3}{N+0.4} \qquad 1 \le i \le N \tag{3.7}$$

Where i is the failure number and N is the sample size. Linearization of straight line Eq $\mathrm{y} = \mathrm{m}'\mathrm{x} + \mathrm{c}$, can be fitted to the experimental data $F(t_i)$ for $i = 1,2,3,4,\ldots.,N$.

By performing the linear regression analysis using linearly transformation of straight line Eq, the parameters β and η can be determined.

Before start fitting the model to the failure data, we need to define some important statistical characteristics that are widely used in reliability calculations:

Mean Time To Failure (MTTF): Measures the average time between failures with the modeling assumption that the failed system is not repaired. Reliability increases as the MTTF increases [47].

An Average (median) life ($T_{0.5}$): the life by which half of the units will survive.

$$\text{MTTF} = \eta\ \Gamma\ (1+\frac{1}{\beta}), \tag{3.8}$$

Where Γ is the Gamma function evaluated at the value of $(1+\frac{1}{\beta})$.The gamma function is defined as:

$$\Gamma(x) = (x-1)\ \Gamma(x-1)$$

$$(T_{0.5}) = \eta\ (ln\ 2)^{\left(\frac{1}{\beta}\right)} \tag{3.9}$$

3.4.1 Weibull Analysis of general turbine failure data (T.T)

In this part the general turbine failure data (T.T) of Lockheed C-130 turbine will be analyzed. By using (MS Excel) which has been programmed to calculate and fit the data on a Weibull plot.

Table A- 1, Appendix A, shows the main calculations to fit general turbine failure data (T.T) to the Weibull model using equations (3.1 to 3.7).

Table 3-1 and Table 3-2 show regression statistics summary output for the C-130 general turbine failure data (T.T).

The result index of fit, R =0.989 (almost 99%), indicating a very strong linear fit to data, thus supporting the hypothesis that the data came from a Weibull distribution. For this high 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. In addition, $\ln\left\{\ln\left[\frac{1}{1-F(t)}\right]\right\}$ versus $\ln(t_i)$ is plotted in Figure 3-2.

Table 3-1 Weibull result of C-130 general turbine failure data (T.T)

SUMMARY OUTPUT	
Regression Statistics	
Multiple R (index of fit)	0.989338178
R Square	0.97879003
Adjusted R Square	0.978561966
Standard Error	0.182003823
Observations	95

Table 3-2 C-130 general turbine failure data (T.T) statistics

	Coefficients	Standard Error	t Stat	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%
Intercept	-17.1472	0.2538	-67.5700	-17.6512	-16.6433	-17.6512	-16.6433
ln(Turbine(T.T))	1.9228	0.0294	65.5113	1.8645	1.9810	1.8645	1.9810
Beta(Shape Parameter)=	**1.92**						
Alpha(Characteristic Life)=	**7465.32**						

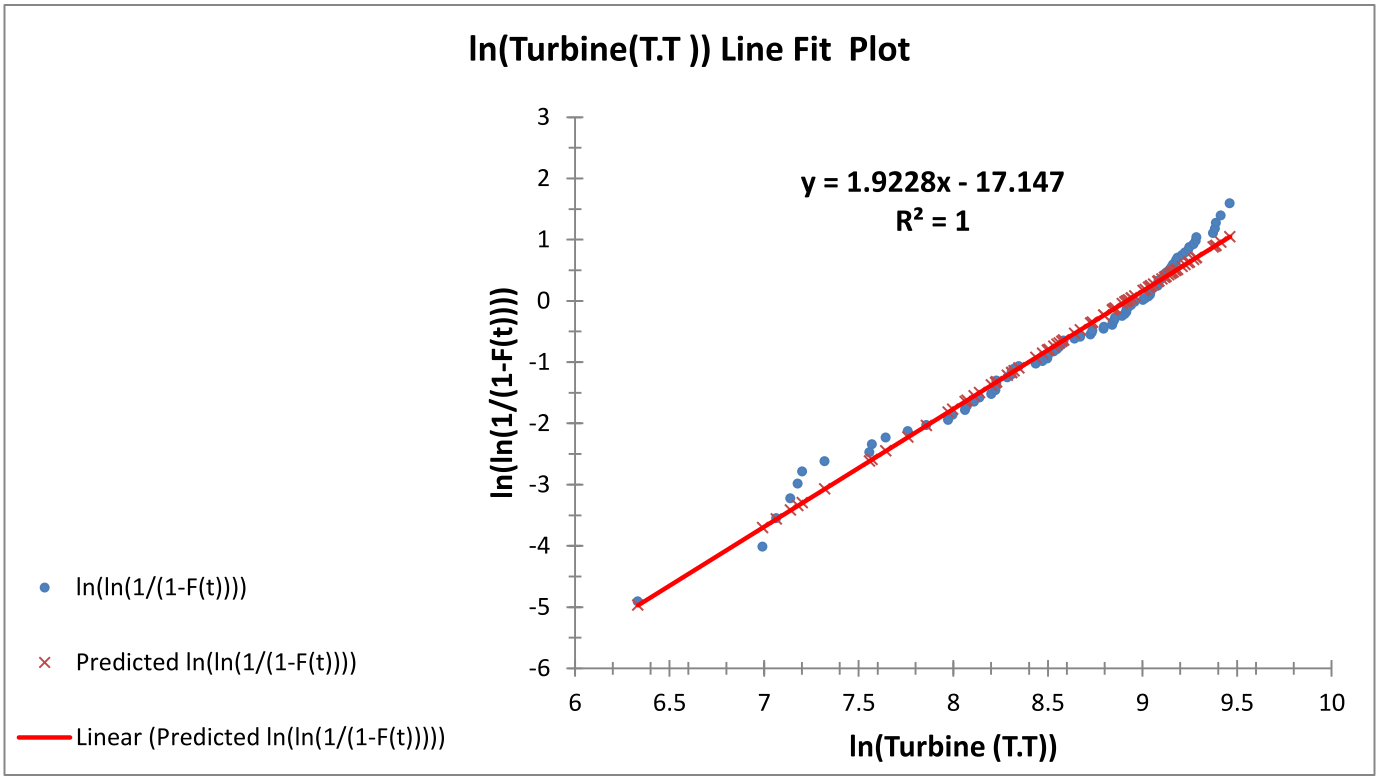


Figure 3-2 Weibull plot for C-130 general turbine failure data

An assessment of Weibull parameters of the turbine general failure data (T.T) indicates that, the straight line equation of Linear (predicted $\ln(\ln(1/(1-F(t))))$) is:

$$y = 1.9228\,x - 17.147$$

Using equation (3.5), shape parameter (slope of the line) $\boldsymbol{\beta}$ = **1.92** is greater than one (β>1) which reflects an increasing failure rate over time. The most common causes of failures in this range are corrosion, erosion, fatigue cracking, etc. Since the component exhibits wear out failure pattern, a hard time maintenance action which involves planned replacement or 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.

As mentioned, $\mathrm{B} = -\beta \ln(\eta)$, which means that:

Scale parameter $\eta = \exp - \left(\frac{\mathrm{b}}{\beta}\right) \exp - \left(\frac{\mathrm{b}}{\beta}\right) = \exp - \left(\frac{-17.14721}{1.92276}\right) = 7465.32$ (hours), which indicates that about 63 percent of the Turbines has failed up to that time.

To support the previous (MS Excel) Weibull programed output, I did further analysis using "Windchill Quality Solution" commercial software, it provides the life data analysis tools necessary to predict failure behavior of data gathered from all phases of a product's life, track reliability growth, analyze product degradation, plan product testing procedures, calculate optimal maintenance periods, and perform warranty forecasting in one, powerful statistical package [48].

Table 3-3 shows a comparison between Weibull analysis done by "Windchill Quality Solution" software and (MS Excel) Weibull programmed. Which indicate high quality result.

Table 3-3 comparison between (MS Excel) Weibull program and "Windchill Quality Solution" software for C-130 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

The Figure 3-3 to Figure 3-9 shows the Weibull analysis for the C-130 general turbine failure data using. "Windchill Quality Solution" software:

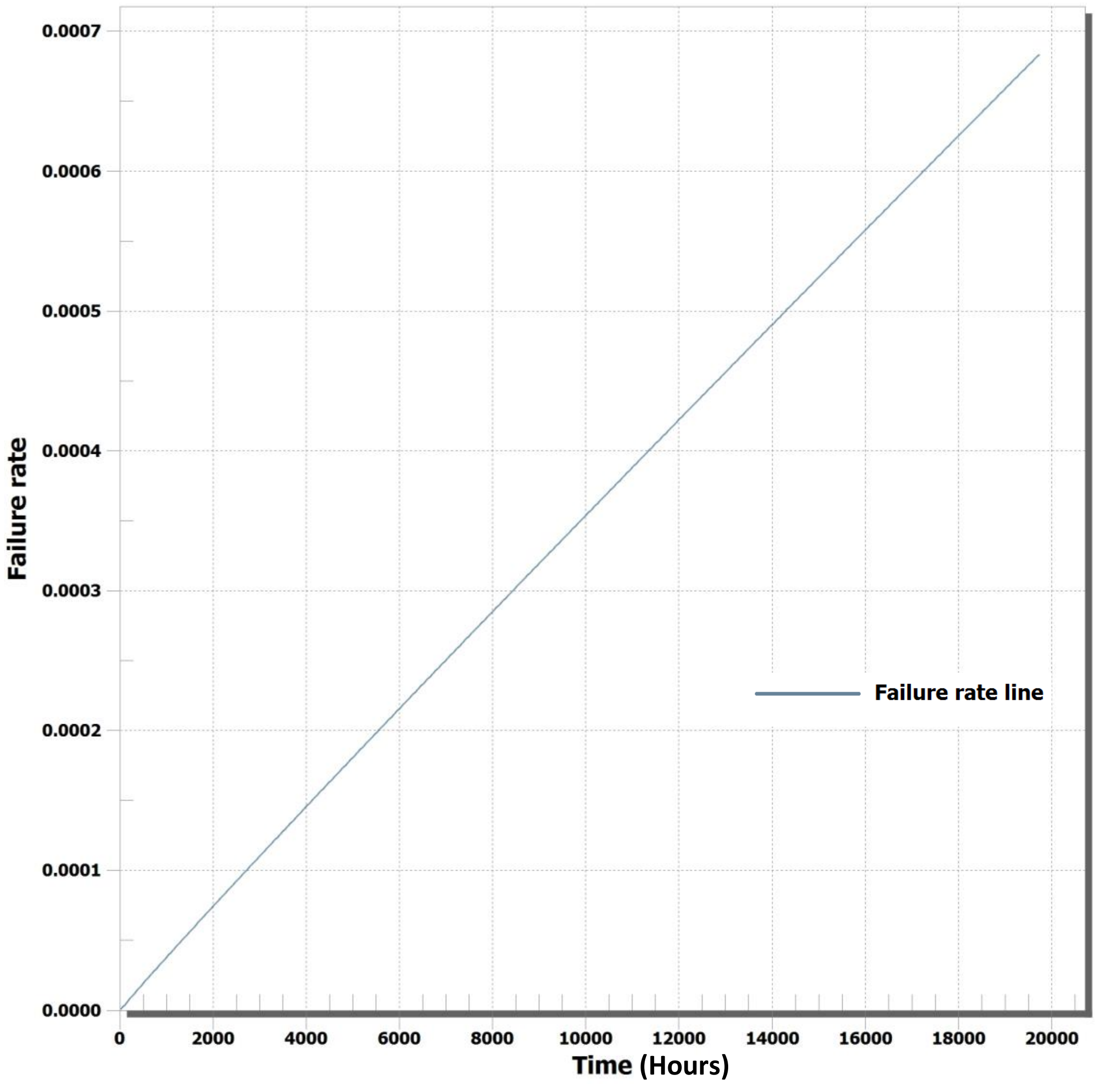


Figure 3-3 General failure rate vs. Time of C-130 Turbine

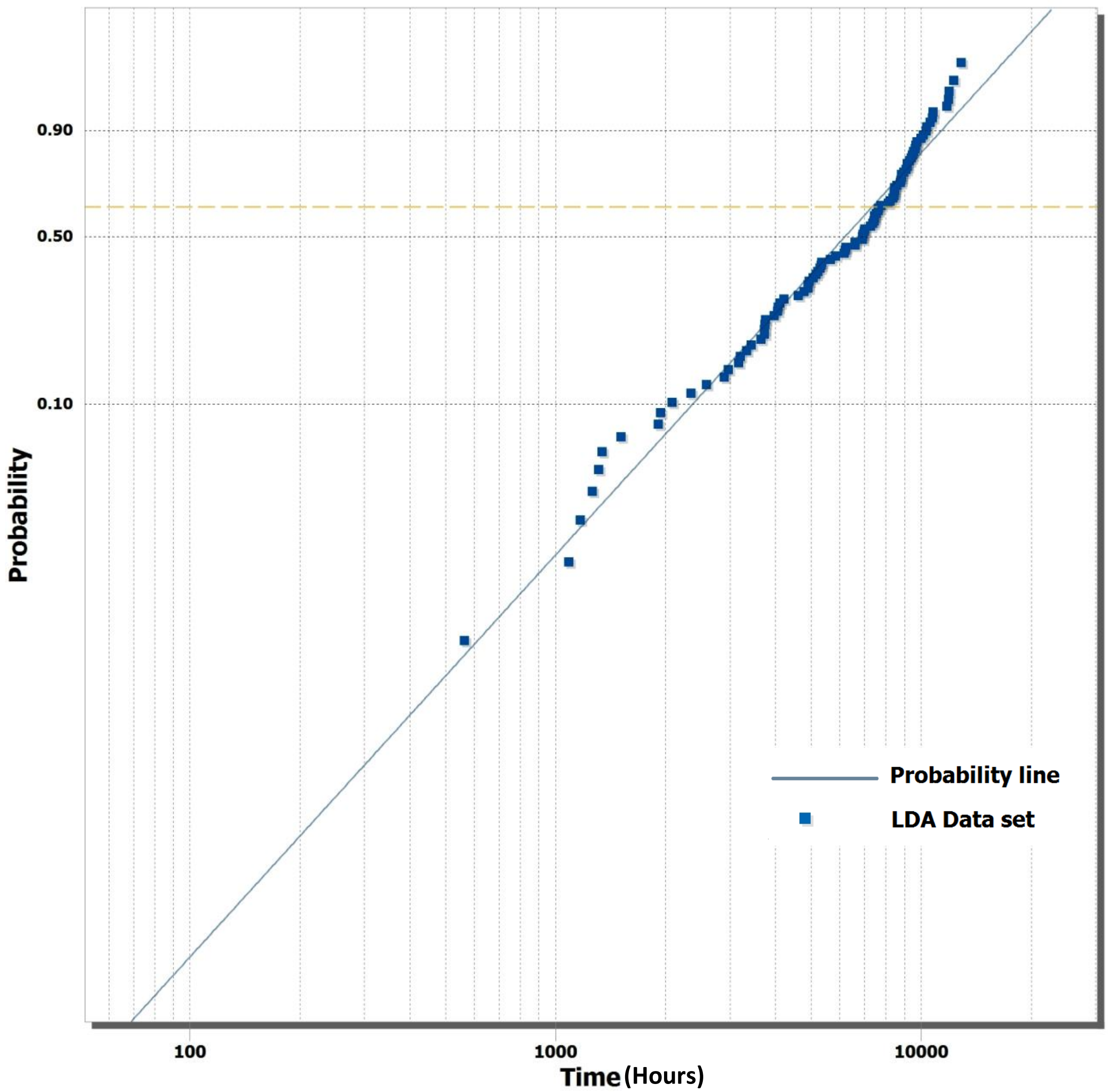


Figure 3-4 Probability of C-130 general turbine failure data (T.T)

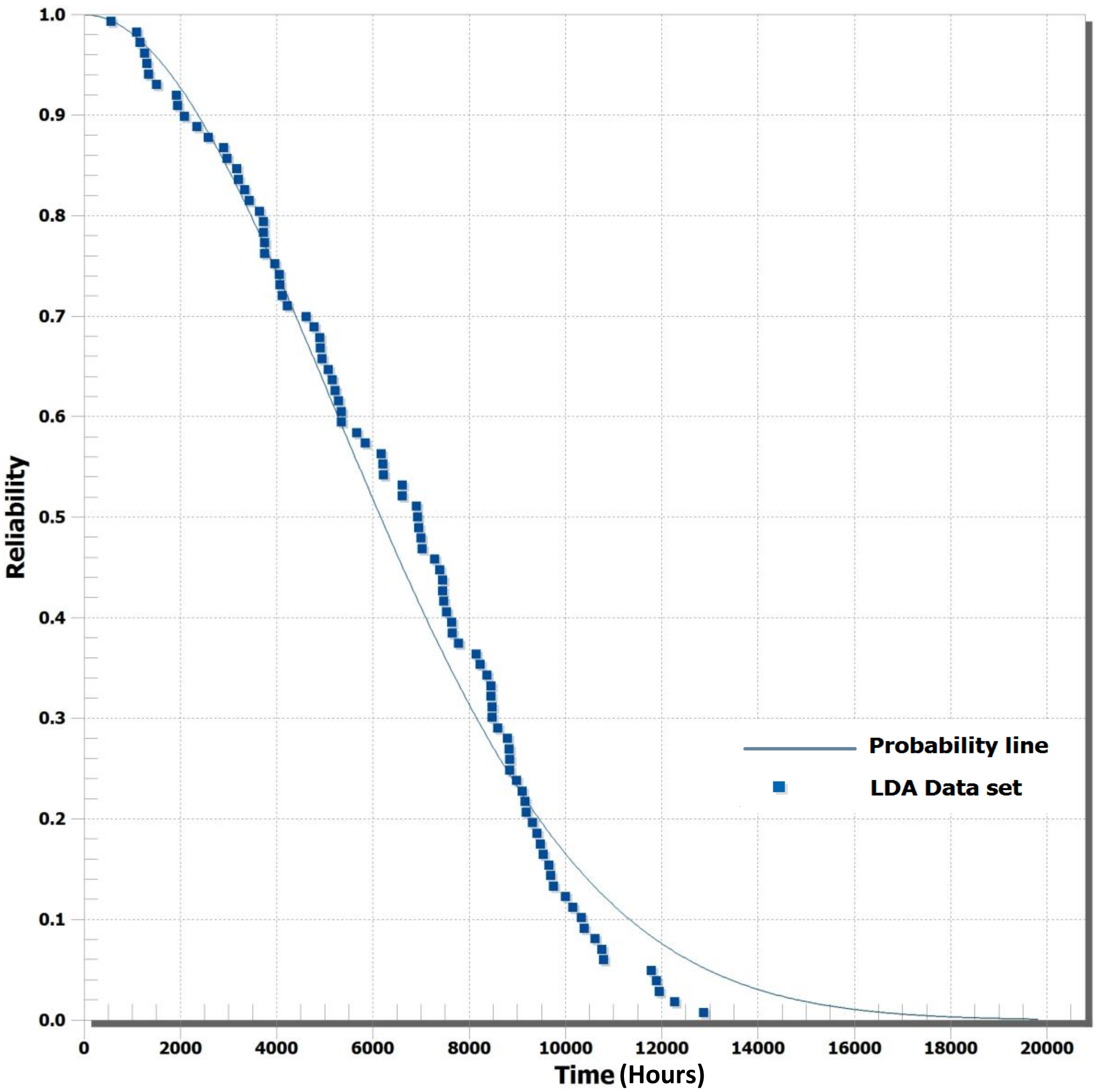


Figure 3-5 Reliability vs. Time of C-130 general turbine failure

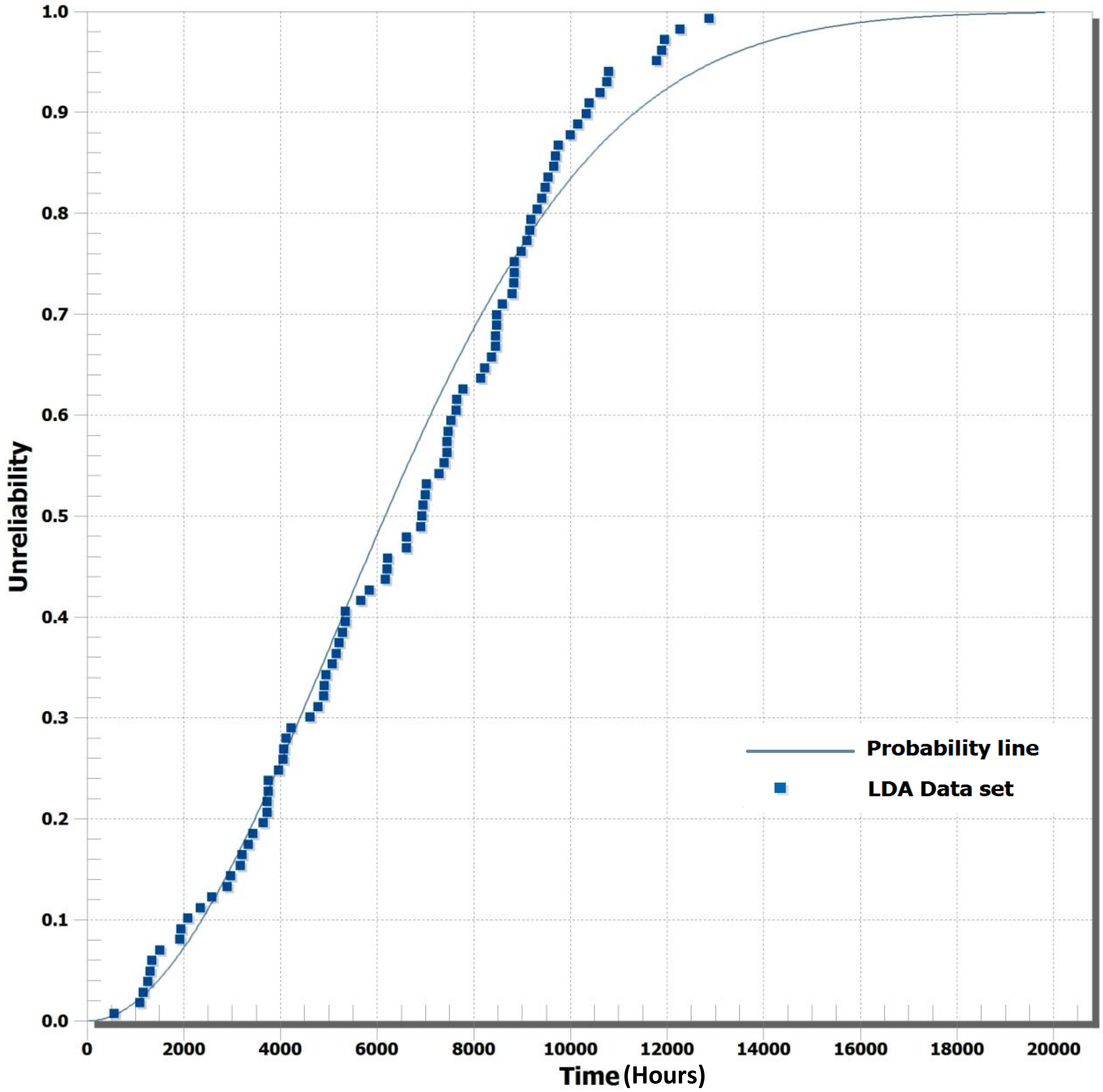


Figure 3-6 Unreliability vs. Time of C-130 general turbine failure

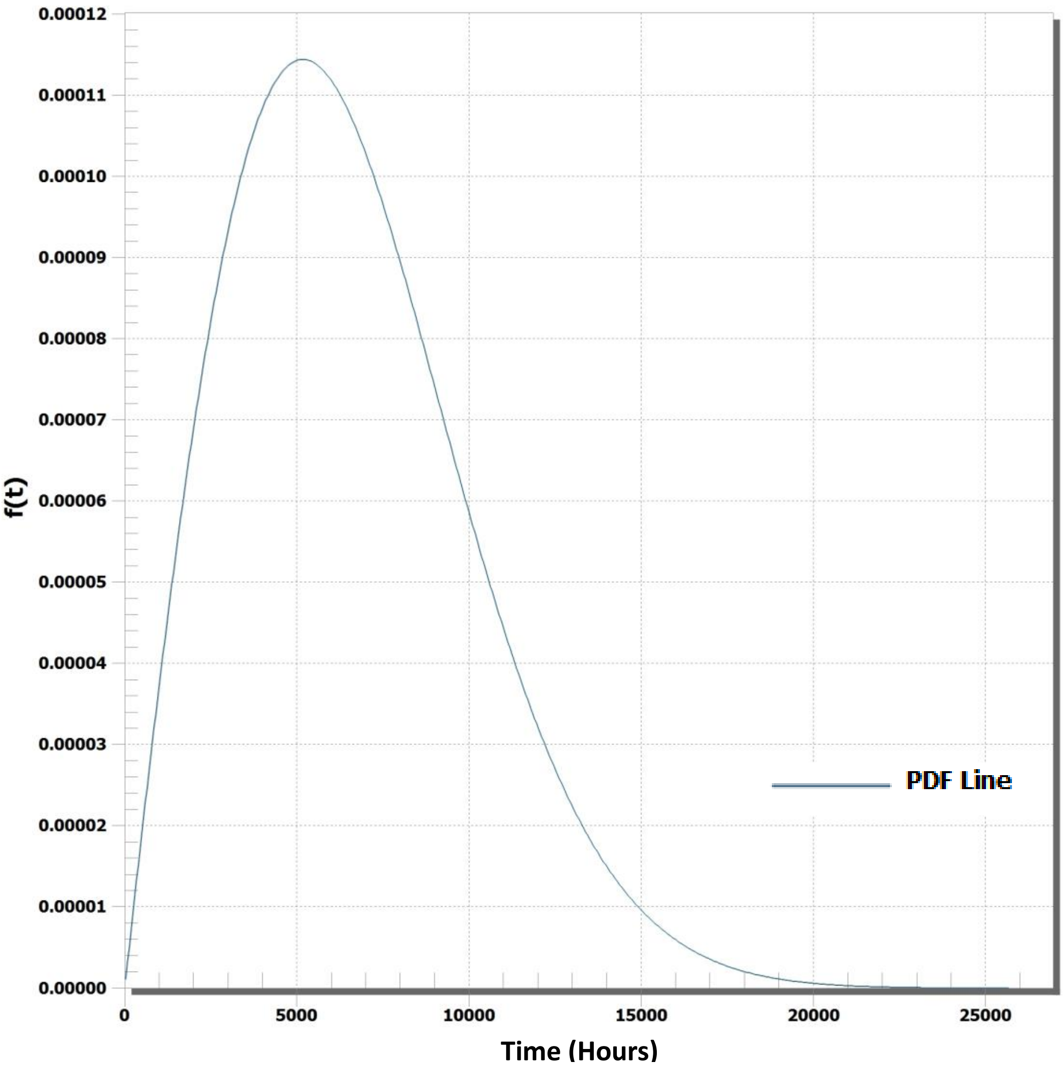


Figure 3-7 PDF plot of C-130 general turbine failure

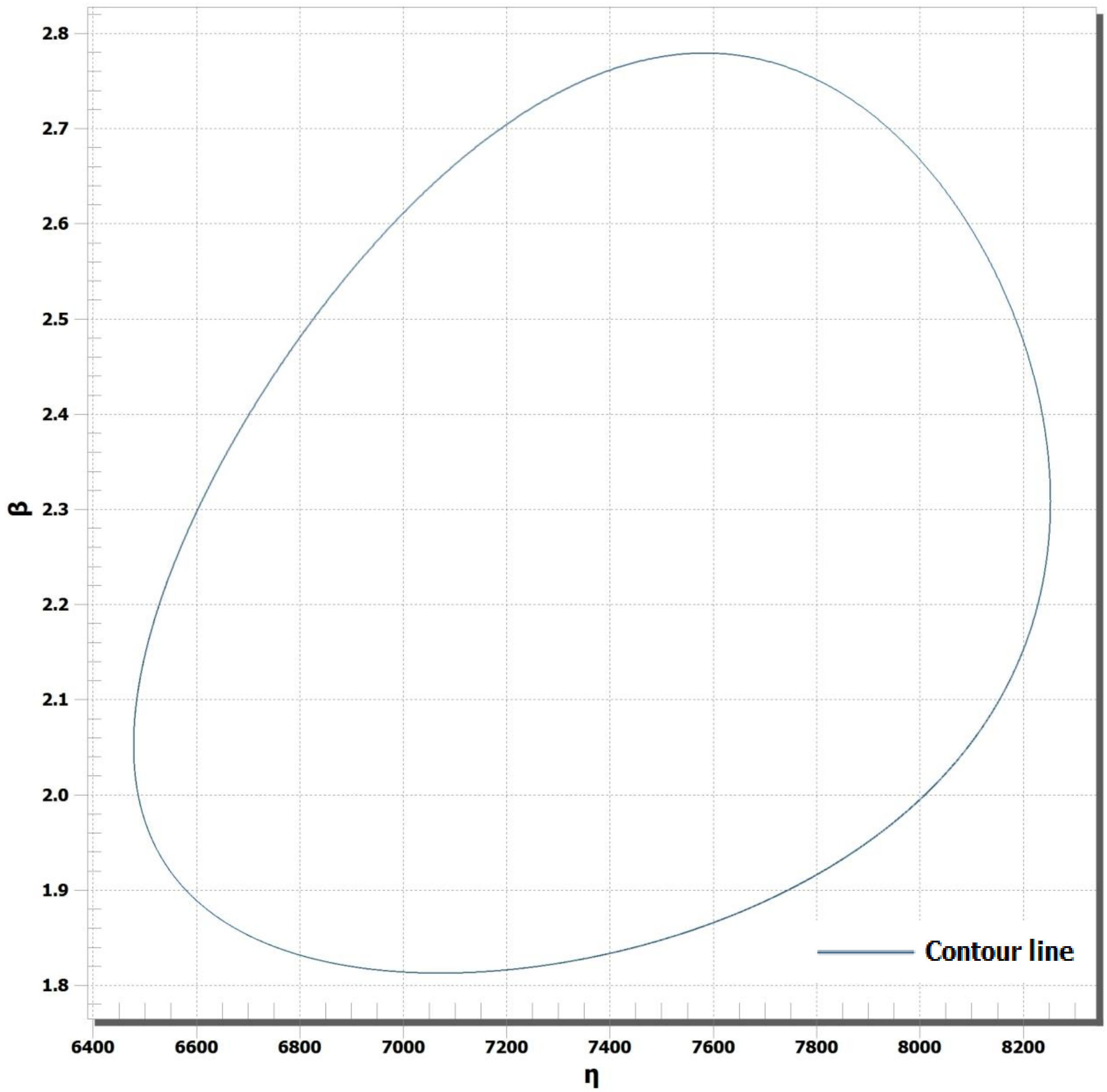


Figure 3-8 *β* vs. *η* contour plot of C-130 general turbine failure

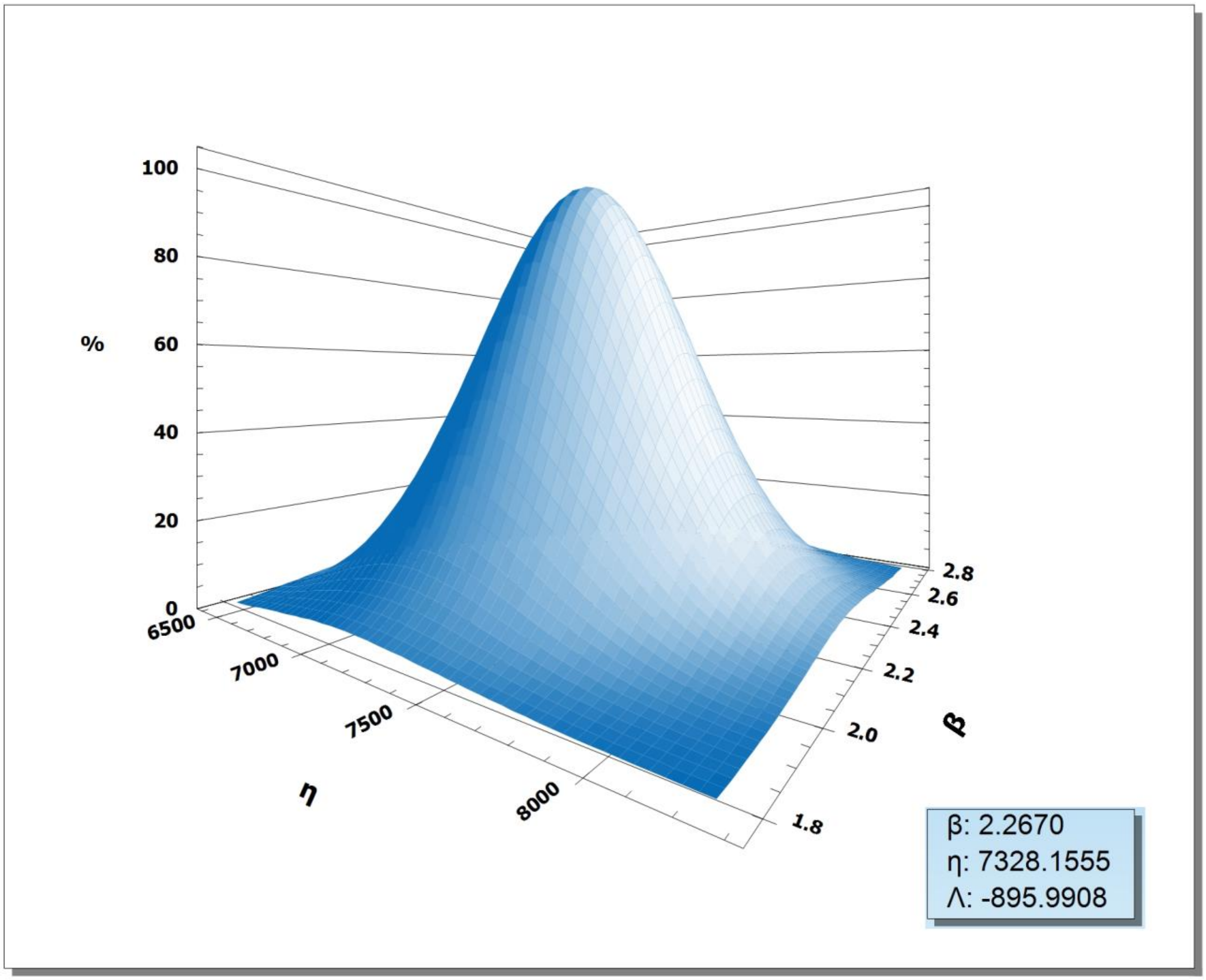


Figure 3-9 β vs. η 3D plot of C-130 general turbine failure

3.4.2 Goodness-of-Fit Test for general turbine failure data (T.T)

The goodness of fit describes how well it fits a set of observations. Measures of goodness of fit typically summarize the discrepancy between observed values and expected values under the model in question. The test consists of statistic computations based on sample of failure times. Then compare it with a critical value obtains from a table of such values [41]. The test compares the distribution function with uniform distribution function of the empirical sample, to calculate the maximum distance between the theoretical and empirical functions. If this distance exceeds a certain value, which depends only on the sample size, we say that the sample does not fit the Weibull method. Kolmogorov-Simirnov (KS) goodness of fit test is widely used in this practice. The advantage of KS test is its flexibility where it can be used with variable of distributions at a small sample [49].

There are several computational methods for the KS. First, sort the data. Then establish the assumed distribution (null hypothesis) and estimate its parameters. Then, obtain both the theoretical (assumed CDF) distribution (F_0) as well as the empirical (F_n) at each data point. Since KS is a distance test, we need to find the maximum distance $|F_0$ -F_n)| between the theoretical and empirical distributions, by two basic functions defined in equation (3.10)

$$F_o(X_i) = P_0(X \leq X_i)\ CDF(X_i). \qquad (3.10)$$

$F_o(X_i)$ is the assumed cumulative distribution function evaluated at X_i, and $F_n(X_i)$ is the empirical distribution function obtained by the proportion of the data smaller than X_i in the data set size n.

$$F_n(X_i) = \frac{i}{N}; \quad i = 1, \dots \dots, n \tag{3.11}$$

Then, define: D+ = F_n - F_0 and D- = F_0 - F_n-1 for every data point X_i. The KS statistic is:

$$\text{D} = \text{Maximum of all D+ and D- } (\geq 0); \text{ for } i = 1 \dots n \tag{3.12}$$

If the maximum KS departure between the assumed CDF and empirical distributions is small, then the assumed CDF will likely be correct. But if this discrepancy is "large" then the assumed F_0 is likely not the underlying data distribution. Using equations (3.10), (3.11), and (3.12).

Table A- 2, Appendix A, Shows calculation for KS tests with the following sample of calculations for Row 1 in:

$$F_0 = F(t) = 1 - \exp\left[-\left(\frac{t}{\eta}\right)^{\beta}\right] = 1 - \exp\left[-\left(\frac{1}{7465.32}\right)^{0.95}\right] = 0.006918$$

$$F_{n-1}(1) = \frac{1-1}{95} = 0 \quad \text{D+} = F_n - F_0 = 0.010417 - 0.006918 = 0.003498825$$

$$\text{D}- = F_0 - F_{n-1} = 0.006918$$

At the end, from Table A- 2, Appendix A,

Max D+ = 0.09346, Max D- = 0.09346, Sample size *N*= 95,

The critical value (CV) for KS test can be calculated using (3.13):

$$\text{CV} = \frac{1.36}{\sqrt{N}} \qquad \text{where } (N) \text{ is the sample size.} \tag{3.13}$$

$$\text{CV} = 0.1395$$

Since max D+ = 0.09346 < CV = 0.1395 ⇒ ∴ the sample is accepted.

3.4.3 Weibull Analysis of failure which required overhaul maintenance (T.S.O)

After analyzing the general Lockheed C-130 failure rate, we will demonstrate Weibull analysis for turbine failures which required overhaul maintenance (T.S.O). Following the same procedures, by using (MS Excel) program to calculate and fit the data on a Weibull plot. Table A- 3, Appendix A, shows the main calculations for fitting the data to the Weibull model.

Using an Excel spread sheet, Table 3-4 and Table 3-5, show regression analysis output and statistics for the failure data given in Table A- 3, Appendix A.

Table 3-4 Weibull result of C-130 failures required overhaul maintenance (T.S.O)

SUMMARY OUTPUT	
Regression Statistics	
Multiple R (index of fit)	0.991197463
R Square	0.982472411
Adjusted R Square	0.982283942
Standard Error	0.165451829
Observations	95

Table 3-5 C-130 failures required overhaul maintenance (T.S.O) statistics

	Coefficients	Standard Error	t Stat	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%
Intercept	-12.71044	0.16904	-75.19284	-13.04611	-12.37476	-13.04611	-12.37476
ln(Turbine(T.T))	1.64133	0.02273	72.20056	1.59619	1.68648	1.59619	1.68648
Beta(Shape Parameter)=	**1.64**						
Alpha(Characteristic Life)=	**2307.62**						

Out of the Weibull regression for the C-130 failures which required overhaul maintenance (T.S.O), the analysis based on the result index of fit, R = 0.99 (99%), shows a strong linear fit to data, reflects the quality of the Weibull distribution. In addition, $\ln\{\ln[1 - F(t)]\}$ versus $\ln(t_i)$ is plotted in Figure 3-10.

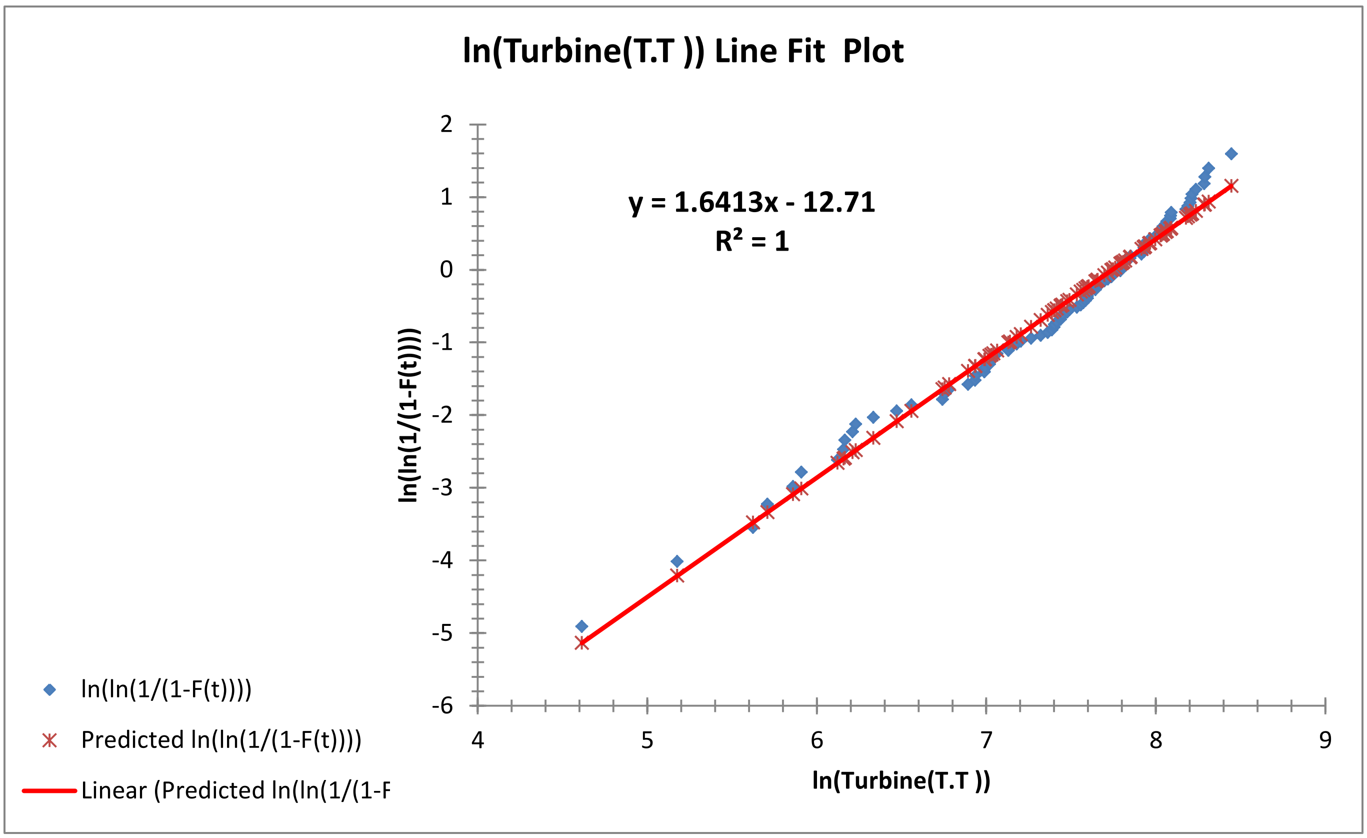


Figure 3-10 Weibull plot for C-130 failures required overhaul maintenance (T.S.O)

The same procedures used in general turbine failure analysis where implemented, as follow:

- Using equation (3.5). Shape parameter (slope of the line) β = 1.64 is greater than one (β>1) which reflects an increasing failure rate over time. The most common causes of failures in this range are corrosion, erosion, fatigue cracking, etc. So hard time maintenance action involves overhaul program is required.

- Scale parameter $\eta = 2307.615$ (hours), which indicate that about 63 percent of the turbines has failed up to that time. References to C-130 Technical Order Book (T.O), manufacturer recommended overhaul maintenance program every 6000 hours interval to reduce in-service failure. During my investigation, I found that the engine shop specialist based on they experience, used to do overhaul maintenance every 2500 hours. Unfortunately; - based in our calculation - overhaul maintenance should be done every (2300) turbine operating hours, this actually about 62% less than what is recommended by the manufacturer - 6000 hours -, due to local environment.

It is clear that the C-130 turbine failure rate experiences a failure rate higher than manufacturer's designed, which is based on overlap of designed-in strength and expected operational load. The C-130 can operate in unprepared runways and rough and dirt strips. The runways at these areas are surrounded by deserts and known for its harsh weather conditions and sand storms.

To uphold the previous analysis, Table 3-6 shows a comparison between Weibull analysis done by "Windchill Quality Solution" software and (MS Excel) Weibull programmed.

Table 3-6 Comparison between (MS Excel) Weibull program and "Windchill Quality Solution" software for C-130 failures required overhaul maintenance (T.S.O).

(MS Excel) Weibull output		"Windchill Quality Solution" output	
Multiple R (index of fit)	0.991197463	Multiple R (index of fit)	0.991237
R Square	0.982472411	R Square	0.982552
Beta(Shape Parameter)	1.641333694	Beta(Shape Parameter)	1.673426
Alpha(Characteristic Life)	2307.615007	Alpha(Characteristic Life)	2293.157439

The Figure 3-11 to Figure 3-17 shows the Weibull analysis for the C-130 failures required overhaul maintenance (T.S.O) data using. "Windchill Quality Solution" software:

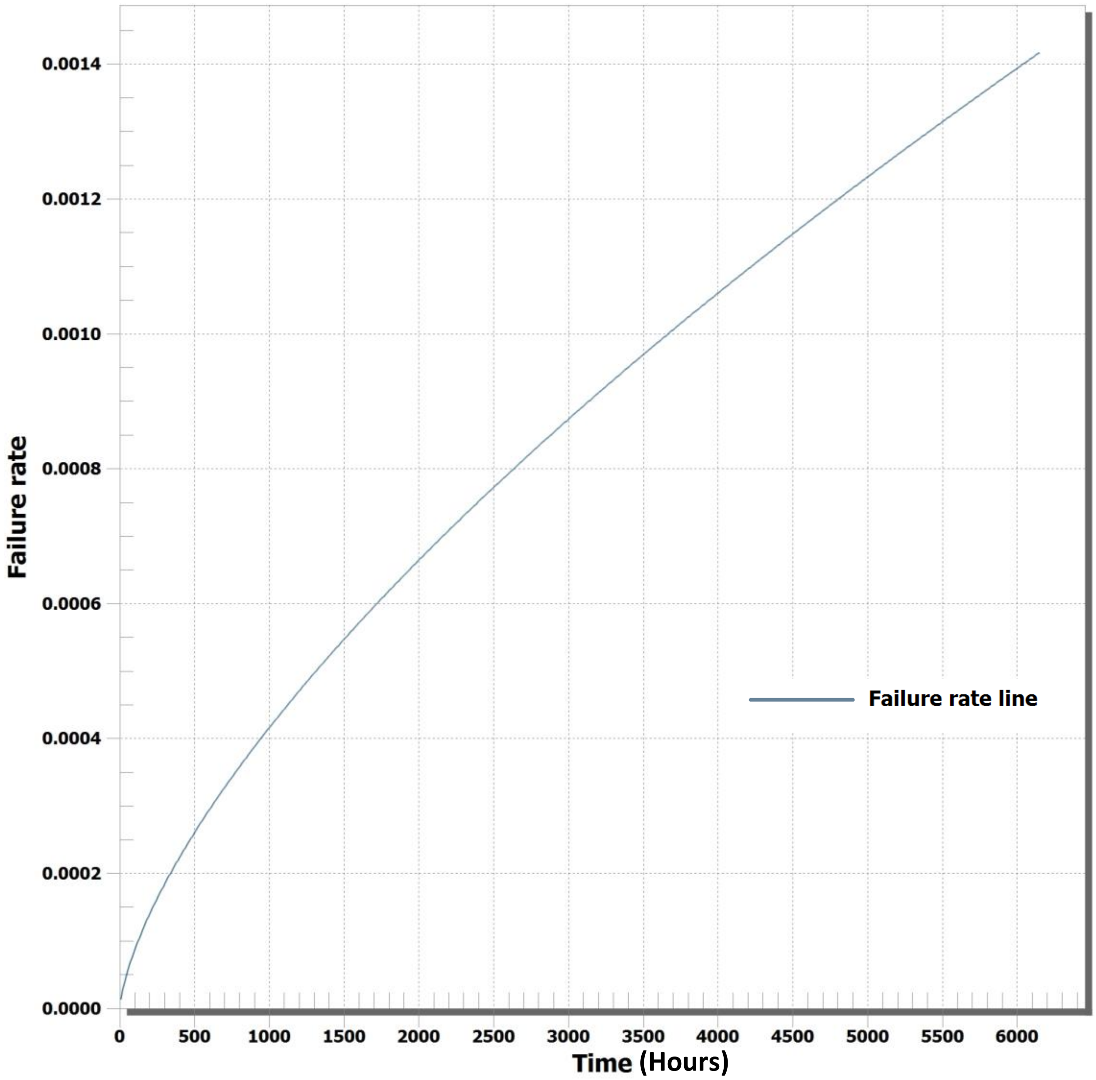


Figure 3-11 Failures required overhaul maintenance (T.S.O) rate vs. Time of C-130 Turbine

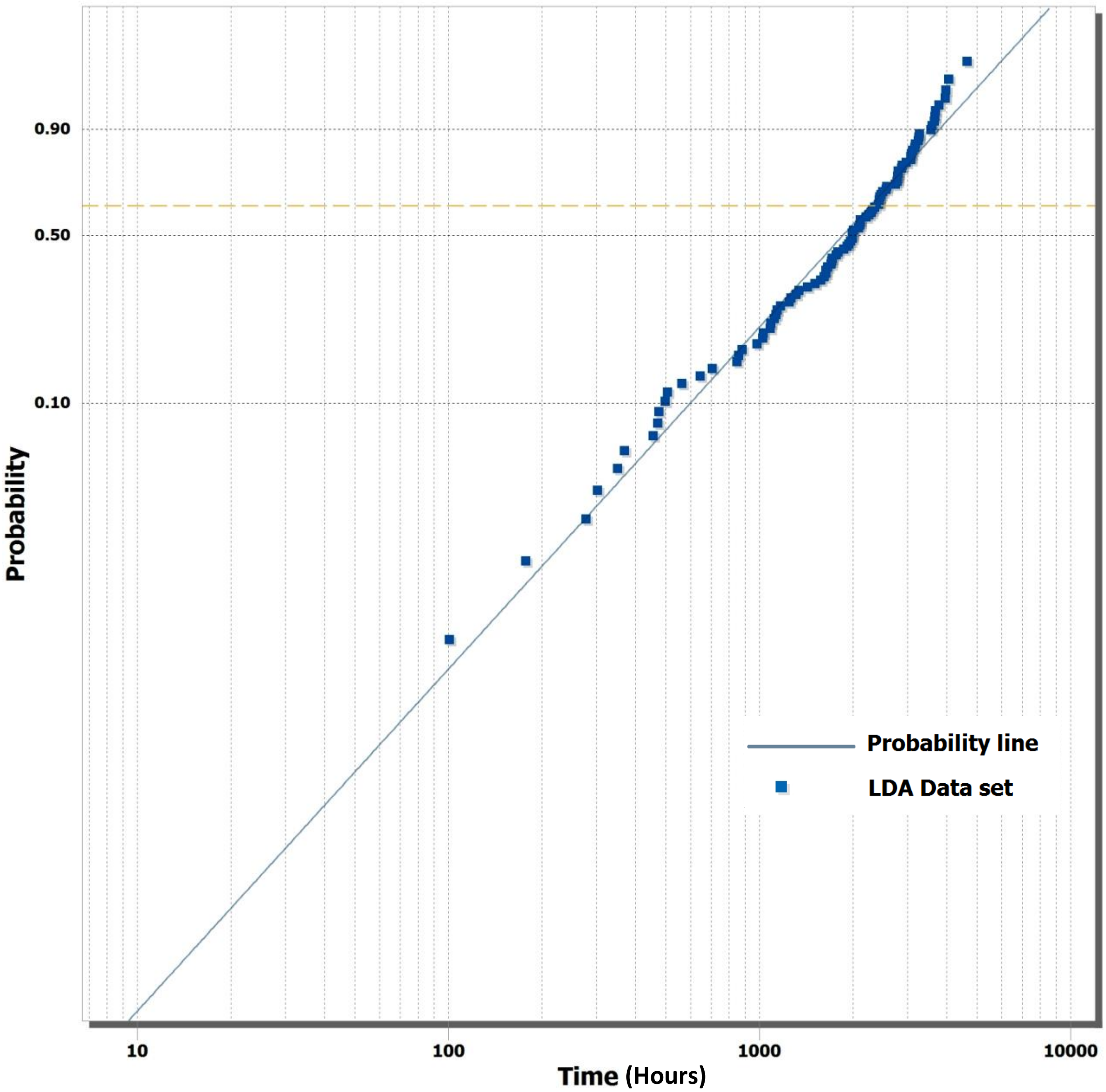


Figure 3-12 Probability of C-130 turbine failures required overhaul maintenance (T.S.O)

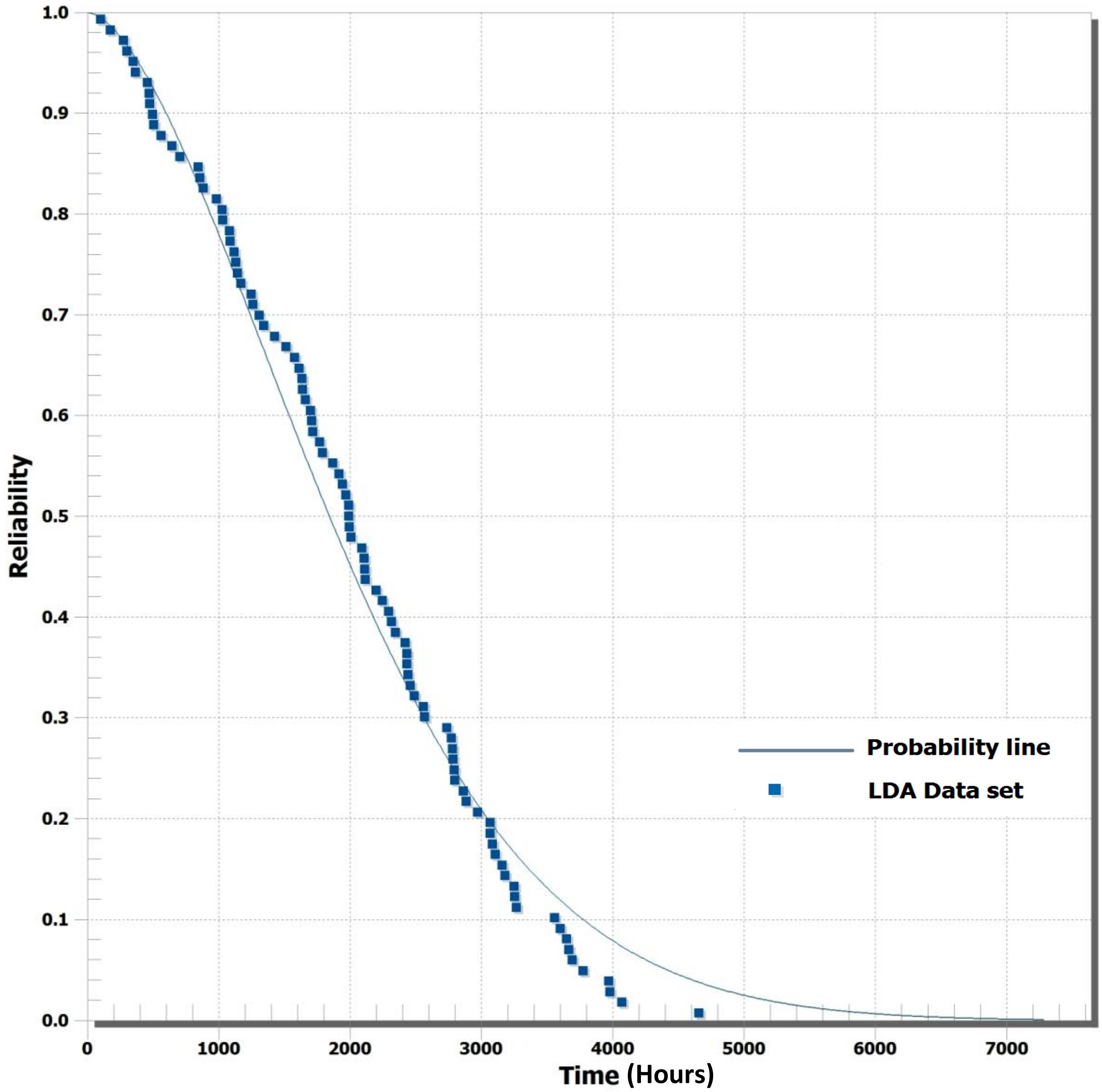


Figure 3-13 Reliability vs. Time of C-130 turbine failures required overhaul maintenance (T.S.O)

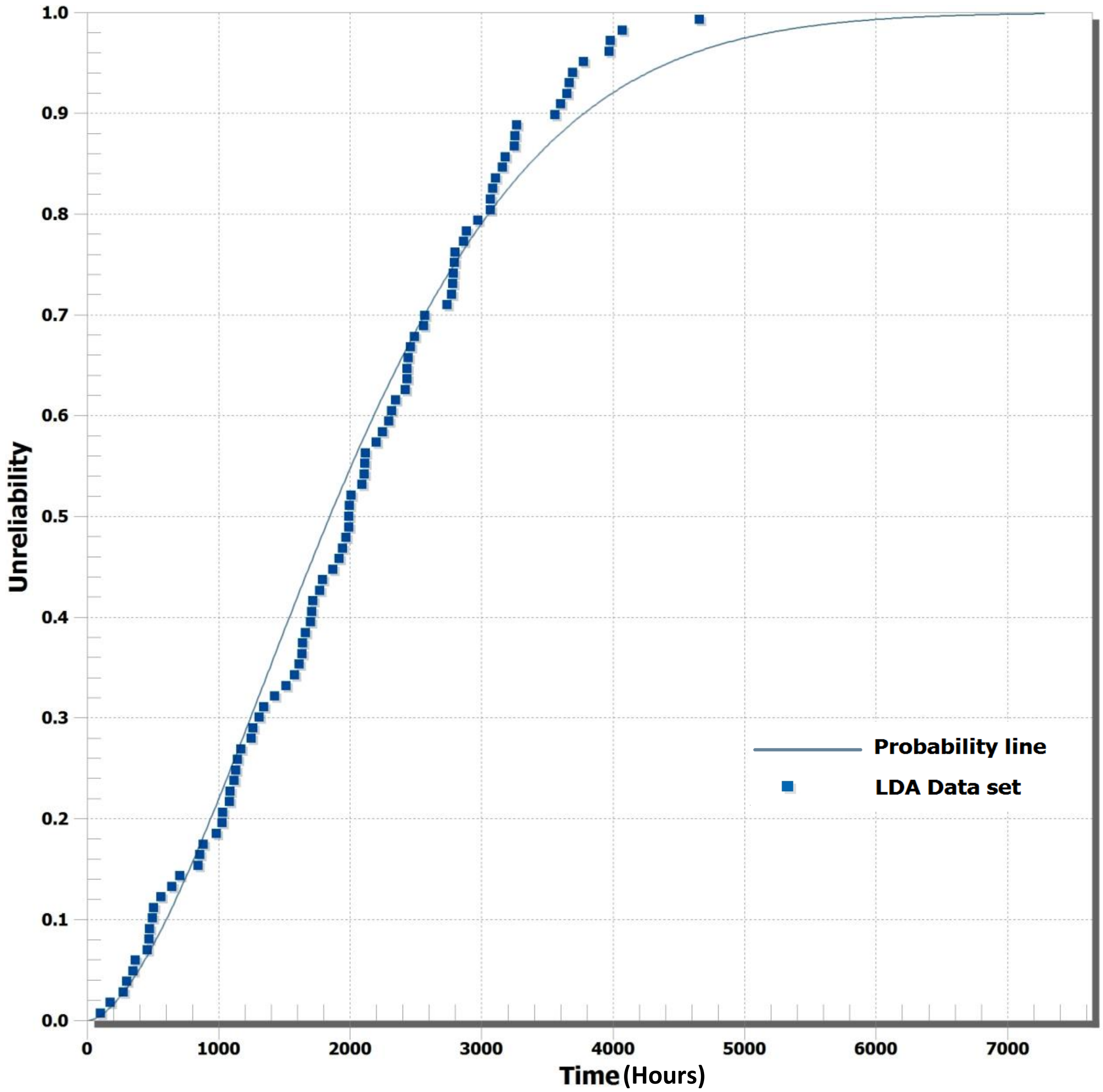


Figure 3-14 Unreliability vs. Time of C-130 turbine failures required overhaul maintenance (T.S.O)

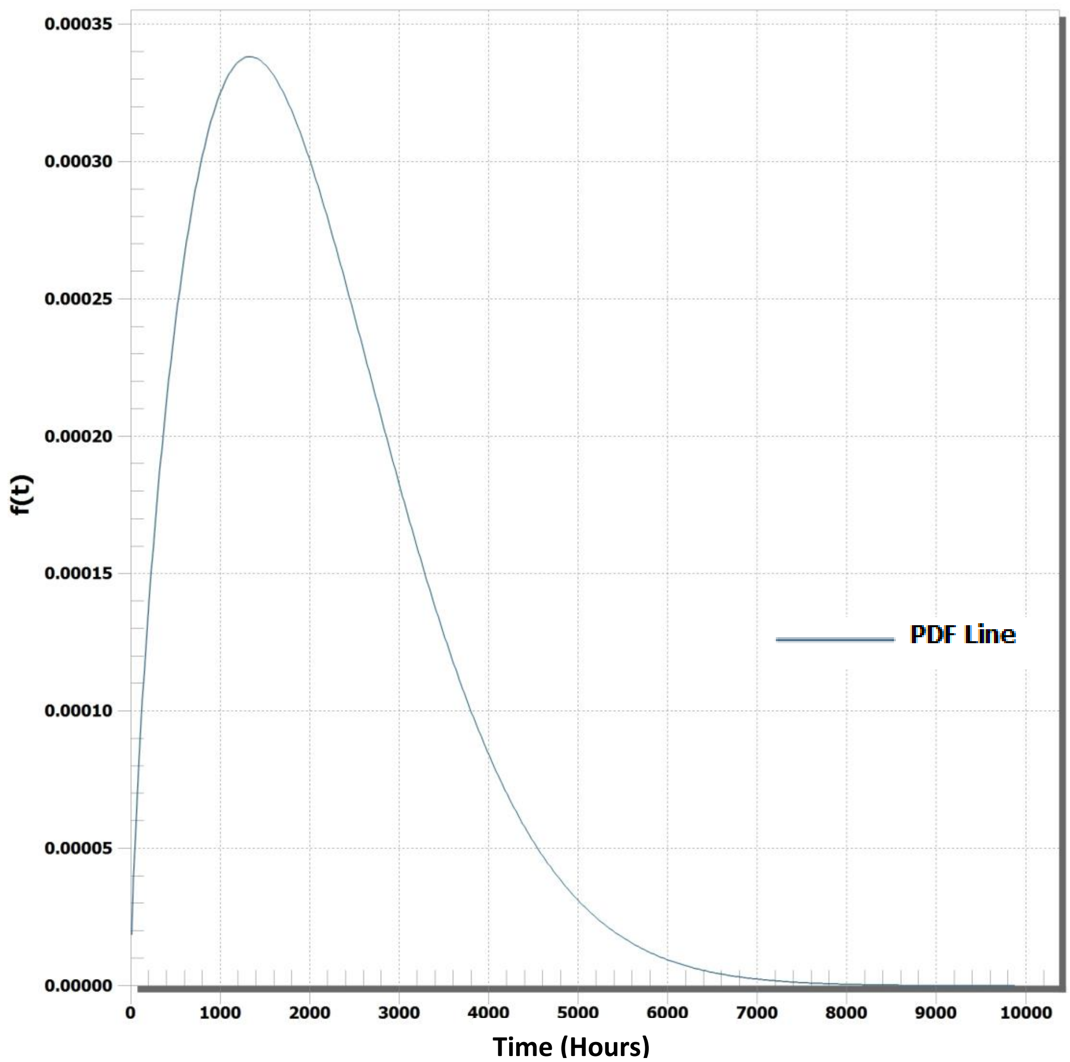


Figure 3-15 PDF plot of C-130 turbine failures required overhaul maintenance (T.S.O)

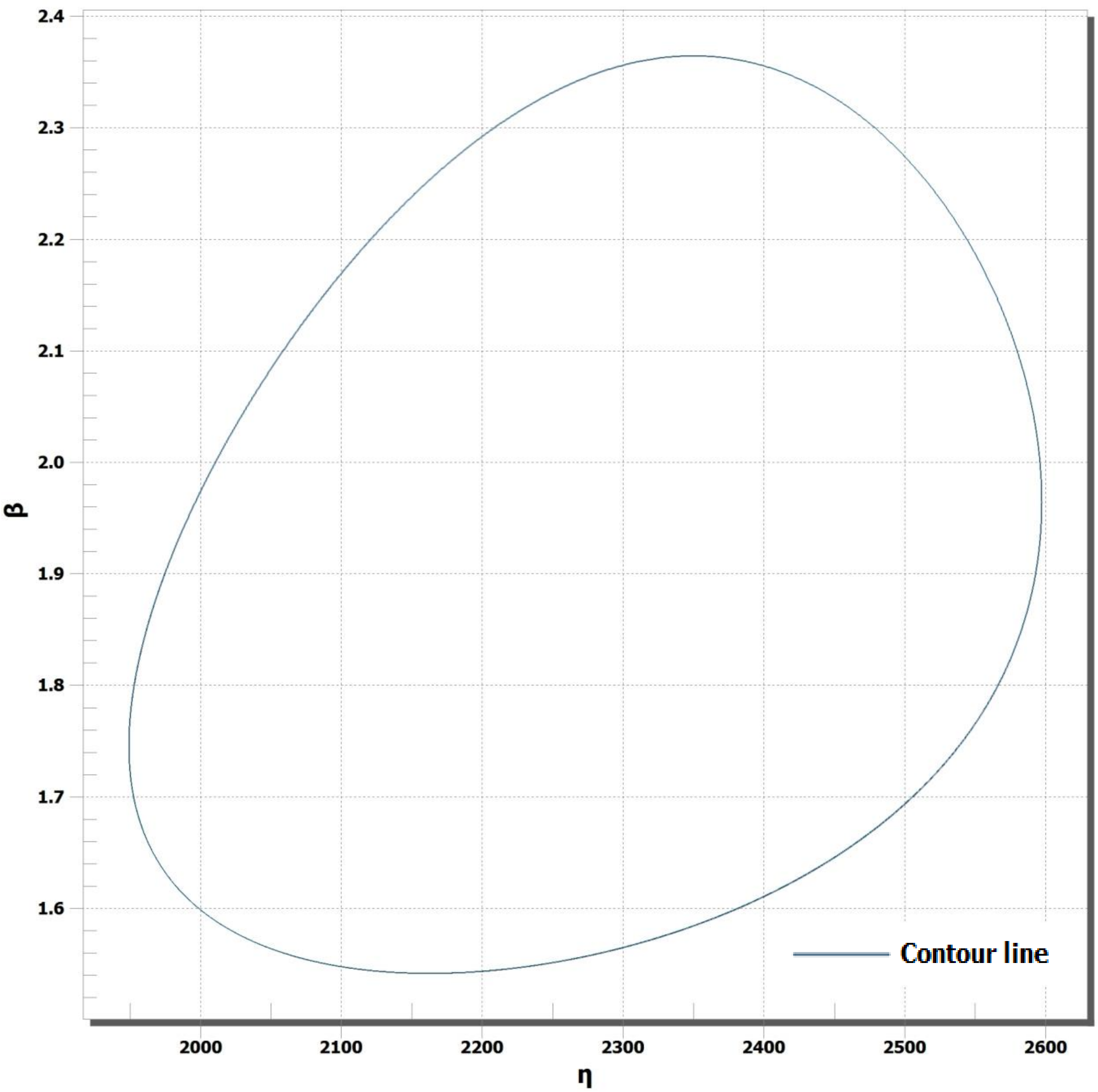


Figure 3-16 *β* vs. *η* contour plot of C-130 turbine failures required overhaul maintenance (T.S.O)

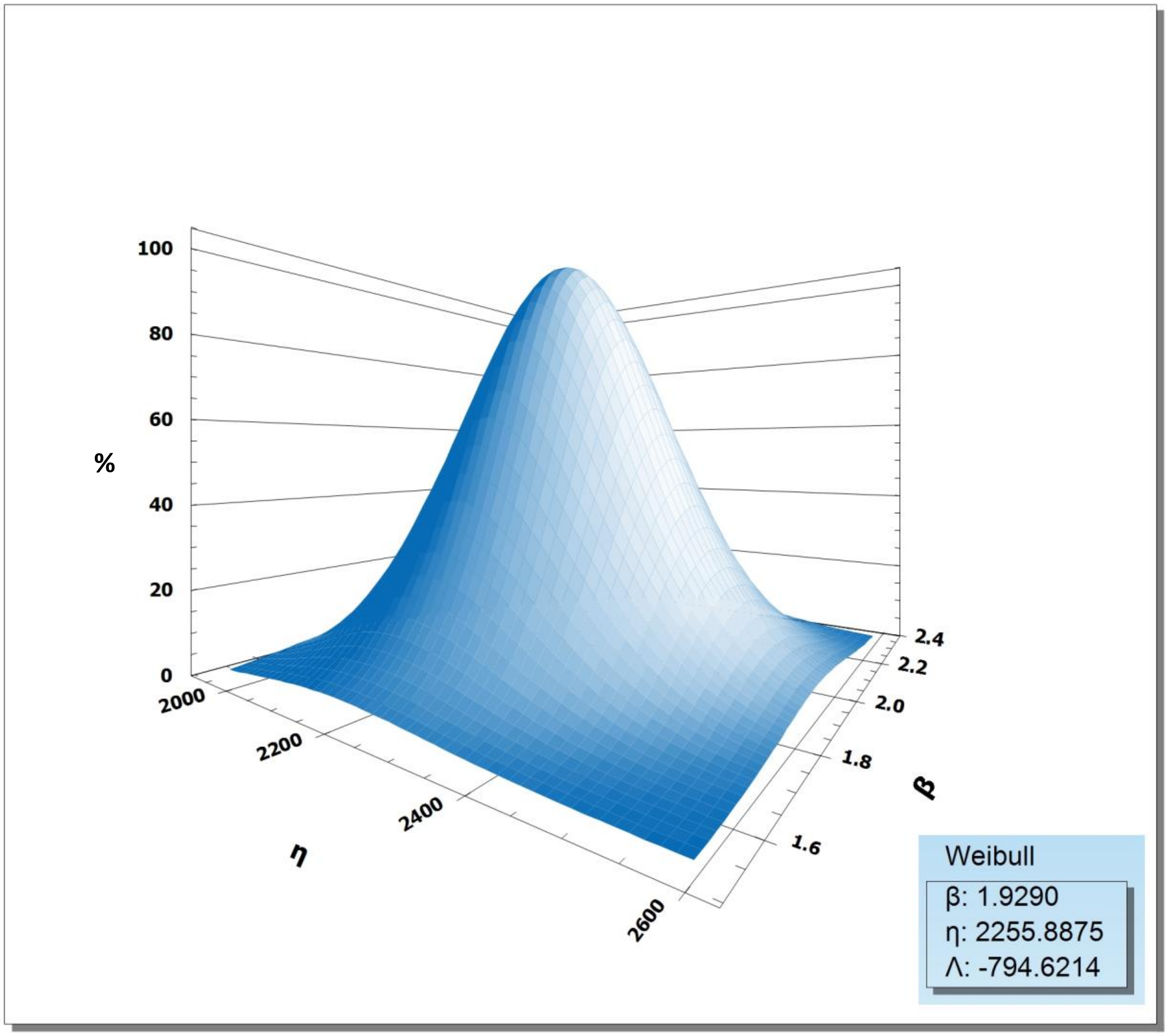


Figure 3-17 *β* vs. *η* 3D plot of C-130 turbine failures required overhaul maintenance (T.S.O)

3.4.4 Goodness-of-Fit Test of failure which required overhaul maintenance (T.S.O)

Following same procedure, the goodness of fit for the C-130 turbine failures required overhaul maintenance (T.S.O) Table A- 4, Appendix A, shows the KS goodness of fit test calculations, indicating that the sample does fit to the Weibull method.

From Table A- 4, Appendix A,

Max D+ = 0.07946

Max D- = 0.07946

Sample size *N*= 95,

The critical value CV for KS test for data of size 95 = 0.1395

Since max **D+ = 0.07946 < CV = 0.1395** $\Rightarrow$ $\therefore$ the sample is accepted.

CHAPTER 4

ANN METHODOLOGY

4.1 Introduction

Artificial neural networks represent a type of non-linear structure computational system based on the how the brain performs computations. An Artificial Neural Network is an information processing system that has certain performance characteristics in common with biological neural networks [50]. The aim of ANNs is to mimic human brain ability to adapt to changing circumstances and the current environment, so it can identify and learn correlated patterns between input data and corresponding target values. This depends on being able to learn from events that have happened in the past and to be able to apply this to future situation. It is a gross simplification of real biological networks of the brain neurons. The human brain contains about 100 billion neurons (neuron cells), interconnected in a complex manner via synapses (junctions between axons and dendrites), thus constituting a network. An ANN is a collection of neurons that are arranged in specific formations. The structure of the simple single layer ANN is shown in Figure 4-1

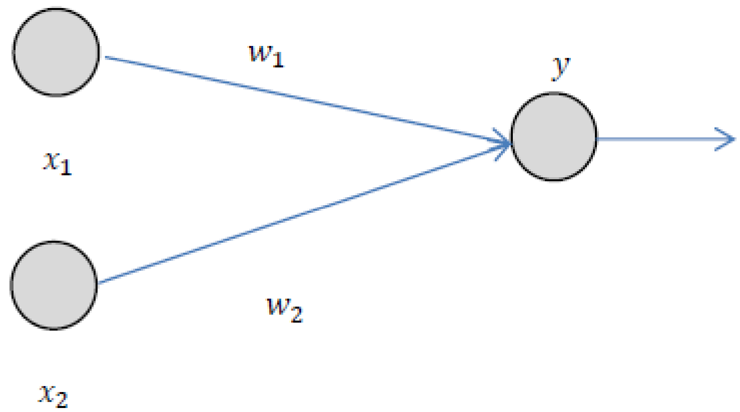


Figure 4-1 A simple Artificial Neural Network

Figure 4-1 shows a simple ANN with two input neurons (x_1 , x_2) and one output neuron (y). The inter-connection weights are given by w_1 and w_2. The number of neurons in the input layer corresponds to the number of parameters that are presented to the network as inputs. In the single layer net there is a single layer of weight interconnections. The same is true for the output layer.

Neural-network analysis is not limited to a single output, and neural nets can be trained to build neuron models with multiple outputs. A typical multi-layer artificial neural network comprises an input layer, one or more hidden (intermediate) layer of neurons, 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 log-sigmoid function). The output is then distributed to other neurons as inputs [51].

A three-layer ANN is shown in Figure 4-2, and a simplified block diagram representation in Figure 4-3. The activity of neurons in the input layer represents the raw information that is fed into the network. The activity of neurons in the hidden layer is determined by the activity of the input neurons and the connecting weight between the input and hidden units. The neurons in the hidden layers are responsible primarily for feature extraction, to provide increased dimensionality and accommodate such tasks as classification and prediction. They can implement arbitrary complex input/output mapping or decision surface separating different patterns. Similarly, the behavior of the output units depends on the activity of the neurons in the hidden layer and the connecting weight between the hidden and output layers.

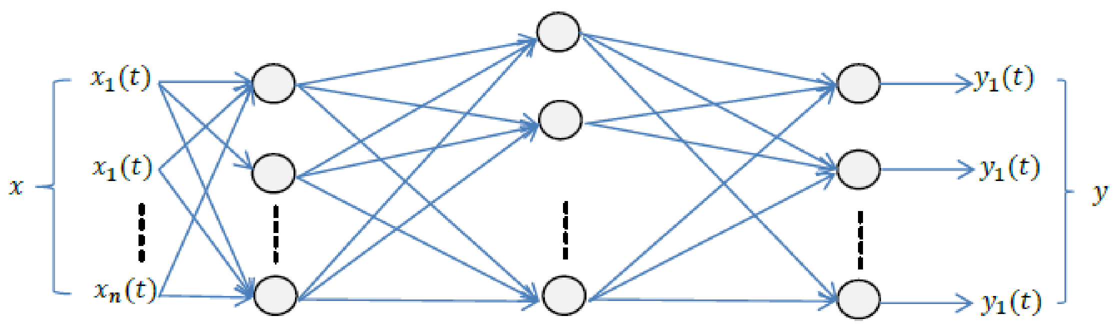


Figure 4-2 a three layer Artificial Neural Network

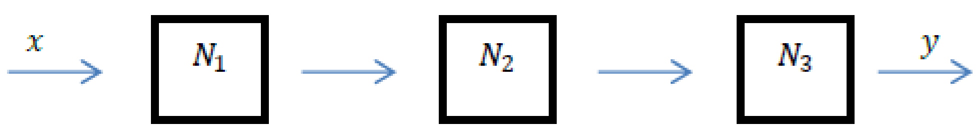


Figure 4-3 A Block diagram representation of a three layer ANN

The multi-layer artificial neural network provides an increase in computational power over a single layer neural network. Many capabilities of neural networks, such as nonlinear functional approximation, Learning, generalization, etc. are in fact performed due to the nonlinear activation function of each neuron. In addition, the ability to deal with incomplete information especially in situations where it is not possible to define the rules or steps that lead to the solution of a problem.

ANN has become a technical folk legend. Among the most popular hardware implementations are Hopfield, Multilayer Perception, Self-organizing Feature Map, Learning Vector Quantization, Radial Basis Function, Cellular Neural, Adaptive Resonance Theory (ART) networks, Counter Propagation networks, Back Propagation networks, and Neo-cognitron, etc. [52].

4.2 ANN Working Methodology

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

4.3 Back-Propagation Algorithm

In this study, the most popular algorithm which is the back-propagation algorithm is utilized to train the network. Back-Propagation (BP) is a systematic method for training multi-layer ANNs. It has a mathematical foundation that is strong and highly practical. The BP algorithm is the most common technique for training a supervised neural network, [53,54]. The BP algorithm is the simplest and well known for its good performance. It is a multi-layer forward network using extend gradient-descent based delta-learning rule, commonly known as back propagation (of error) rule. BP provides a computationally efficient method for changing the weights in a feed-forward network, with differentiable activation function units, to learn a training set of input-output. The back propagation ANN algorithm concept is based on a gradient descent algorithm that is used to continually adjust the network weights to maximize performance, being a gradient descent method it minimize the total squared error of the output computed by the net, and it is trained by supervised learning method. The aim of the network is to train the net 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 responses to the input that are similar. [50].

BP process could be divided into two segments, which are the forward-propagation and the back-propagation. Before beginning training, some small random numbers are usually used to initialize each weight on each connection. BP requires preexisting 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. Transforming the incoming signals to an output signal is accomplished by an activation function which could be a log-sigmoid function or any other function depends on the structure and the nature of the network. 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. [55]. Figure 4-4 shows ANN with log-sigmoid function, and Figure 4-5 shows the basic concept of the back-propagation algorithm.

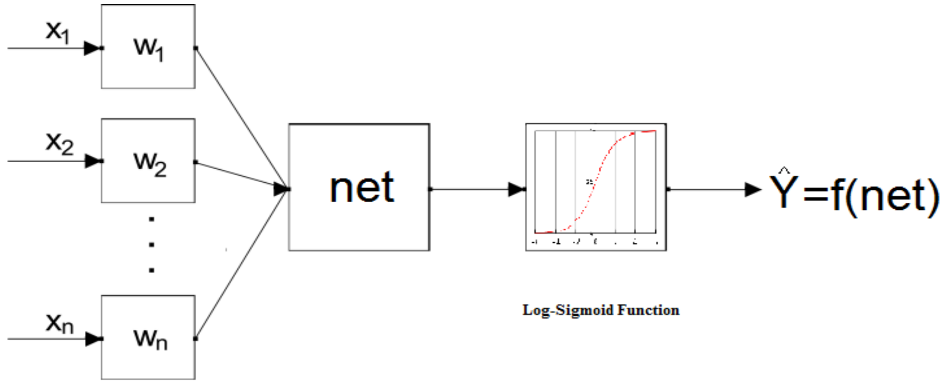


Figure 4-4 ANN With log-sigmoid activation function

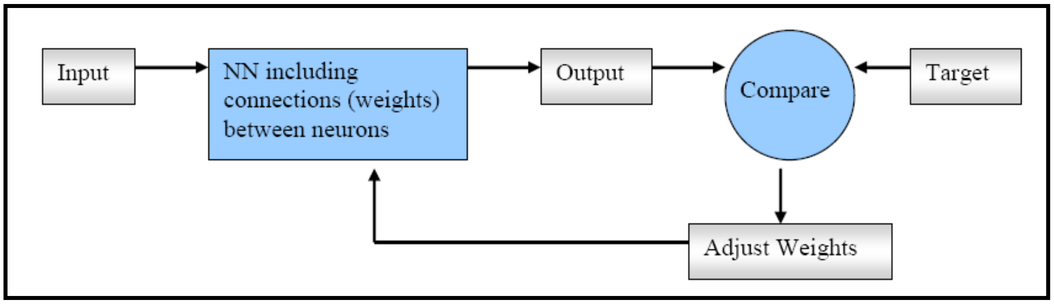


Figure 4-5 Basic concept of the back-propagation algorithm

In the following, we will demonstrate the basic mathematical equations that describe the fundamental concept of the back-propagation algorithm [56,57].

$$x_j = \text{normalized } X_d\ , \qquad \text{where} \quad 1 < d \le M \tag{4.1}$$

$$net_k = \sum_{j=1}^{k-1} W_{kj} x_j\ , \qquad \text{where} \quad m \le k \le N + n \tag{4.2}$$

$$x_k = f(net_k)\ , \qquad \text{where} \quad m < k \le N + n \tag{4.3}$$

$$O_s = X_{N+s}, \qquad \text{where} \quad 1 \le s \le n \tag{4.4}$$

Where the function in Eq (4.3), is usually the following log-sigmoidal function:

$$f(net_k) = \frac{1}{1+e^{-net_k}} \tag{4.5}$$

Where *m* is the number of inputs to the network, *n* is the number of outputs of the neural network, and X_d represents the actual inputs to the network (which have to be normalized and then initially stored in x_j). The non-linear activation function $f(net_k)$ in Eq. (4.5) is a log-sigmoid function. It determines the relation between the inputs and outputs of a node and a network. There are some other functions like hyperbolic function, cosine function, and linear functions. The log-sigmoid activation function is easy to differentiate and applied to the input and squashes the output into the ranges from 0 to 1, Figure 4-6. N is a constant, which represents the number of intermediate neurons in the neural network. It can be any integer as long as it is not less than m. The value of $N + m$ determines how many neurons are there in the network (if we include the inputs as neurons). W is the weight matrix in each layer, whose size depends on the number of neurons in the corresponding adjacent layers of neural network. 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 the neural network. The significance of these equations is illustrated in Figure 4-7, which shows the connection in the network.

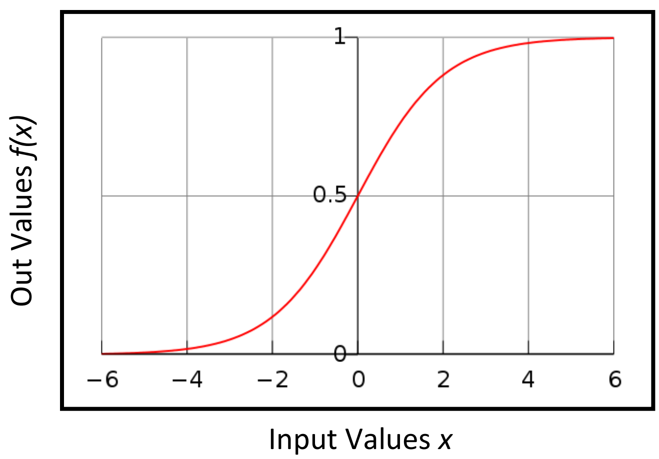


Figure 4-6 Log-sigmoid activation functions

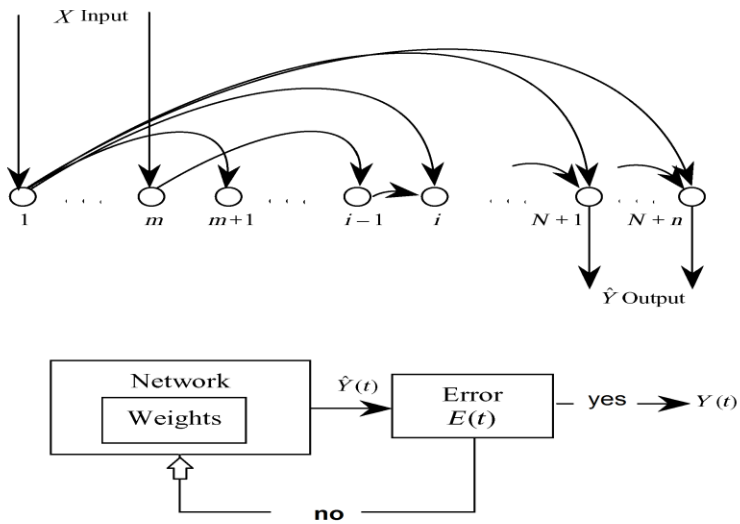


Figure 4-7 Network design for BP

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

4.4 BP ANN Training Performance

In this section, MATLAB code was used to build the BP ANN to model the failure rate of Lockheed C-130 aircraft engine Turbines for the two cases, general turbine failures and turbine failures which require overhaul maintenance action. The input to the neural network is time in hours, and the output is the failure rate corresponding to that time.

In our modeling of each two cases, we will test and compare a set ANN configuration as follow:

1) Two input m = 2, one output n = 1, and four intermediate neurons N =4. -(2,4,1) configuration-.
2) Three input m = 3, one output n = 1, and six intermediate neurons N =6. -(3,6,1) configuration-.
3) Four input m = 4, one output n = 1, and eight intermediate neurons N =8. -(4,8,1) configuration-.
4) Four input m = 4, one output n = 1, and ten intermediate neurons N =10. -(4,10,1) configuration-.
5) Four input m = 4, one output n = 1, and twenty intermediate neurons N =20. -(4,20,1) configuration-.

While Learning rate, and the moment is constant (LR=0.2), and (MOM=0.05). Method was adopted, such as that used by Al-Garni. [37].

The non-linear activation function log-sigmoidal function Eq (4.5), which is the most suitable function to serve the purpose of our problem, is utilized. Failure rates are predicted using the forward-pass calculation of Eq (4.1) to (4.4). The back-propagation technique [58] was used to train the neural network with the scope of minimizing the sum squared error given by:

$$\text{error} = \sum[F(t) - O(t)]^2 \tag{4.6}$$

Where *F(t)* is the actual failure of the component (input to the network), and *O(t)* is the calculated failure of the component (output of the network). The initial error is high because the weights are assigned randomly and the number of passes is usually high. Throughout the training process, this error decreases and converges to minimum value.

Training the back-propagation of the network starts first by selecting the next training pair from the training set and applying the input vector to the network input terminal, during this stage, we initialize the weights, and some small random values are assigned. The second step is to calculate the output of the network using Eq (4.1) to (4.3), forward pass. The first and second steps are the forward pass while steps three and four are the reverse pass. The third step in training is calculation of the error, which is the difference between the network output and desired output. In the fourth step, the weights of the network are adjusted to minimize the error. Finally, the four steps are repeated for each vector in the training set, until an acceptable error for the whole set is reached. For F_1 and F_2, the resultant weight matrices are W_1 and W_2 .

These steps can easily be understood by the flow chart shown in Figure 4-8.

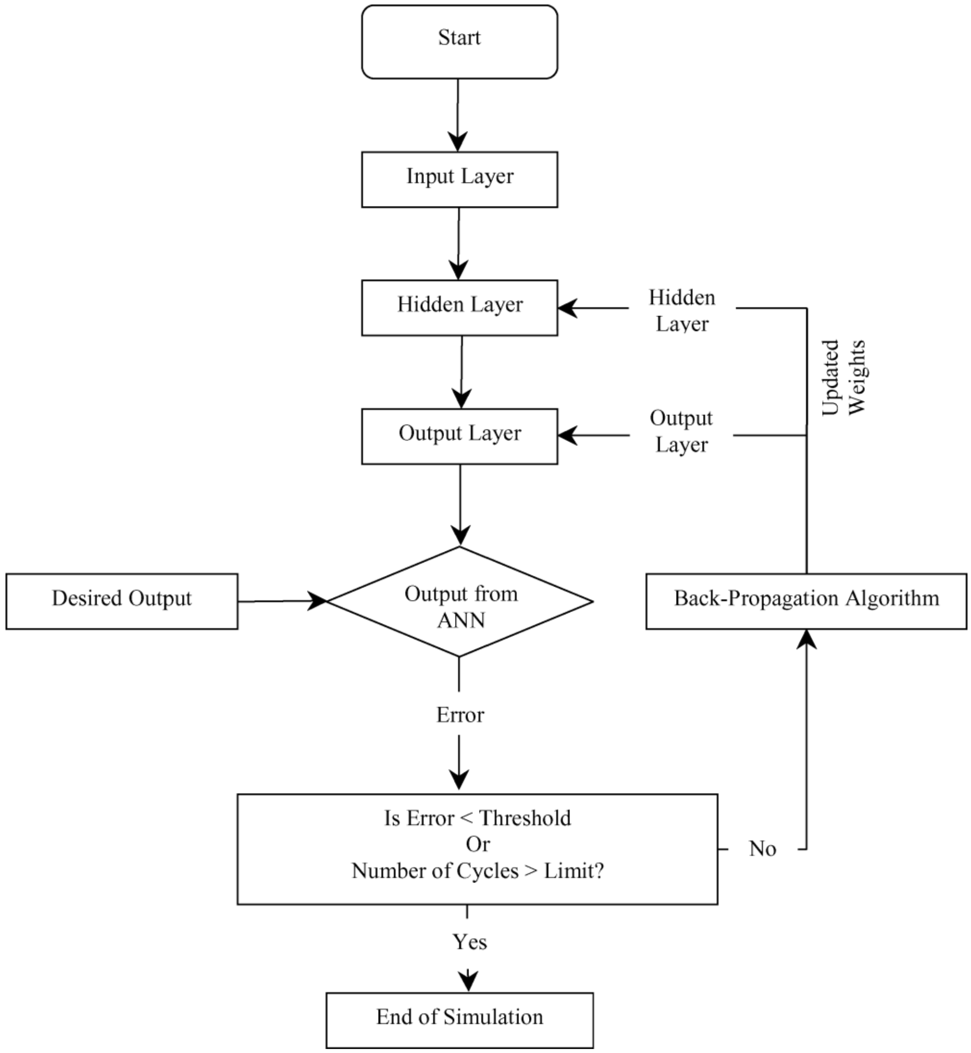


Figure 4-8 Flow chart of neural-network algorithm

4.5 Radial Basis Function (RBF) Neural Networks

Radial Basis Function (RBF) neural network model on MATLAB tool box 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 early prototype vector which will be learned and tested from [59].

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, Figure 4-9.

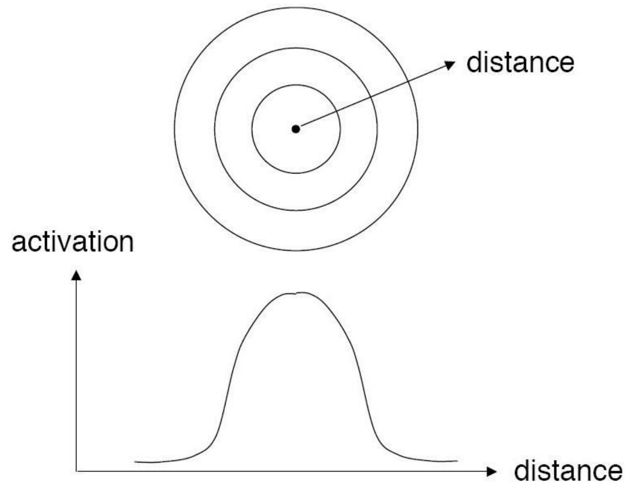


Figure 4-9 Radial Basis Function (RBF) neural networks

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 [60]. 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:

$$f(x) = \exp\left(-\frac{1}{\theta_\alpha}\sum_k |x_k - \mu|^\alpha\right) \tag{4.7}$$

Where the parameter $\alpha \in (0, \infty)$; 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:

$$\mu = \frac{1}{N}\sum_{k=1}^{N} x_k \quad \text{and} \quad \theta_\alpha = \sum_{k=1}^{N} |x_k - \mu|^\alpha \tag{4.8}$$

The distance between any vector $\boldsymbol{x}$ and the center μ is obtained as:

$$\|x - \mu\|_{\ell_\alpha} = \left(\sum_k |x_k - \mu|^\alpha\right)^{1/\alpha} \tag{4.9}$$

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 k^{th} epoch is defined as a distance function.

$$M_k \equiv d(f_{nom}, f_k) \tag{4.10}$$

The neurons in the hidden layer contain Gaussian transfer functions Figure 4-10, whose outputs are inversely proportional to the distance from the center of the neuron.

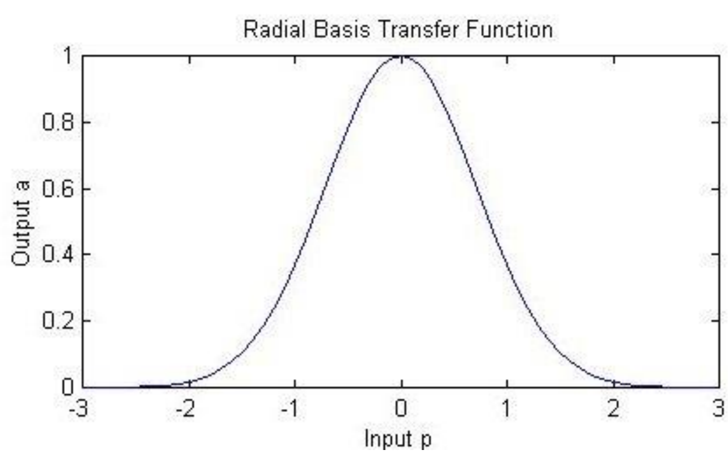


Figure 4-10 Gaussian transfer functions

RBF networks have three layers Figure 4-11:

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 neuron's 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.

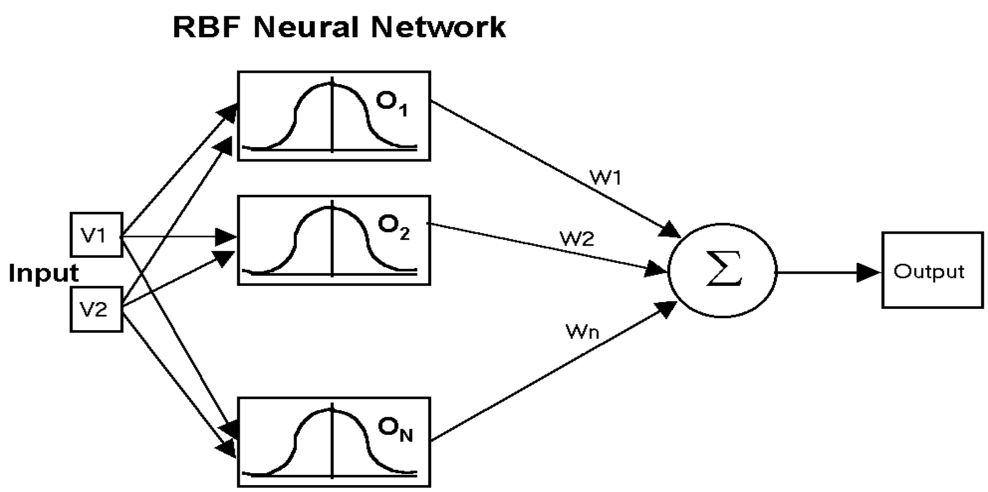


Figure 4-11 RBF Network Architecture

4.6 BP ANN Analysis of general turbine failure data (T.T)

In this part the general turbine failure data (T.T) of Lockheed C-130 turbine will be analyzed. The MATLAB programing language will be used in order to build and design a code to simulate the failure data using "Feed-forward back-propagation" ANN algorithm.

Table B- 1, Appendix B, shows the main calculation for the turbine general failure data (T.T), with different BP network structures in comparison to Weibull regression and RB ANN.

The comparison of all five BP ANN configuration structures is presented in the Figure 4-12, Figure 4-13, Figure 4-14, Figure 4-15, and Figure 4-16. The average percentage differences of the Turbines general failures rate with that of the actual Turbines general failure data are found to be 25.64%, 5.22%, 4.01%, 1.53%, and 0.96%, for the (2,4,1), (3,6,1), (4,8,1), (4,10,1), and (4,20,1) ANN configuration structures respectively. Table 4-1 shows the percentage error for all BP ANN configurations compared with actual data.

Table 4-1 General turbine failure (T.T) percentage error compared to actual data

Curve	Mean Percentage Error (compared to F(t))
ANN (2,4,1)	25.64%
ANN (3,6,1)	5.22%
ANN (4,8,1)	4.01%
ANN (4,10,1)	1.53%
ANN (4,20,1)	0.96%

We found out from several literatures - 15000 iterations -, that the number of neuron and layers are the most significant parameters that will drastically affect our calculation. For BP ANN having two, three, and four input. It is evident from the percentage differences that the ANN results improve as the number of inputs increase but the model with more than four inputs does not bring drastic improvement in results from that of four inputs. Therefore, four inputs ANN model have been adopted.

Furthermore, the analysis was also extended to study the effect of the number of intermediate neurons in case of the ideal "four" inputs ANN structure, as shown in the Figure 4-14, Figure 4-15, and Figure 4-16. The percentage differences for eight, ten, and twenty, intermediate neurons came out to be 4.01%, 1.53%, and 0.96%, respectively. It is obvious from the percentages that little improvement has been achieved by increasing the number of neurons beyond "twenty" at the expense of more complexity in the network and program execution time. Hence, twenty intermediate neurons are selected for the analysis. The ANN model of the present study uses a single intermediate layer of neurons, since single hidden / intermediate layer is commonly used and gives reasonable results [14].

So in our circumstances 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 Eq (4.6). The ANN architecture employed is shown in Figure 4-17. The sizes of the weight matrices W_1, and W_2 are 20x4 and 1x20 respectively.

Finally, the back-propagation algorithm provides an approximation to the trajectory in weight spaced computed by the method of steepest descend [52]. In back-propagation networks, the weight change is in a direction that is a combination of a current gradient and the previous gradient. This approach is beneficial when some training data are very different from a majority of the data. Based on that concept, a small training rate is used in order to avoid a major disruption of the direction of learning when there is unusual pair of training pattern. Minimizing the learning rate causes smaller changes to the synaptic weights in the network from iteration to the next, and the smoother will be the trajectory in weight spaces, keeping in mind that this is achieved at the cost of a slower rate of learning – several hours in our case -. On the other hand, if we make the leaning rate parameter too large, to speed up the rate of learning, this will result in larger changes to the synaptic weights and the network will be unstable. So by using try and error method, we found that learning rate of 0.2 is the most optimum. Finally increasing the momentum to the weight caused the convergence to be faster. The main purpose of the momentum is to accelerate the convergence of error propagation algorithm. This method makes the current weights adjustment with a fraction of recent weights adjustment. Also by using try and error method, the most optimum momentum set was 0.05. All network parameters are listed in Table 4-2.

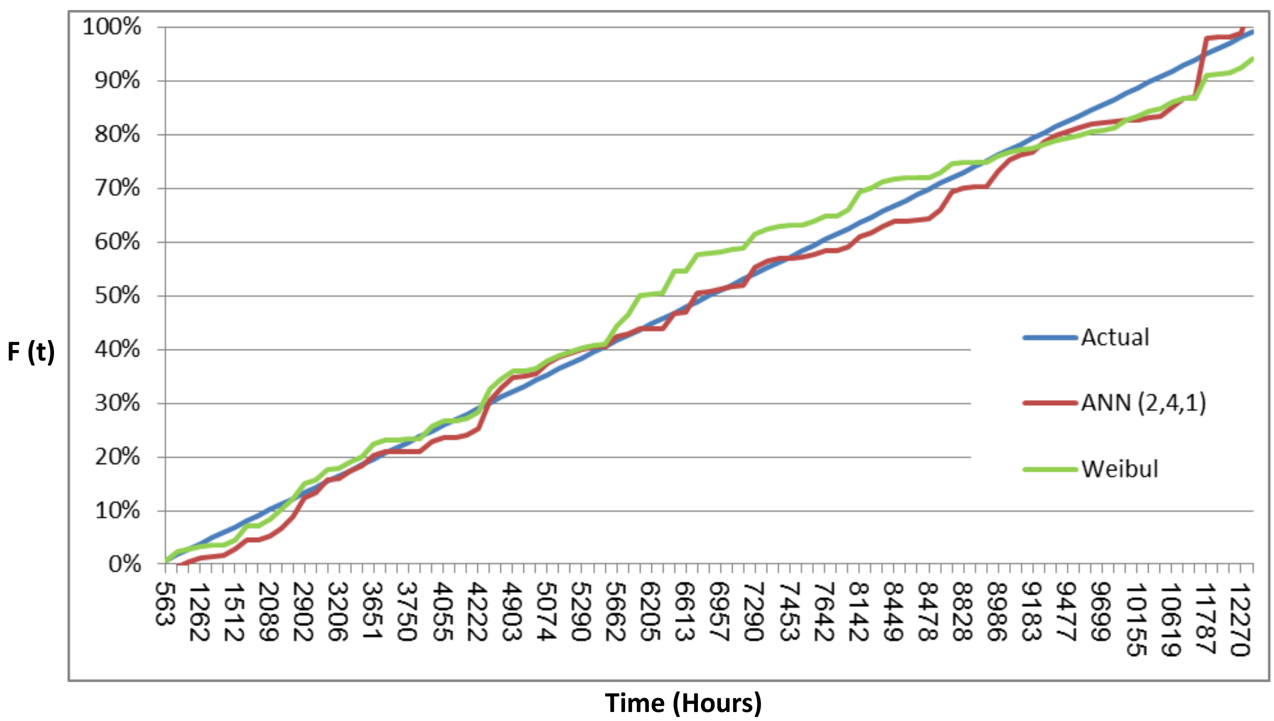


Figure 4-12 Comparison of general turbine failure rate predicted by using (2, 4, 1) ANN structure, Weibull and actual failure rate against time

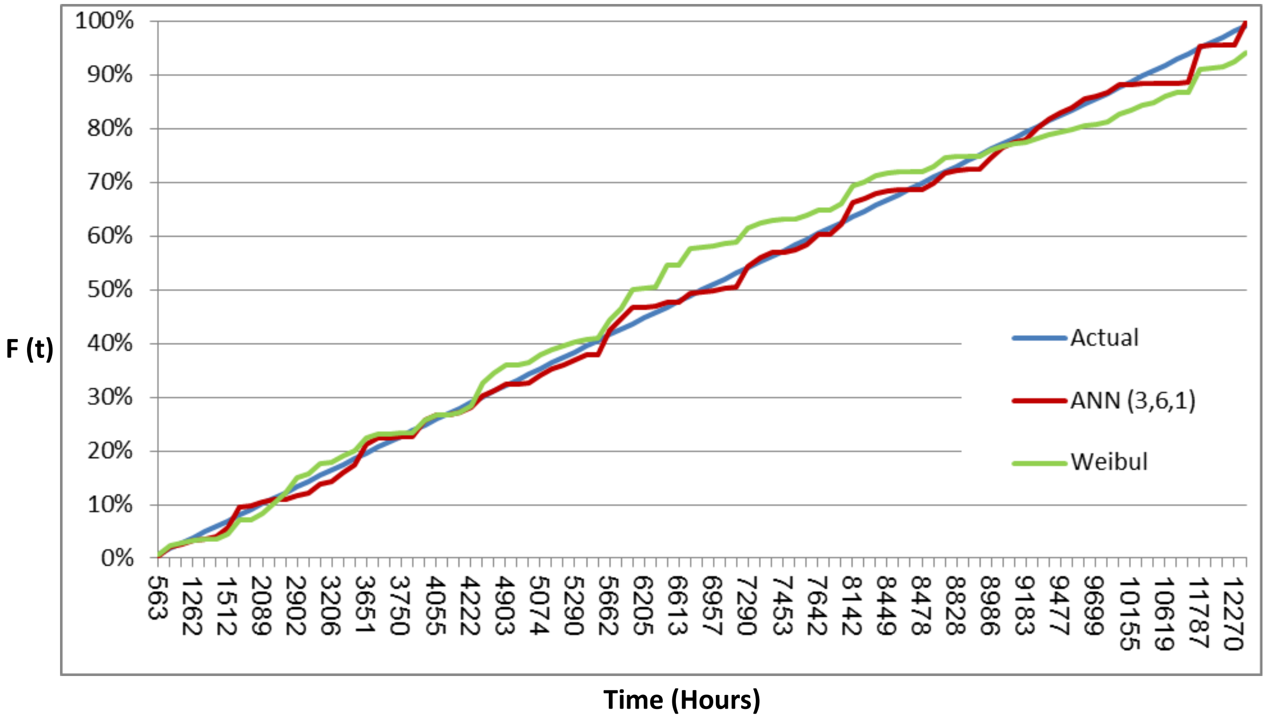


Figure 4-13 Comparison of general turbine failure rate predicted by using (3, 6, 1) ANN structure, Weibull and actual failure rate against time

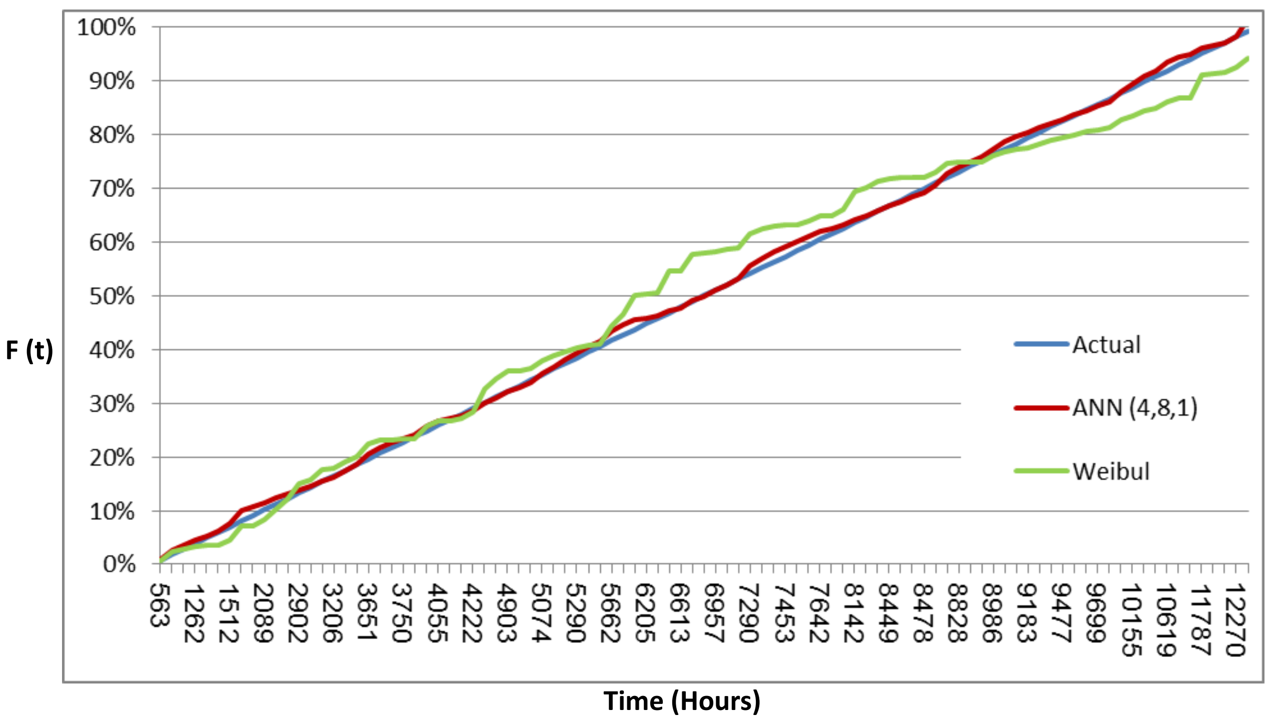


Figure 4-14 Comparison of general turbine failure rate predicted by using (4, 8, 1) ANN structure, Weibull and actual failure rate against time

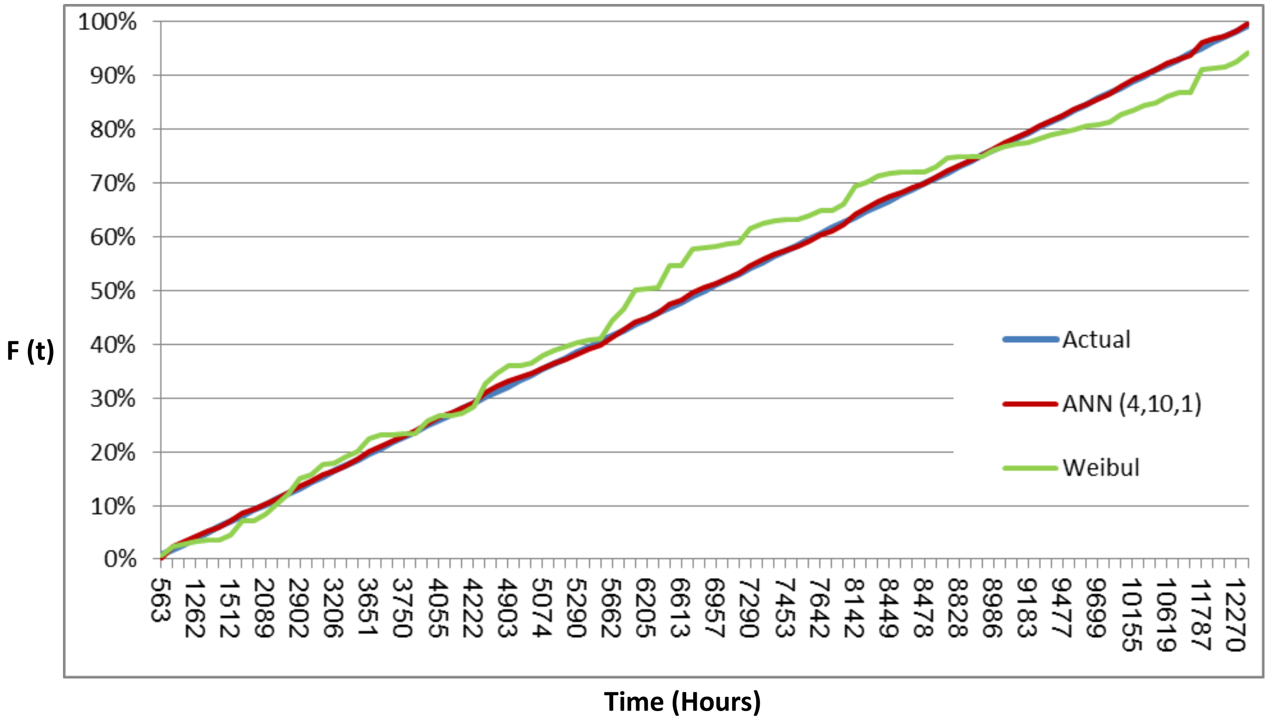


Figure 4-15 Comparison of general turbine failure rate predicted by using (4, 10, 1) ANN structure, Weibull and actual failure rate against time

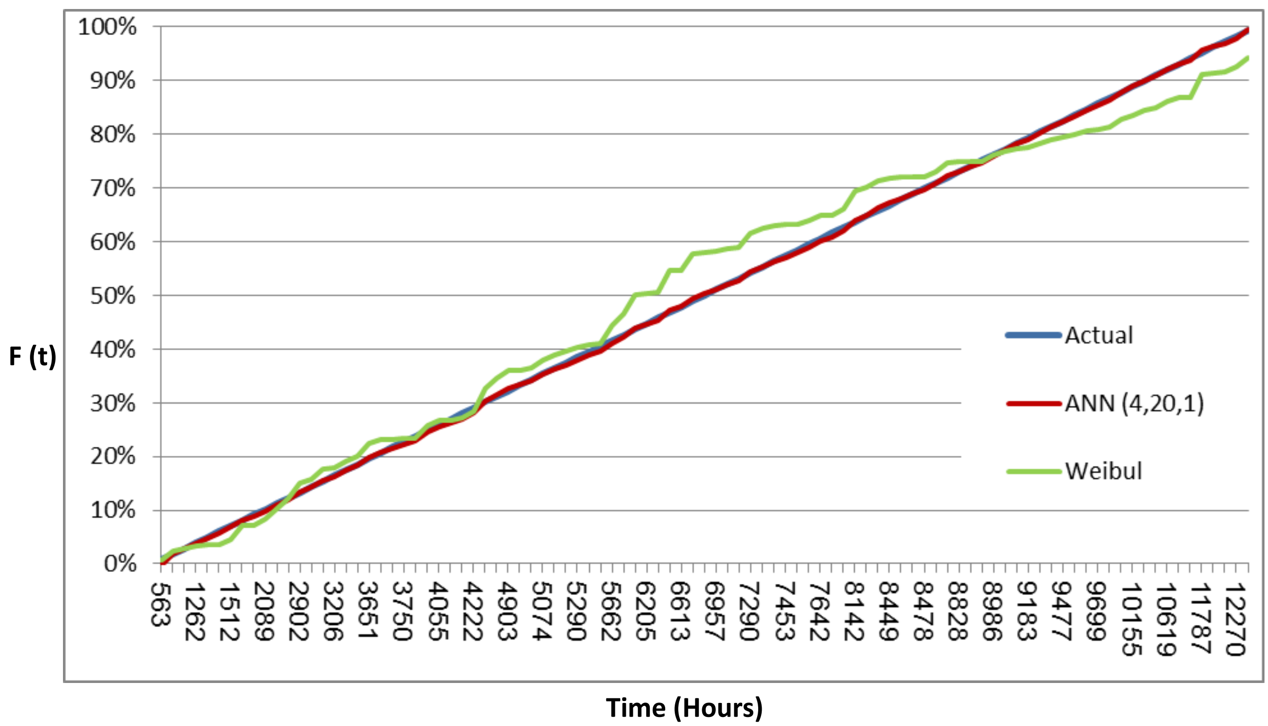


Figure 4-16 Comparison of general turbine failure rate predicted by using (4, 20, 1) ANN structure, Weibull and actual failure rate against time

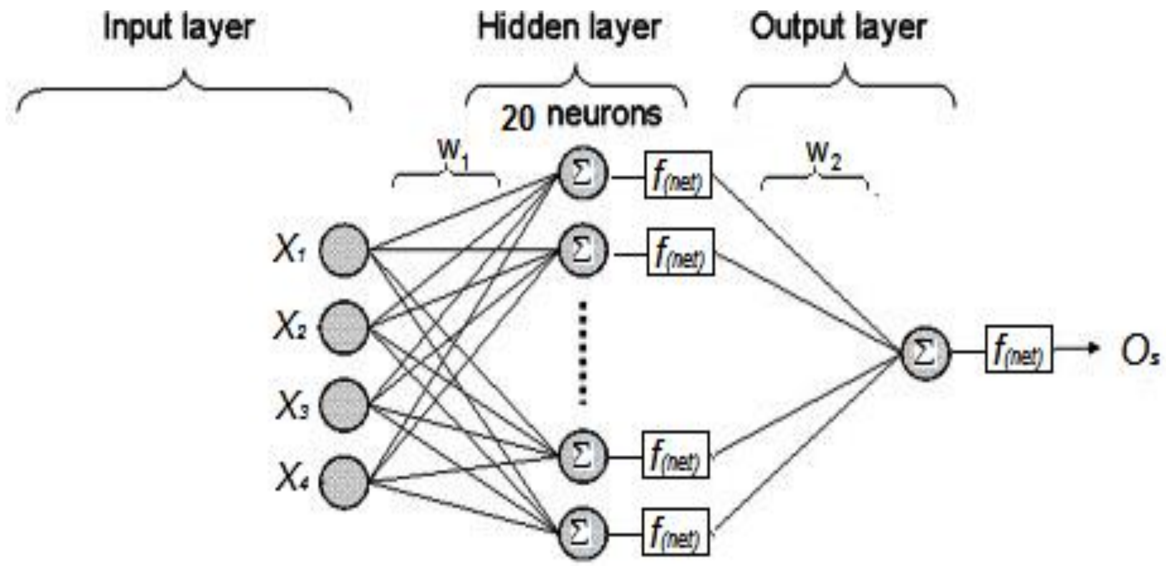


Figure 4-17 ANN (4, 20, 1) Architecture

Table 4-2 General turbine failure (T.T) Major network parameters

Parameters	
Network architecture	(4, 20, 1)
Network leaning rate	0.2
Network momentum constant	0.05

4.6.1 BP ANN Analysis of turbine failure which required overhaul maintenance (T.S.O)

After analyzing the general Lockheed C-130 failure rate, we will demonstrate the ANN analysis for turbine failures which required overhaul maintenance (T.S.O). Following the same procedures, by using MATLAB programming language using "Feed-forward back-propagation" algorithm, Table B- 2, Appendix B, shows the main calculation for the turbine failure which required overhaul maintenance (T.S.O) with different BP network structures in comparison to Weibull regression and RB ANN.

In same manners, the comparison of all five ANN configuration structures is presented in Figure 4-18, Figure 4-19, Figure 4-20, Figure 4-21, and Figure 4-22.

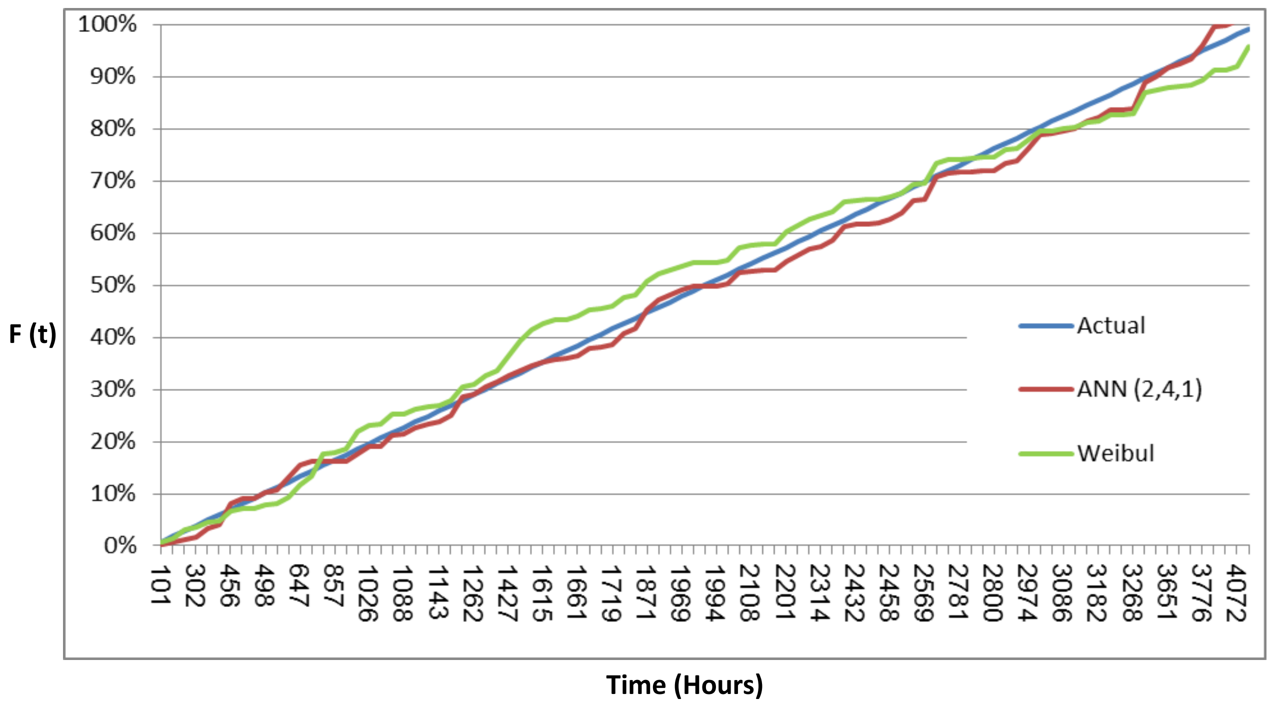


Figure 4-18 Comparison of turbine failure which required overhaul maintenance (T.S.O) predicted by using (2, 4, 1) ANN structure, Weibull and actual failure rate against time

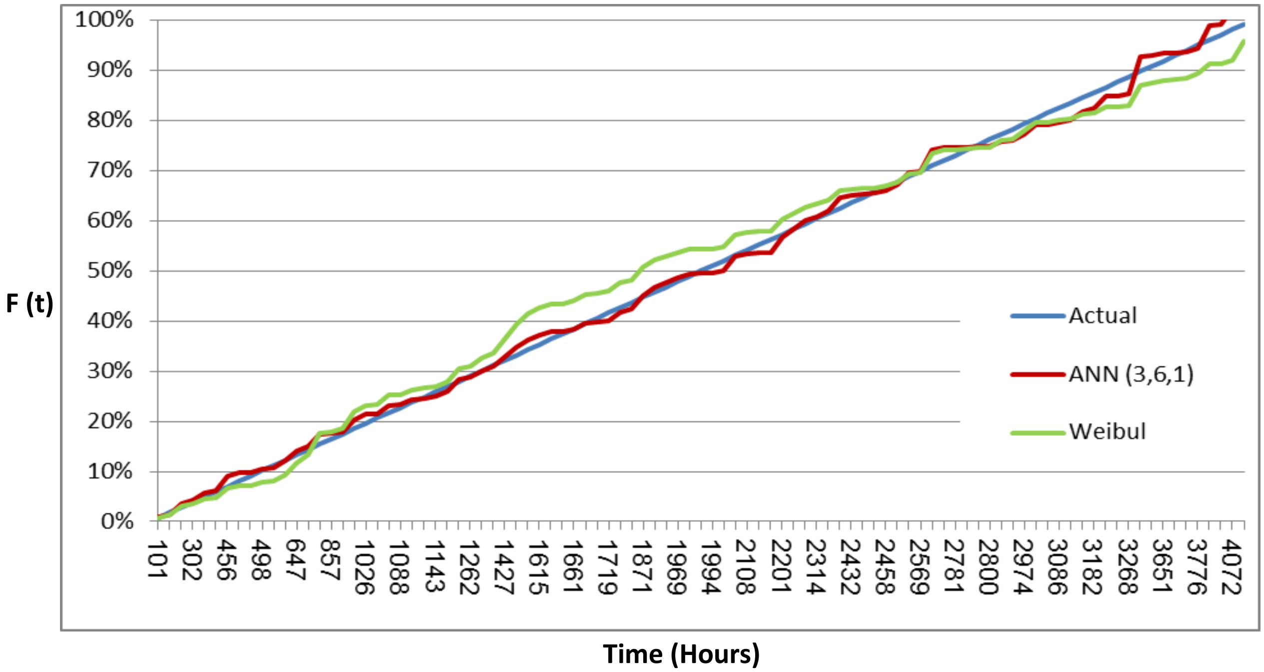


Figure 4-19 Comparison of turbine failure which required overhaul maintenance (T.S.O) predicted by using (3, 6, 1) ANN structure, Weibull and actual failure rate against time

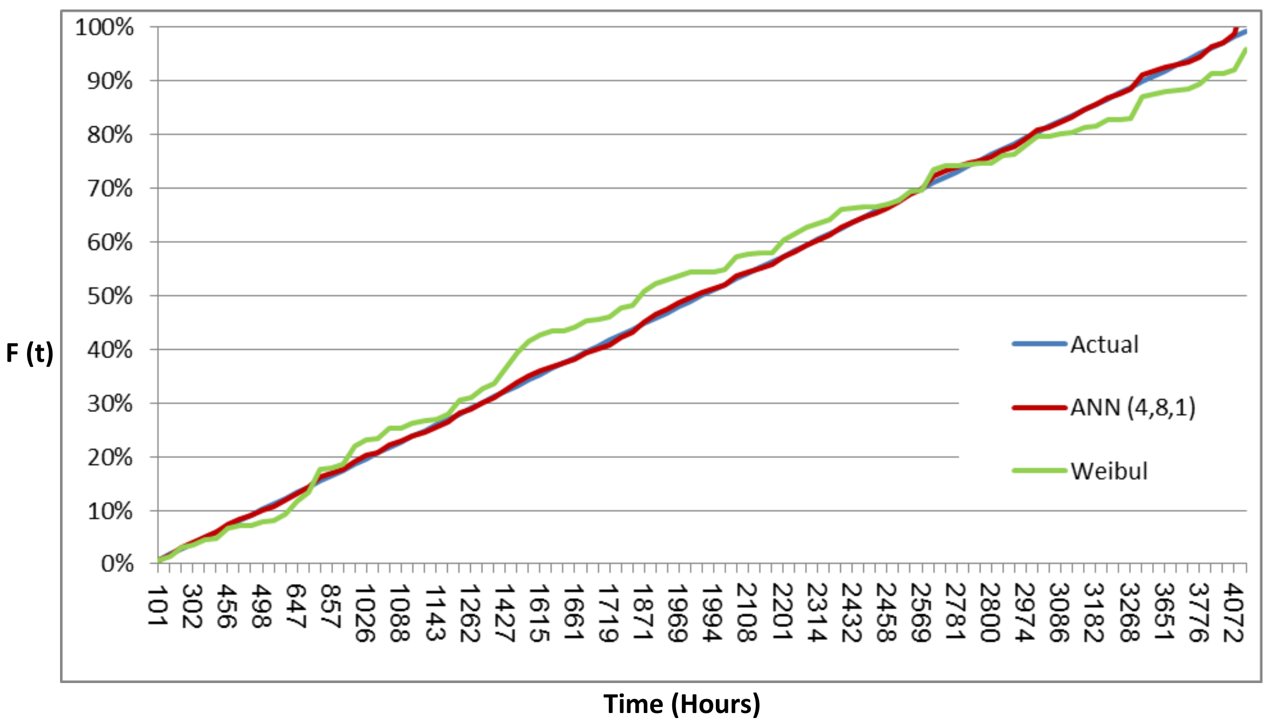


Figure 4-20 Comparison of turbine failure which required overhaul maintenance (T.S.O) predicted by using (4, 8, 1) ANN structure, Weibull and actual failure rate against time

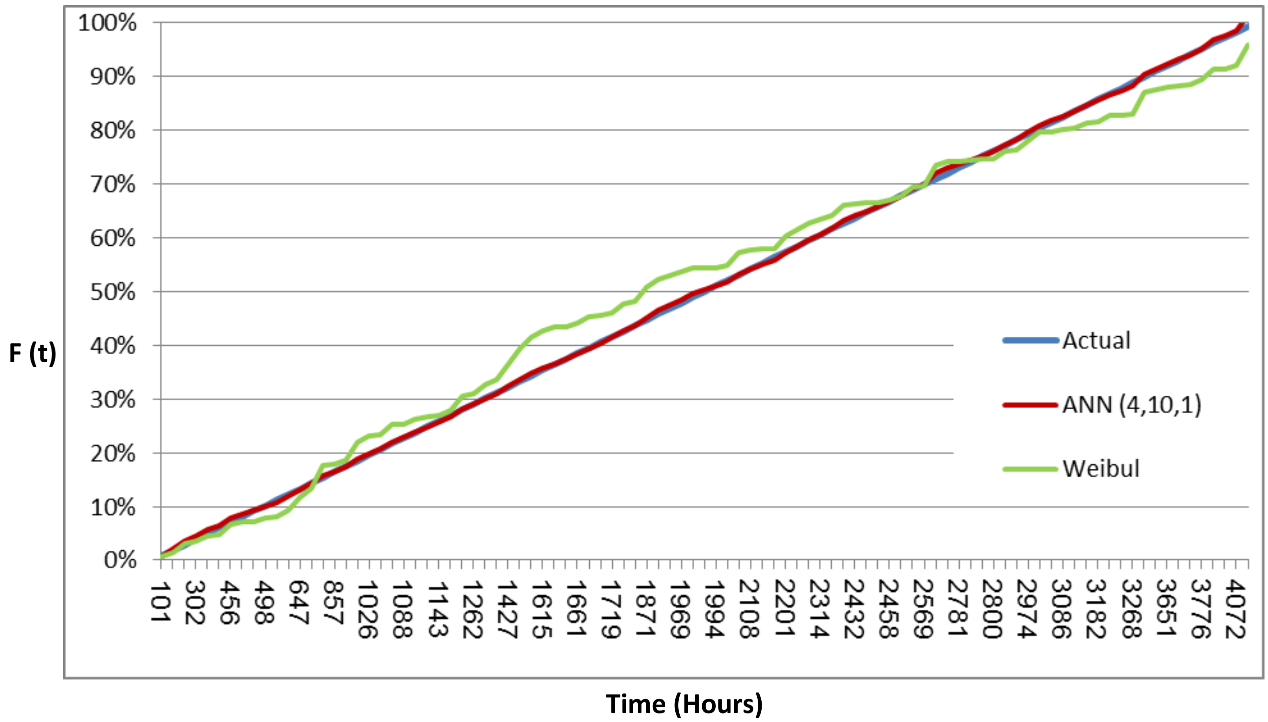


Figure 4-21 Comparison of turbine failure which required overhaul maintenance (T.S.O) predicted by using (4, 10, 1) ANN structure, Weibull and actual failure rate against time

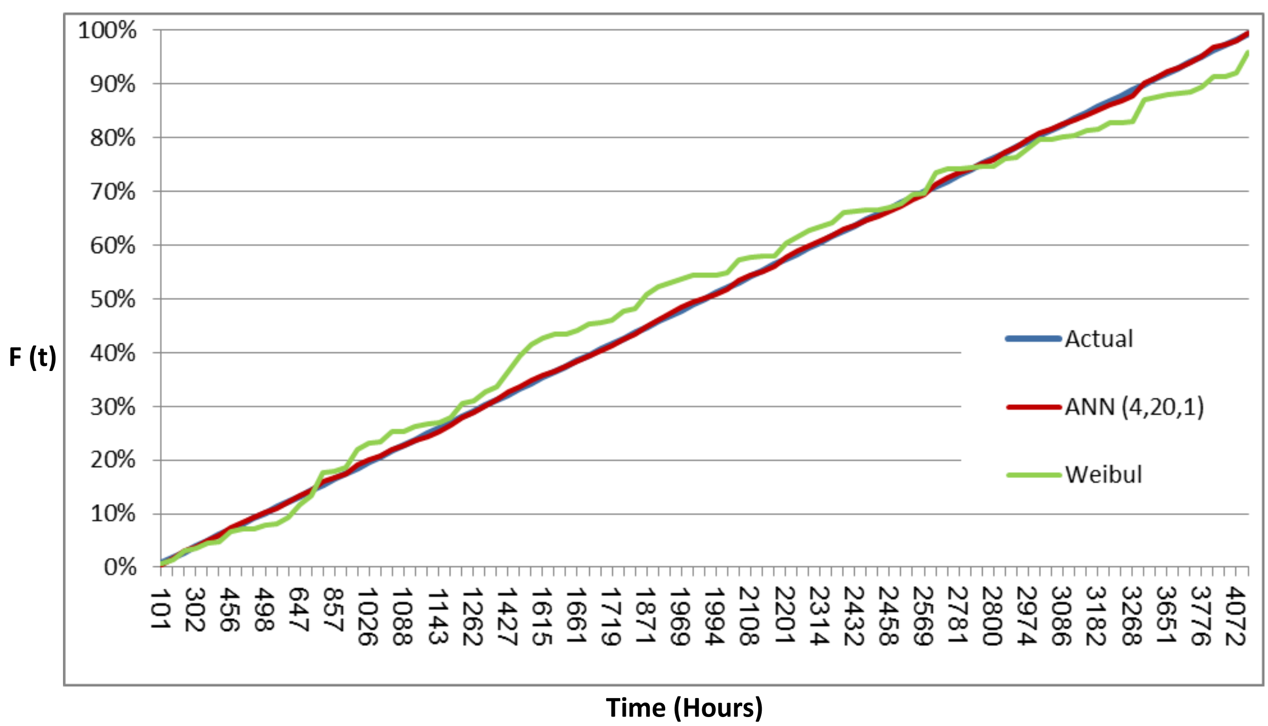


Figure 4-22 Comparison of turbine failure which required overhaul maintenance (T.S.O) predicted by using (4, 20, 1) ANN structure, Weibull and actual failure rate against time

Table 4-3 shows the percentage error for all ANN configurations compared to actual data.

Table 4-3 Turbine failure which required overhaul maintenance (T.S.O) percentage error compared to actual data

Curve	Mean Percentage Error (compared to F(t))
ANN (2,4,1)	6.85 %
ANN (3,6,1)	4.51 %
ANN (4,8,1)	1.51 %
ANN (4,10,1)	1.00 %
ANN (4,20,1)	0.84 %

From the table above, it can be clearly observed that ANN with (4, 20, 1) configuration has the most accurate output. The network training is drastically improved with minimum change to the network structure, while modifying other parameters like the learning rate and momentum constant did not indicate any noticeable effect on the accuracy of the network output. All network parameters for turbine failures which required overhaul maintenance are listed in Table 4-4.

Table 4-4 Turbine failure which required overhaul maintenance (T.S.O) Major network parameters

Parameters	
Network architecture	(4, 20, 1)
Network leaning rate	0.2
Network momentum constant	0.05

4.7 Model Adequacy and Comparison

Model adequacy is an important part to examine whether the fitted model is in agreement with the observed data. To assist our model validation, we have used the radial basis neural network model on MATLAB tool box to simulate both engine turbine general failure data and turbine failure which required overhaul maintenance. An informal visual assessment has been adopted by comparing each of the Weibull regression, and BP ANN MATLAB structures output, with the radial basis neural network model on MATLAB tool box and actual field data.

4.7.1 General turbine Failure Data (T.T) model Adequacy and Comparison

To evaluate my previous analysis, the

Table B- 1, Appendix B, and Table 4-5, show a comparison between Weibull regression, (4,20,1) BP ANN MATLAB output, and radial basis neural network model on MATLAB tool box - which gives negligible average error of (7.54E-16 %) - in relation to actual data. Figure 4-23 shows that the BP ANN MATLAB code with (4, 20, 1) structure, comes in close agreement with radial based ANN tool box 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 4-5 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

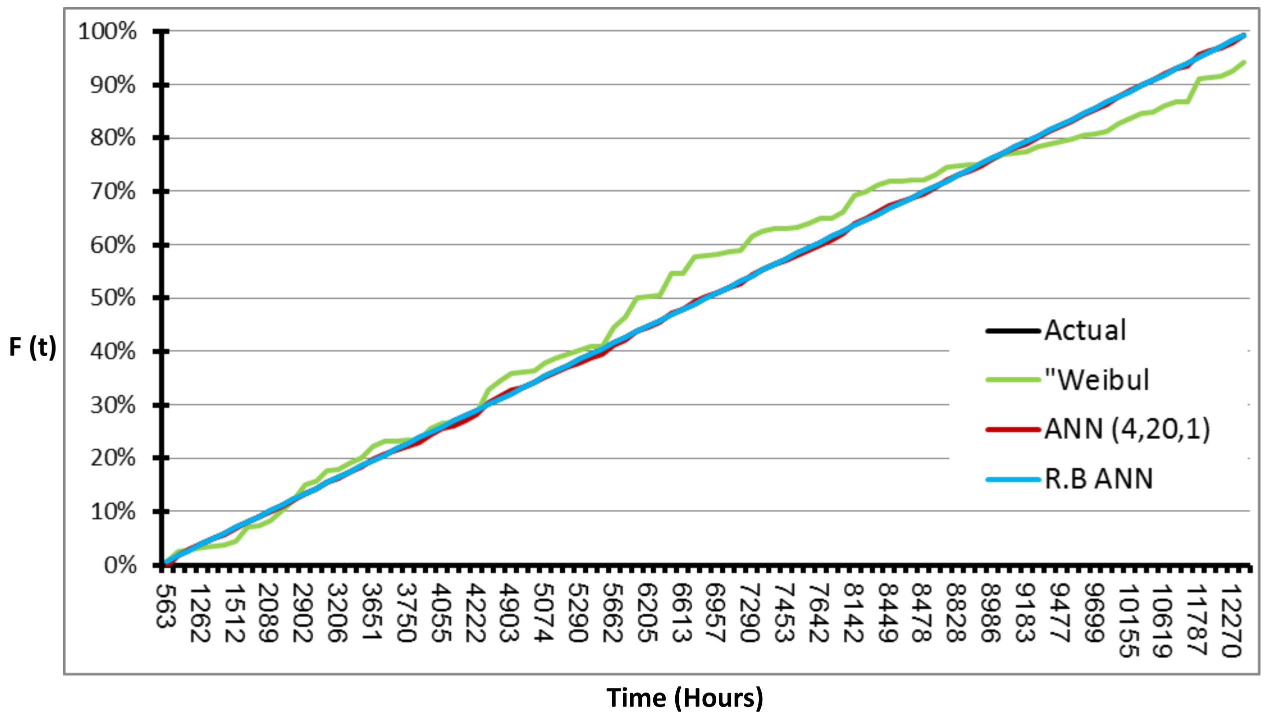


Figure 4-23 Comparison between General turbine failure data (T.T) predicted by using Weibull, (4, 20, 1) ANN structure, RB ANN and actual failure rate against time

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) about 70% was used for training of the BP ANN model and the remaining, about 30% were used for model validation, method was adopted such as that used by Al-Garni. [37]. Training and validating set 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 4-6, shows the twenty nine points about (30%) validation data and the related error of each point in relation to actual data.

Table 4-6 General turbine failure (T.T) Validation 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

Average Error (%) = 0.96028

Figure 4-24 shows the BP ANN model results of the 70% trained general turbine failure training data, and Figure 4-25 shows the 30% general turbine failure tested data.

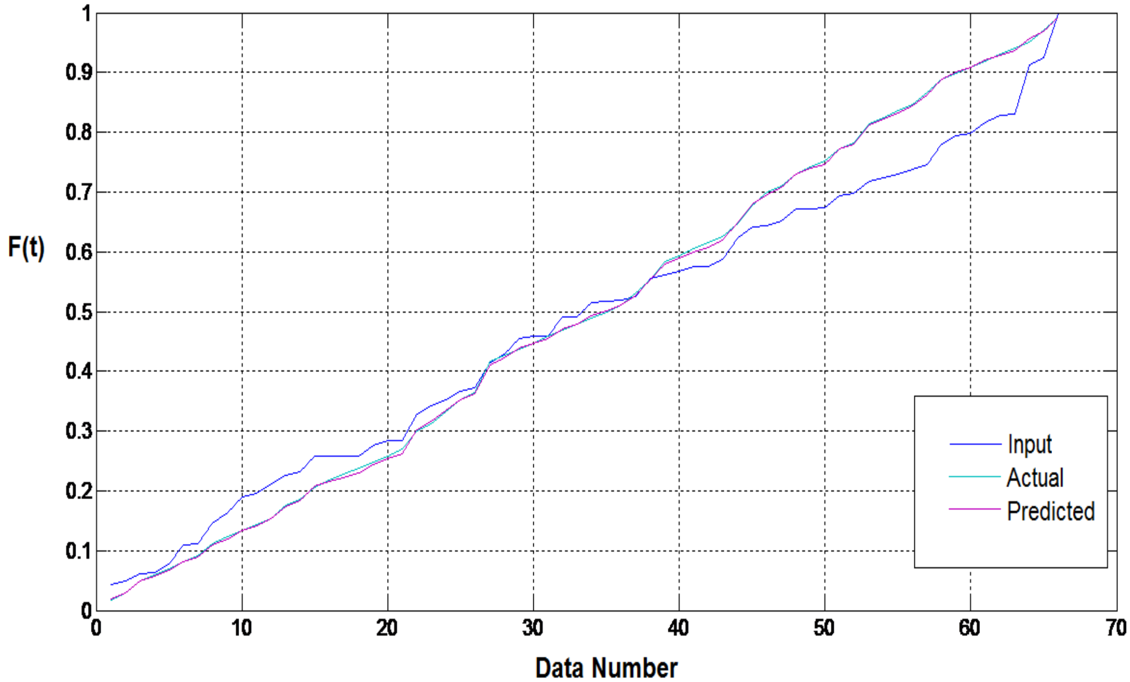


Figure 4-24 The BP ANN model results of general turbine failure (T.T) training data

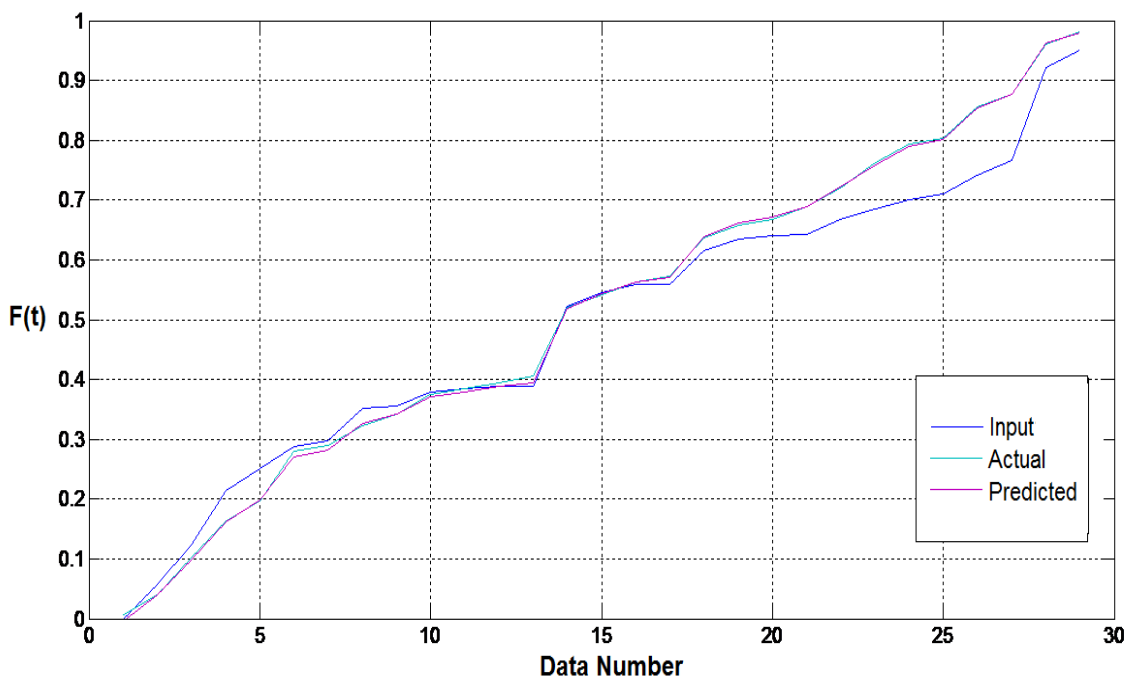


Figure 4-25 The BP ANN model results of general turbine failure (T.T) validation data

Figure 4-24 and Figure 4-25 show an excellent agreement between the trained values, and the validation 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.

Also, in the Figure 4-26, and Figure 4-27, MATLAB code was used to determine the equivalent dispersion coefficient, a descriptive statistic which measures dispersion and used to make comparisons within and between data sets, using back-propagation approach, which shows a very good symmetry between Actual data and predicted data, with average error of 2.43 %.

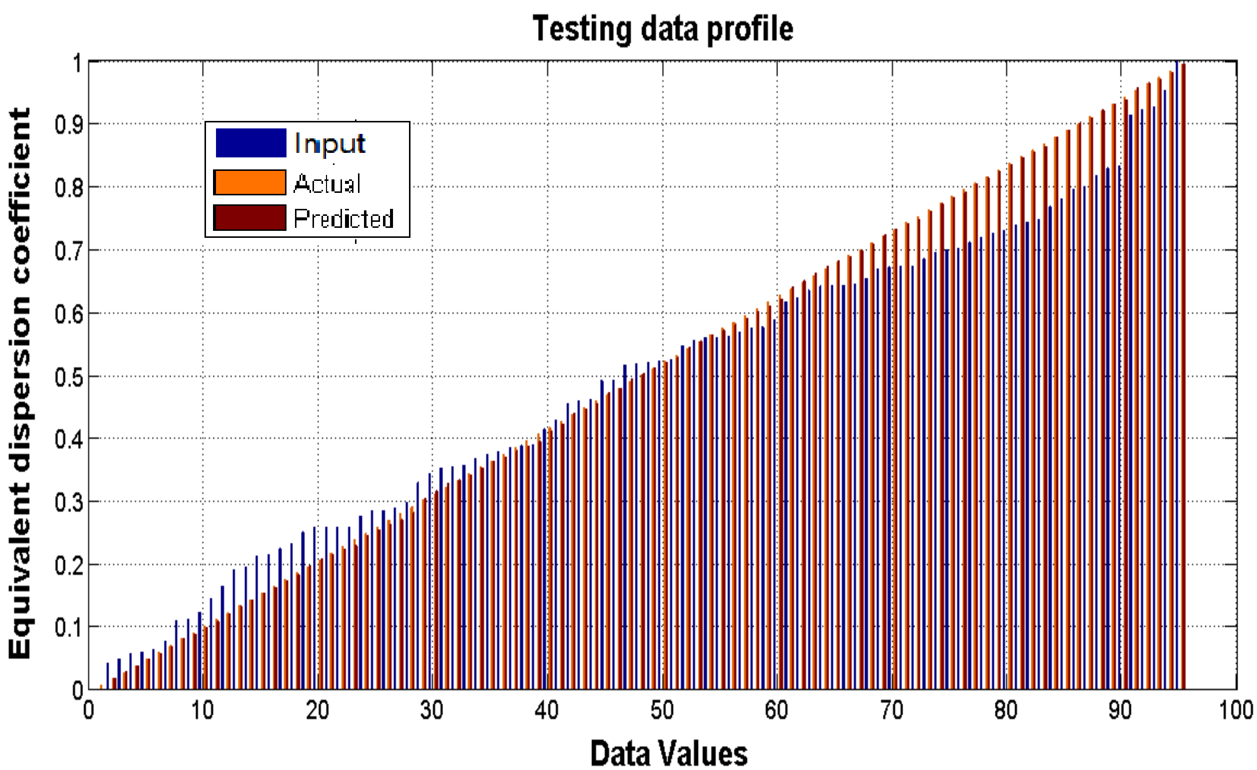


Figure 4-26 Equivalent dispersion coefficient of general turbine failure data (T.T)

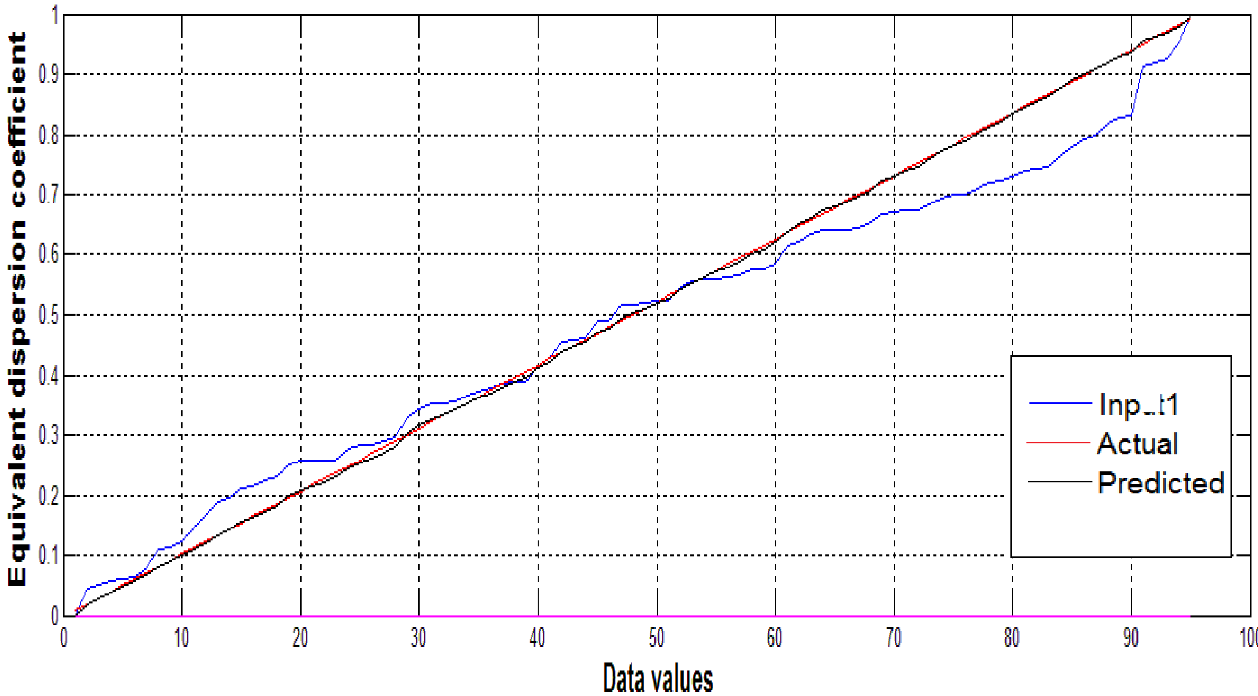


Figure 4-27 Equivalent dispersion coefficient of general turbine failure data (T.T)

4.7.2 Turbine failure which required overhaul maintenance (T.S.O) model Adequacy and Comparison

The same approach is used to evaluate turbine failure which required overhaul maintenance (T.S.O) BP ANN analysis, Table B- 2, Appendix B, and Table 4-7 show a comparison between Weibull regression, (4,20,1) BP ANN MATLAB output, and radial basis neural network model on MATLAB tool box - which gives negligible average error of (1.09E-15 %) - in relation to actual data.

Table 4-7 Comparison between turbine failure which required overhaul maintenance (T.S.O) average error predicted by Weibull, (4, 20, 1) BP ANN, and RB ANN with actual failure

Curve	Mean Percentage Error (compared to F(t))
Weibull	16.55 %
BP ANN (4,20,1)	0.84 %
Radial based ANN	1.09E-15 %

Figure 4-28 also, represents the advantage of the neural network in predicting more accurate data compared to Weibull model. That BP ANN MATLAB code with (4, 20, 1) structure, shows close agreement with radial based ANN tool box in relation to the actual data, rather than Weibull regression.

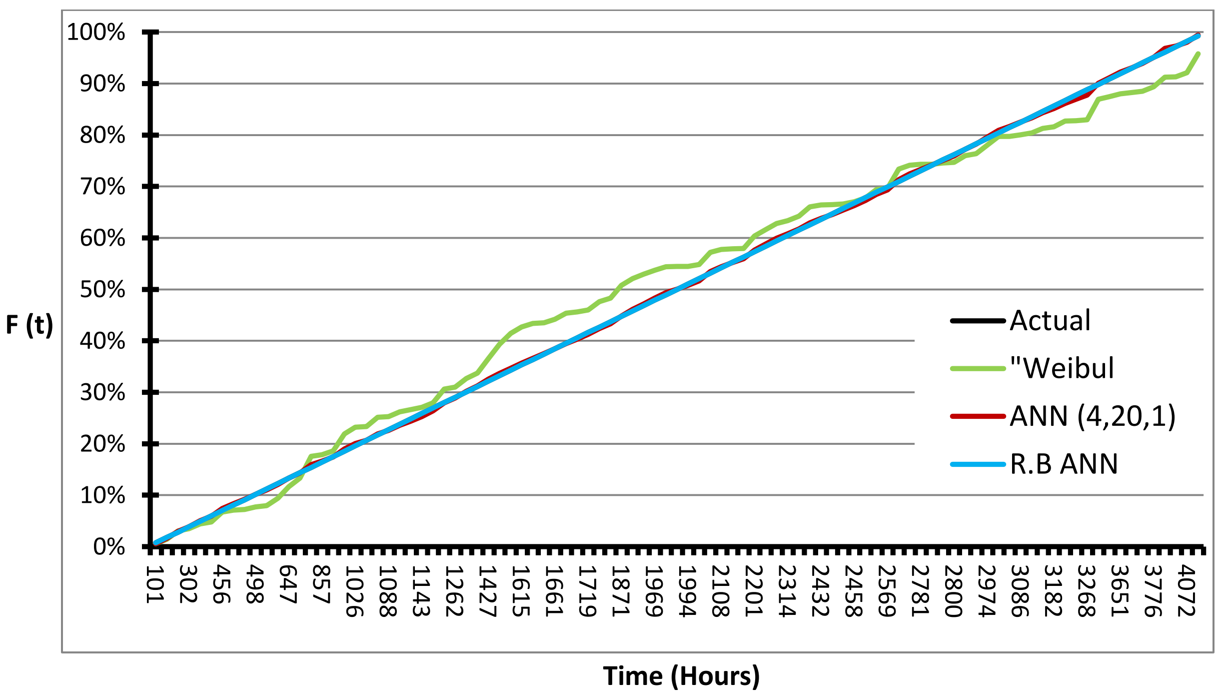


Figure 4-28 Comparison between turbine failure which required overhaul maintenance (T.S.O) predicted using Weibull, (4,20,1) ANN structure, R.B ANN and actual failure rate against time

Following the same approach to construct model validation, Table 4-8 Turbine failure which required overhaul maintenance (T.S.O) validation data, shows the twenty nine points about 30% validated data and the related error of each point in relation to actual data. The Figure 4-29, and Figure 4-30, illustrate a representative set of turbine failures which required overhaul maintenance data (T.S.O) for a set of randomly selected 70% training points and 30% validating points of the (4,20,10) BP ANN model structure, which indicate an excellent agreement between the trained values, and the tested sample in relation to the actual failure data, which prove its capability of prediction.

Table 4-8 Turbine failure which required overhaul maintenance (T.S.O) validation data

No	Target	Calculation	Error (%)
1.0	0.00734	0.00331	54.920
2.0	0.01782	0.01535	13.854
3.0	0.02830	0.02914	2.978
4.0	0.03878	0.03900	0.554
5.0	0.13312	0.13129	1.375
6.0	0.15409	0.15897	3.168
7.0	0.18553	0.18948	2.128
8.0	0.22746	0.22660	0.381
9.0	0.31132	0.30982	0.481
10.0	0.33229	0.33692	1.396
11.0	0.35325	0.35796	1.333
12.0	0.41614	0.41082	1.279
13.0	0.47904	0.48242	0.707
14.0	0.48952	0.49292	0.694
15.0	0.50000	0.50122	0.244
16.0	0.54193	0.54259	0.122
17.0	0.55241	0.55001	0.434
18.0	0.61530	0.61454	0.125
19.0	0.62579	0.62819	0.384
20.0	0.64675	0.64492	0.283
21.0	0.68868	0.68732	0.198
22.0	0.74109	0.74337	0.308
23.0	0.80398	0.80828	0.535
24.0	0.81447	0.81617	0.210
25.0	0.84591	0.84479	0.133
26.0	0.86688	0.86522	0.191
27.0	0.91929	0.92443	0.559
28.0	0.92977	0.93067	0.096
29.0	0.97170	0.96868	0.310

Average Error (%) = 0.81170

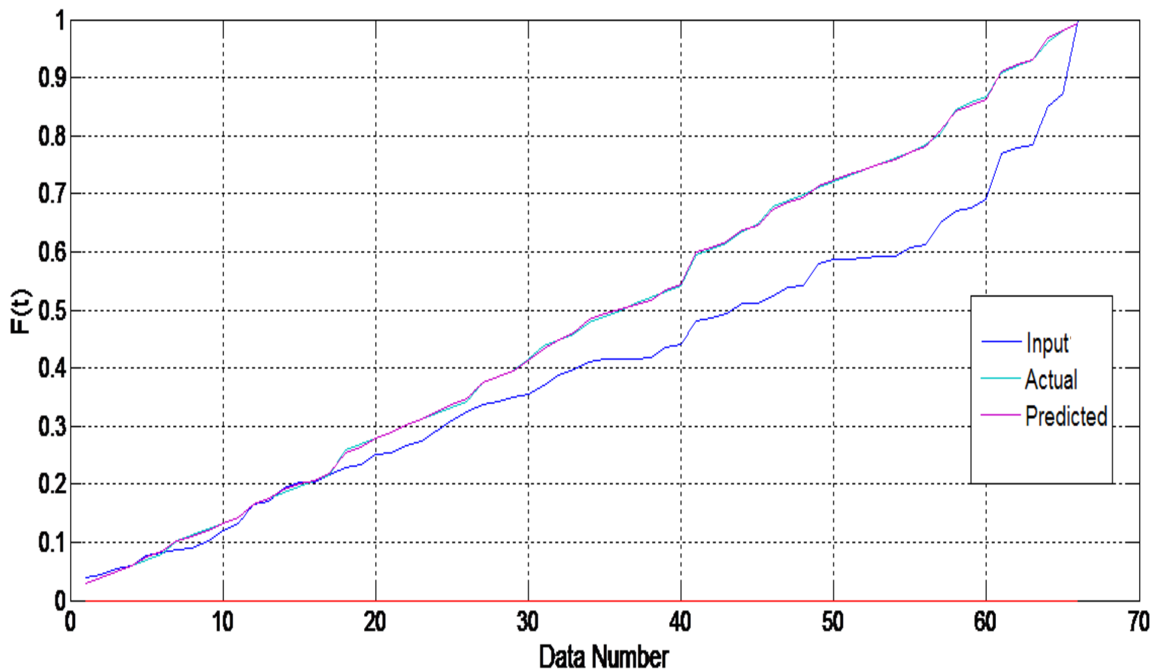


Figure 4-29 The BP ANN model result of turbine failure which required overhaul maintenance (T.S.O) training data

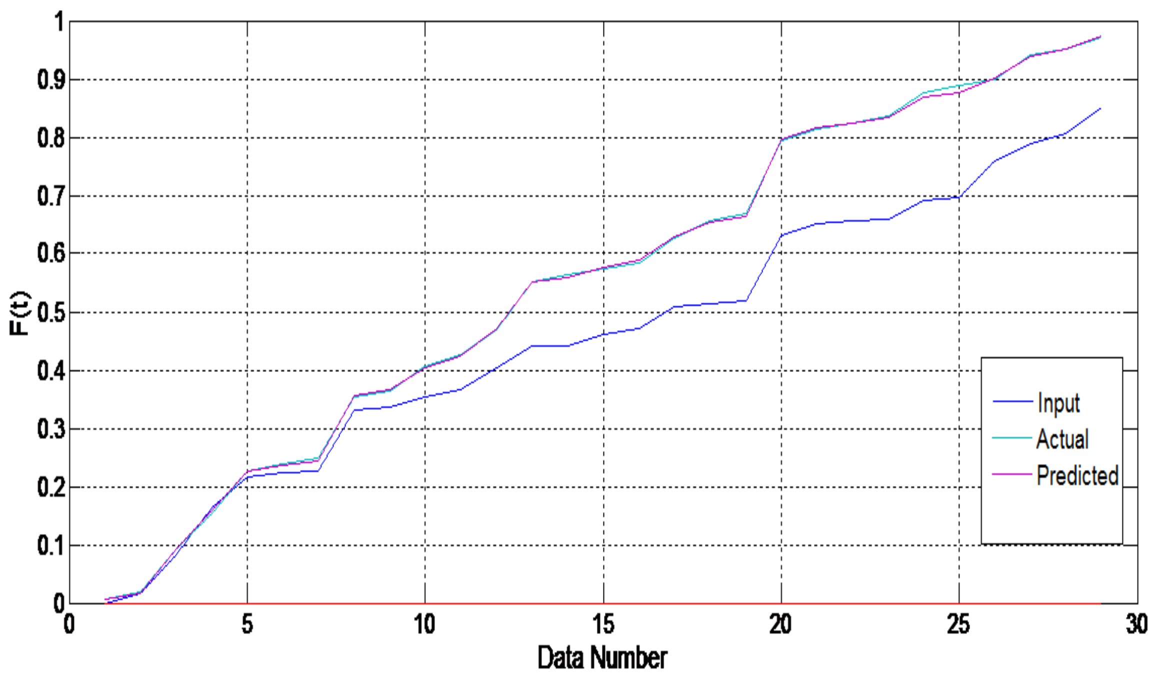


Figure 4-30 The BP ANN model result of turbine failure which required overhaul maintenance (T.S.O) testing data

Also, Figure 4-31 and Figure 4-32 determine the equivalent dispersion coefficient using back-propagation approach, which indicate a very good symmetry between Actual data and predicted data, with average error of 1.50476 %.

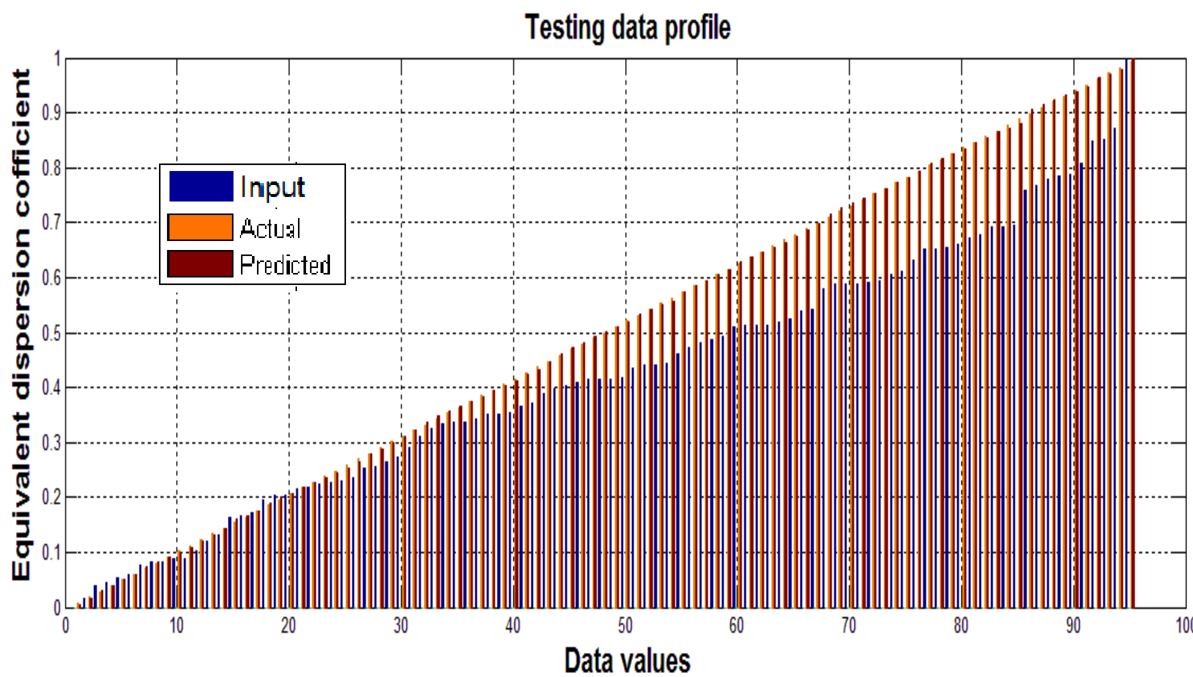


Figure 4-31 equivalent dispersion coefficient of turbine failure which required overhaul maintenance (T.S.O)

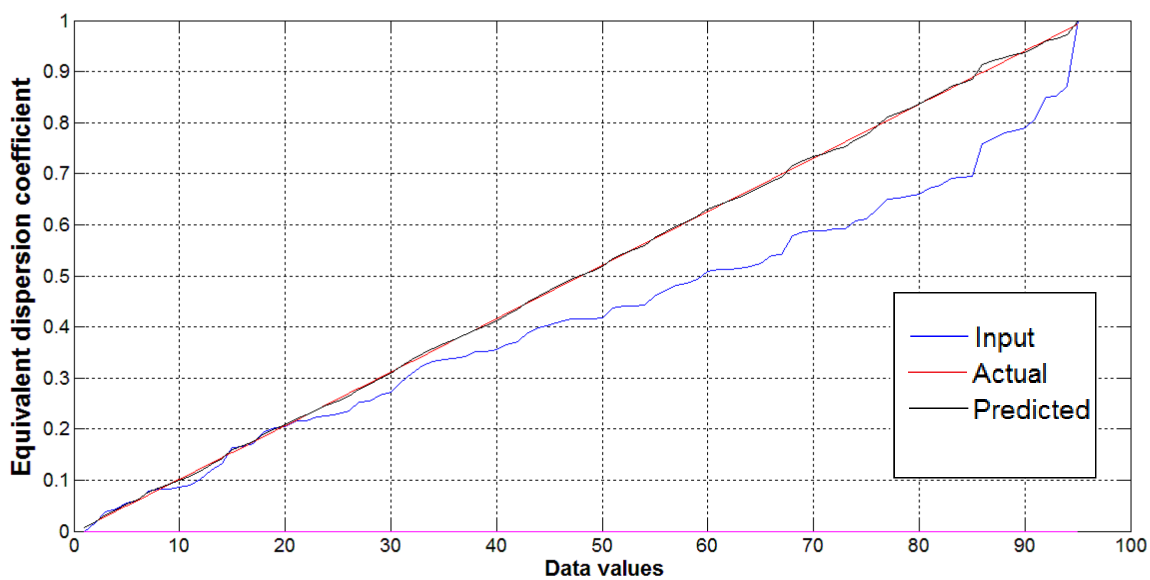


Figure 4-32 equivalent dispersion coefficient of turbine failure which required overhaul maintenance (T.S.O)

4.8 Multilayer Perceptron Neural Network

The turbine components are replaced due to many reasons. As we concluded in examining the mortality characteristics of C-130 turbine components, Page 29. The values of β come out to be more than 1, which indicates an increasing failure rate over time. The most common causes of failures in this range are corrosion, erosion, fatigue, cracking, worn out, etc. 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. Maintenance records for the Lockheed C-130 Engine turbine were reviewed in detail. This enabled the determination of whether a field removal was a confirmed failure or a "no-fault- found", thus eliminating false removals in the data. A total of 235 confirmed failures were observed for all turbines. Few items have failed sufficient often. Table 4-9 presents the common failures and replacement causes of Lockheed C-130 turbine for the whole fleet of airplanes with total number and percent contribution of each failure category.

Table 4-9 Common C-130 turbine failure and replacement causes

No.	Component failure and replacement causes	Total	
		No.	%
1	General failures	95	41.28
2	Failures required overhaul maintenances	57	24.26
3	Structures failures	51	21.70
4	Failures due to other maintenance	17	7.23
5	Failures caused Performance reduction	7	2.98
6	Leaks failures	4	1.70
7	Failures caused by Foreign object damage (FOD)	1	0.43
8	Reason not mentioned	1	0.43
TOTAL		235	100

To enhance maintenance planning, we will model all above C-130 engine turbine failures and replacement causes, using Multilayer Perceptron Neural Network (MLP) model on well-known DTREG commercial predictive modeling software [61]. DTREG software builds classification and regression Decision Trees Neural, and Multilayer Perceptron Neural Networks, Support Vector Machine, Gene Expression programs, Discriminant Analysis and Logistic Regression models that describe data relationships and can be used to predict values for future observations. It also has full support for time series analysis. It analyzes data and generates a model showing how best to predict the values of the target variable based on values of the predictor variables. DTREG can create classical, singletree models and also Tree-Boost and Decision Tree Forest models consisting of ensembles of many trees. It includes a full Data Transformation Language (DTL) for transforming variables, creating new variables and selecting which rows to analyze [62]. One of the classification/regression tools available in DTREG is MLP neural networks, like the standard MLP; DTREG-MLP consist of units arranged in layers [63]. Each layer is composed of nodes and in the fully connected network -considered here- each node connects to every node in subsequent layers. Each MLP is composed of a minimum of three layers consisting of an input layer, one or more hidden layers and an output layer. A typical three layer network is shown in Figure 4-33.

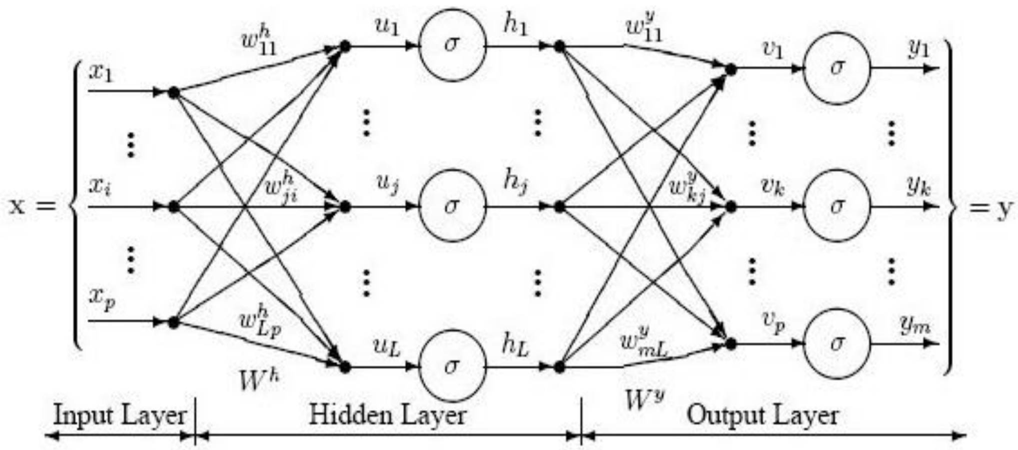


Figure 4-33 A perceptron network with three layers

Input layer – distributes the inputs to subsequent layers. Input nodes have linear activation functions and no thresholds. A vector of predictor variable values $(x_1 \ldots x_p)$ is presented to the input layer. The input layer standardizes these values by subtracting the median and dividing by the interquartile range and distributes the values to each of the neurons in the hidden layer. In addition to the predictor variables, there is a constant input of 1.0, called the bias that is fed to each of the hidden layers; the bias is multiplied by a weight and added to the sum going into the neuron.

Hidden Layer – The hidden unit nodes have nonlinear activation functions. Hence, each signal feeding into anode in a subsequent layer has the original input multiplied by a weight w_{ji} -with a threshold added-, and the resulting weighted values are added together producing a combined value u_j. The weighted sum u_j is fed into a transfer function σ, that may be linear or nonlinear (hidden units), which outputs a value h_j. The outputs from the hidden layer are distributed to the output layer. When there is more than one hidden layer, the output from one hidden layer is fed into the next hidden layer and separate weights are applied to the sum going into each layer.

Output layer – Arriving at a neuron in the output layer, the value from each hidden layer neuron is multiplied by a weight w_{kj}, and the resulting weighted values are added together producing a combined value v_j. The weighted sum v_j is fed into a linear transfer function, σ, which outputs a value v_k. The y values are the outputs of the network. If a regression analysis is being performed with a continuous target variable, then there is a single neuron in the output layer, and it generates a single y value. For classification problems with categorical target variables, there are *N* neurons in the output layer producing *N* values, one for each of the *N* categories of the target variable.

The network diagram shown in Figure 4-34 is a full-connected, three layers, feed forward perception neural network. For nearly all problems, one hidden layer is sufficient. Two hidden layers are required for modeling data with discontinuities such as a saw tooth wave pattern. Using two hidden layers rarely improves the model, and it may introduce a greater risk of converging to local minima. One of the most important characteristics of a multilayer perceptron network is the number of neurons in the hidden layer. If an inadequate number of neurons are used, the network will be unable to model complex data, and resulting in poor fit.

If too many neurons are used, the training time may become excessively long, and, worse, the network may over fit the data. When over fitting occurs, the network will begin to model random noise in the data. The result is that the model fits the training data extremely well, but it generalizes poorly to new, unseen data. Validation must be used to test for this.

DTREG includes an automated feature to find the optimal number of neurons in the hidden layer, and it will build models using varying numbers of neurons and measure the quality using either "cross validation" or "hold-out data not used for training". This is a highly effective method for finding the optimal number of neurons, but many models must be built, and each model has to be validated. [63].

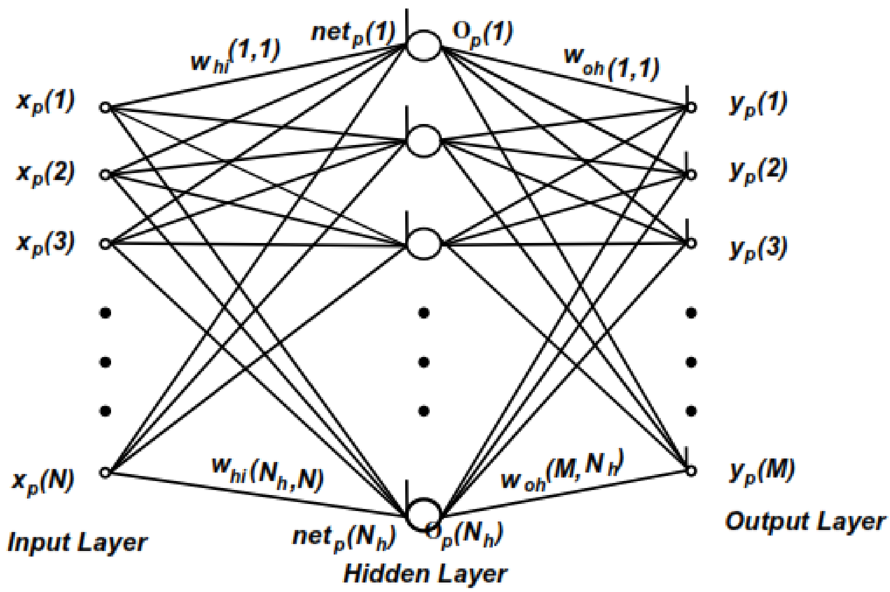


Figure 4-34 Typical three layer multilayer perceptron neural network

In Figure 4-34, the training data consist of a set N_V training pattern (x_P, t_p) where P represents the pattern number. The, X_P corresponds to the N-dimensional input vector of the P*th* training pattern and Y_P corresponds to the M-dimensional output vector from the trained network for the P*th* pattern. The input to the J*th* hidden unit $net_p(j)$ is expressed as [63]:

$$net_p(j) = \sum_{k=1}^{N+1} w_{hi}(j,k) \cdot x_p(k) \qquad 1 \le j \le N_h \tag{4.11}$$

With the output activation for the P^{th} training pattern, $O_P(j)$ being expressed by:

$$O_p(j) = f\left(net_p(j)\right) \tag{4.12}$$

The nonlinear activation is typically chosen to be the log-sigmoid function

$$f\left(net_p(j)\right) = \frac{1}{1 + e^{-net_p(j)}} \tag{4.13}$$

In Eq (4.11) and (4.12), the N input units are represented by the index K and W_{hi} (J, K) denotes the weight connecting the K^{th} input unit to the J^{th} hidden unit.

The overall performance of the MLP is measured by the mean square error MSE expressed by:

$$E = \frac{1}{N_v}\sum_{p=1}^{N_v} E_p = \frac{1}{N_v}\sum_{p=1}^{N_v}\sum_{i=1}^{M}\left[t_p(i) - y_p(i)\right]^2 \tag{4.14}$$

Where:

$$E_p = \sum_{i=1}^{M}\left[t_p(i) - y_p(i)\right]^2 \tag{4.15}$$

E_p Corresponds to the error for the P^{th} pattern and t_P is the desired output for the P^{th} pattern. This is also allows the calculation of the napping error for the i^{th} output unit to be expressed by:

$$E_i = \frac{1}{N_v}\sum_{p=1}^{N_v}\left[t_p(i) - y_p(i)\right]^2 \tag{4.16}$$

With the i^{th} output for the P^{th} training pattern expressed by:

$$y_p(i) = \sum_{k=1}^{N+1} w_{oi}(i,k)\cdot x_p(k) + \sum_{j=1}^{N_h} w_{oh}(i,j)\cdot O_p(j) \tag{4.17}$$

In (4.17), W_{oi} (i, k) represents the weight from the input nodes to the output nodes and W_{oh} (i, j) represents the weight from the hidden nodes to the output nodes.

There are several issues involved in designing and training a multilayer perceptron network:

1. Selecting how many hidden layers to use in the network.
2. Deciding how many neurons to use in each hidden layer.
3. Finding a globally optimal solution that avoids local minima.
4. Converging to an optimal solution in a reasonable period of time.
5. Validating the neural network to test for over fitting.

A full-connected, three layers, feed forward, perceptron neural network with one hidden layer will be considered in this work since these networks have been shown to approximate any "Categorical" function [64,65]. The hidden layer consists of two neurons as the DTREG calculated optimal size, and has Logistic activation function. For the actual three layers MLP, all of the inputs are connected directly to all of the outputs, and the output unit has linear activations. To find the optimal number of neurons, network size evaluation was performed using a "4-fold cross-validation" option.

Table 4-10 shows all MLP network architecture and Figure 4-35 shows DTREG determined relative importance of variables.

Table 4-10 MLP Neural network architecture

Layer	Neurons	Activation	Min. Weight	Max. Weight
Input	8	Pass-through	--	--
Hidden (1)	2	Logistic	-1.975e+001	1.664e+001
Output	1	Linear	1.586e-001	5.206e-001

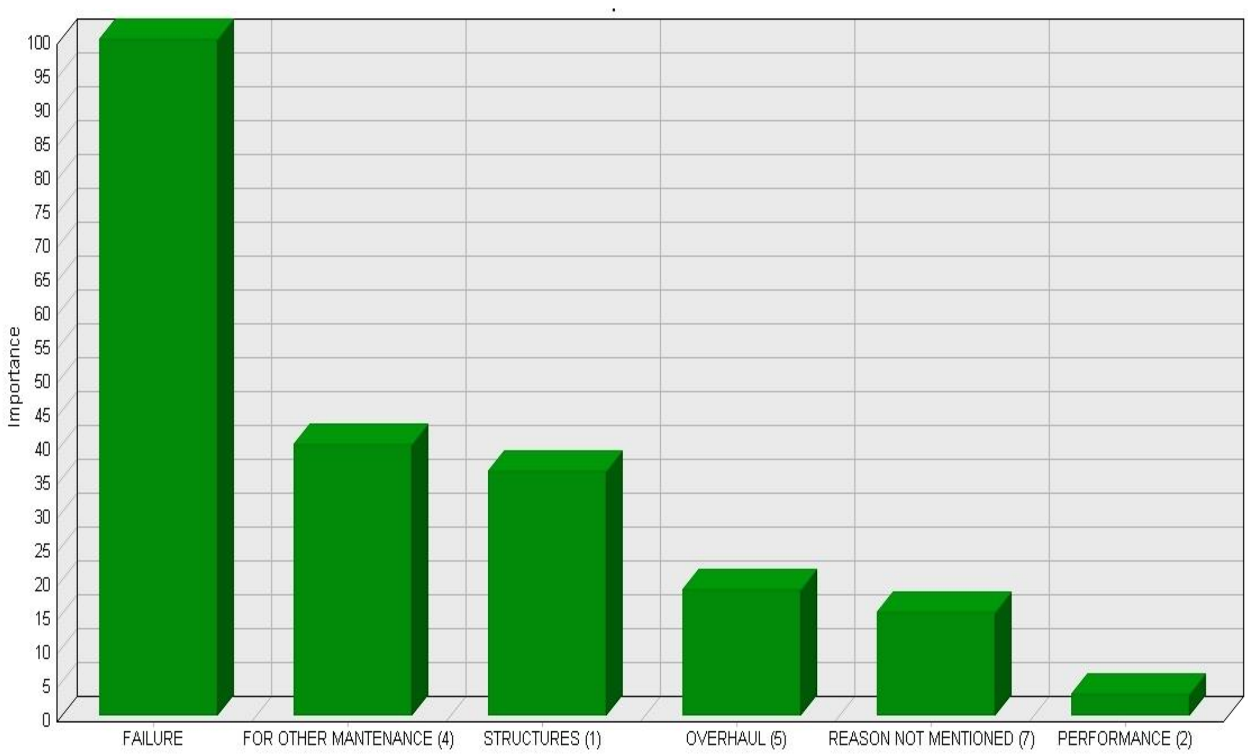


Figure 4-35 Relative importance of variables

Table 4-11 shows Training data results summary, and Table 4-12 shows Validation data results summary.

Table 4-11 MLP Training data result summary

Performance	MLP ANN 8:2:1
Mean target value for input data	6435.15
Mean target value for predicted values	6435.15
Variance in input data	1.3804e+007
Residual (unexplained) variance after model fit	5.3296e-025
Proportion of variance explained by model	100 %
Correlation between actual and predicted	1.0
Maximum error	1.819e-012
MSE (Mean Squared Error)	5.3296e-025
MAE (Mean Absolute Error)	4.2372e-013
MAPE (Mean Absolute Percentage Error)	3.4044e-014

Table 4-12 MLP Validation data results summary

Performance	MLP ANN 8:2:1
Mean target value for input data	12871.95
Mean target value for predicted values	12871.95
Variance in input data	0.8525
Residual (unexplained) variance after model fit	1.3442e-024
Proportion of variance explained by model	100 %
Correlation between actual and predicted	1.0
Maximum error	1.819e-012
MSE (Mean Squared Error)	1.3442e-024
MAE (Mean Absolute Error)	7.3896e-013
MAPE (Mean Absolute Percentage Error)	5.7409e-015

From MLP options a Time Series model has been selected to forecast future failures, in the way that the error between the predicted value of the target variable and the actual value is as small as possible. The primary difference between time series models and other types of models is that lag values of the target variable are used as predictor variables. DTREG provides automatic generation of lag variables, it includes a built-in validation system that builds a model using the first observations in the series and then evaluates (validates) the model by comparing its forecast to the remaining observations at the end of the series, we specify about a third of the data -32 observations- for validating Time Series model. DTREG will build a model using only the observations prior to these held-out observations, it will then use that model to forecast values for the observations that were held out.

Figure 4-36, Figure 4-37, Figure 4-38, and Figure 4-39 show the quality of the validated and predicted values.

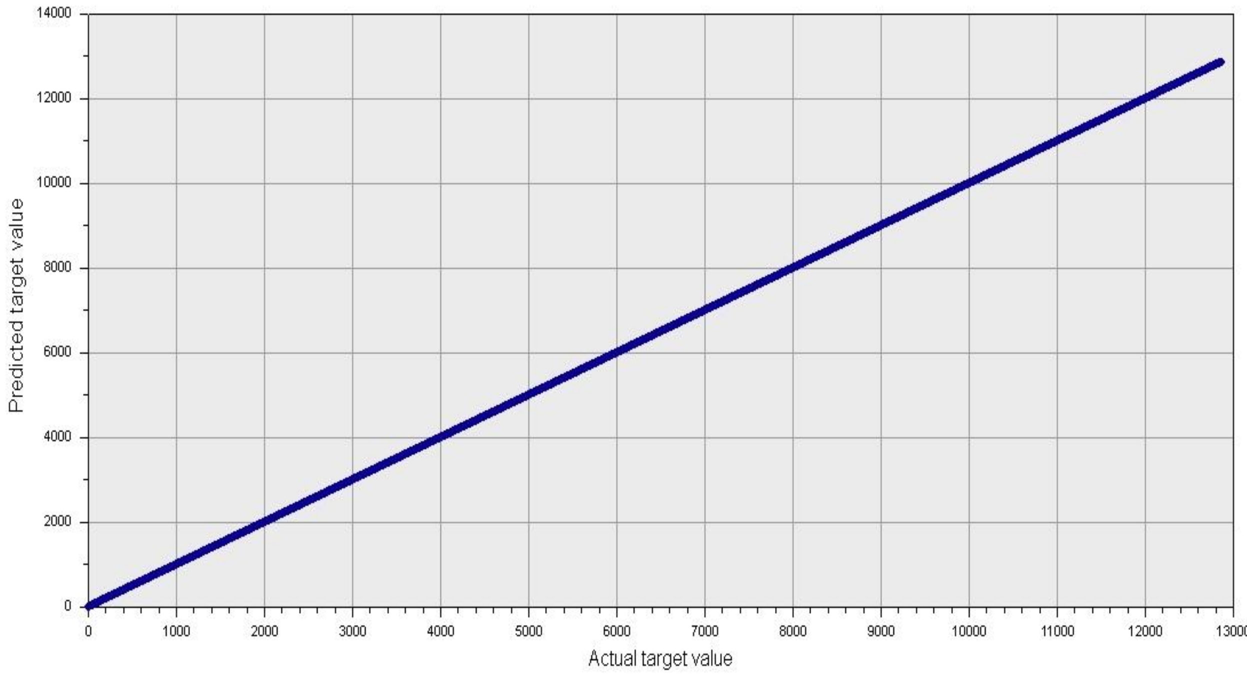


Figure 4-36 Actual versus predicted values of time

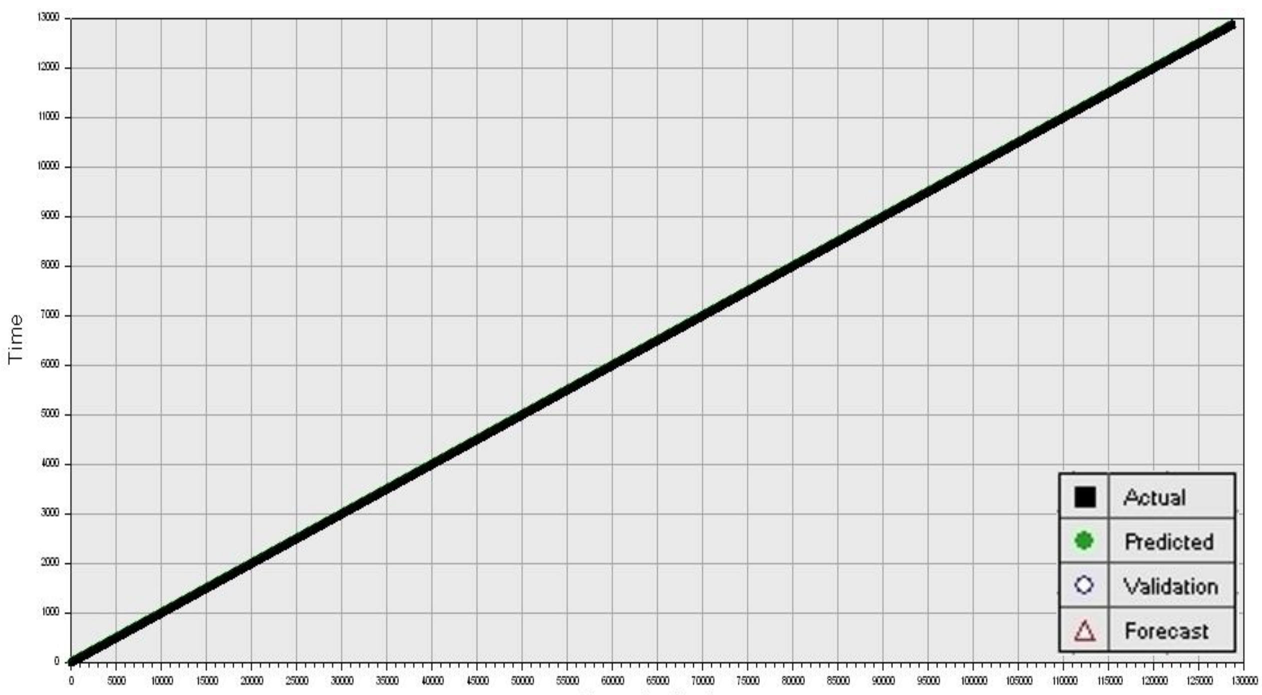


Figure 4-37 Time Series value of time

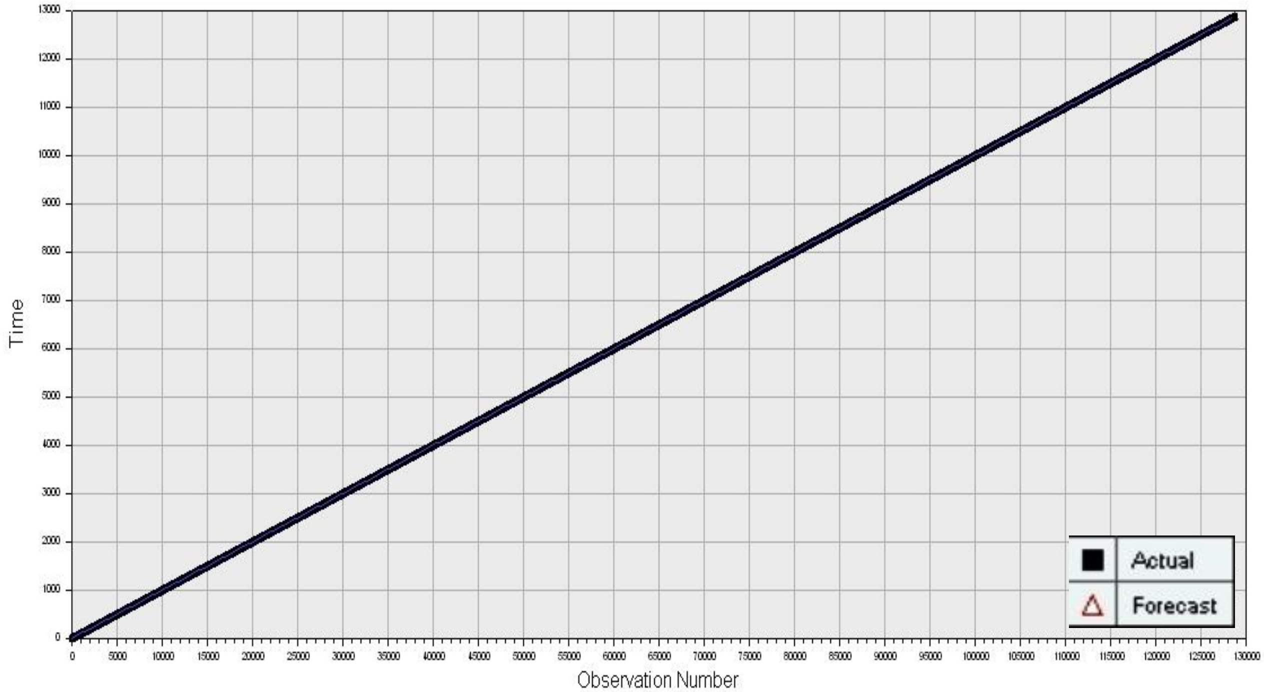


Figure 4-38 Time Series trend for time

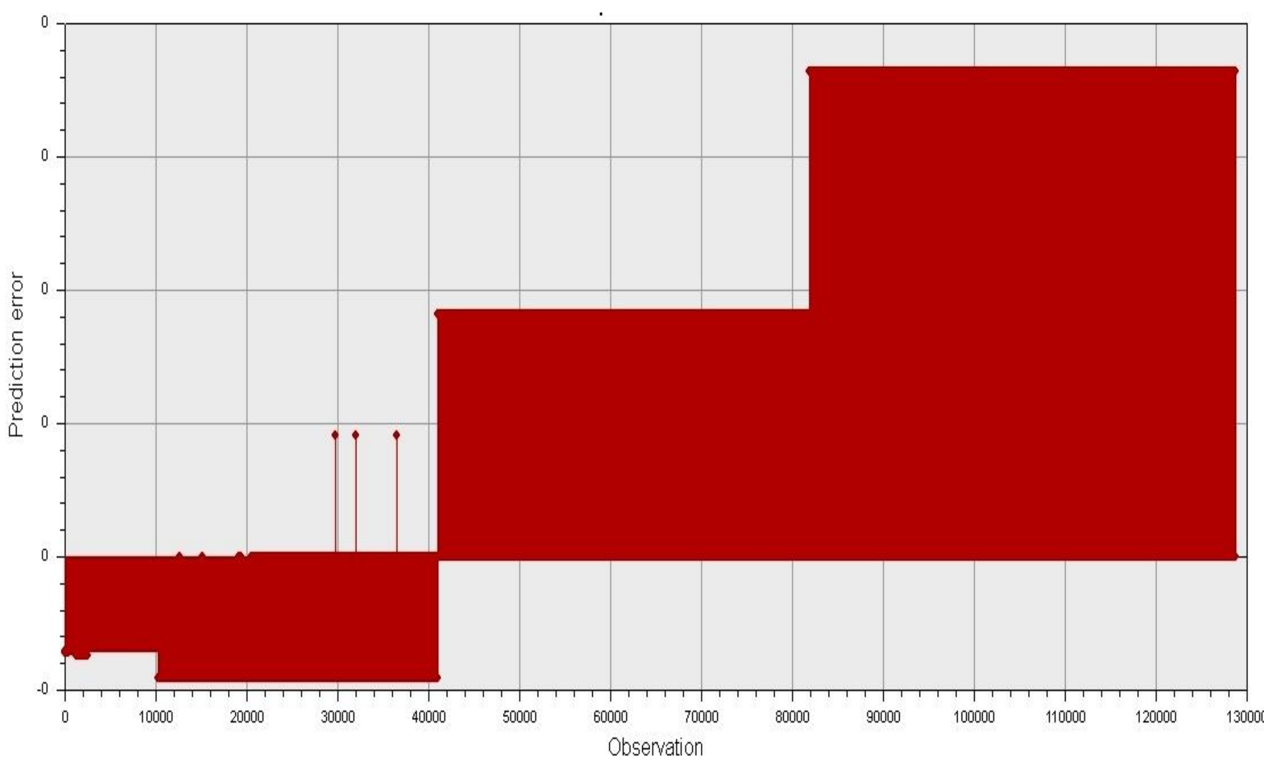


Figure 4-39 Time Series prediction error for time

CHAPTER 5

CONCLUSION AND FUTURE WORK

In this study, more than thirty years of local operational field data were used to predict and validate the failure rate of the Lockheed C-130 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. Field data is highly desirable for aircraft operators because it inherently captures the operational and environmental stresses associated with actual usage conditions which are not always possible to accurately simulate in tests conducted by the manufacturer. The main disadvantage of the field data is incomplete or lost information. But this problem is less and can be overcome in large aviation organization level which usually operates with strict data reporting requirements. Hence methods presented in this study can be used to assess the failure characteristics of any system or component and customize the manufacturer recommended maintenance program through appropriate inspection, replacement, and spare part plans based on the organization unique operational and environmental conditions.

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 high 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 62% less turbine operating hours than what is recommended by the manufacturer, due to the operation in high 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 C-130 turbine failures and overhaul requirements corresponding to an optimal level of turbine reliability.

To evaluate my MATLAB programed ANN analysis, a further radial based ANN analysis were used and gave a negligible average error in relation to actual data. A comparison between ANN MATLAB code output, and radial basis neural network model on MATLAB tool box shows 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 tool box in relation to the actual data.

From the comparison between ANN and Weibull regression models in the present application, it can be conducted that ANN model predicts better than the Weibull regression model for both cases, general failure, and failures require overhaul maintenance. Also it has 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.

Finally, to enhance maintenance planning, we have modeled general turbine failures, failures which required overhaul maintenance, and six categorical failures classified by reasons of failure and its consequences, which are: failures effecting structure, failure degrading performance, failure causing leaks, failure caused by foreign object damage (FOD), failure effecting other maintenance, and Failure with reason not mentioned, using Multilayer Perceptron Neural Network (MLP) model on DTREG commercial software. The results gave 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 to schedule a preventive policy for turbine component replacement corresponding to an optimal level of turbine reliability [66], which assists in determining logistic support for a specified planning horizon, using MLP prediction [67].

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 [6]. Figure 5-1. Also to exercise restrict hot weather and erosive environment maintenance and operational procedures, as recommended by the manufacturer.

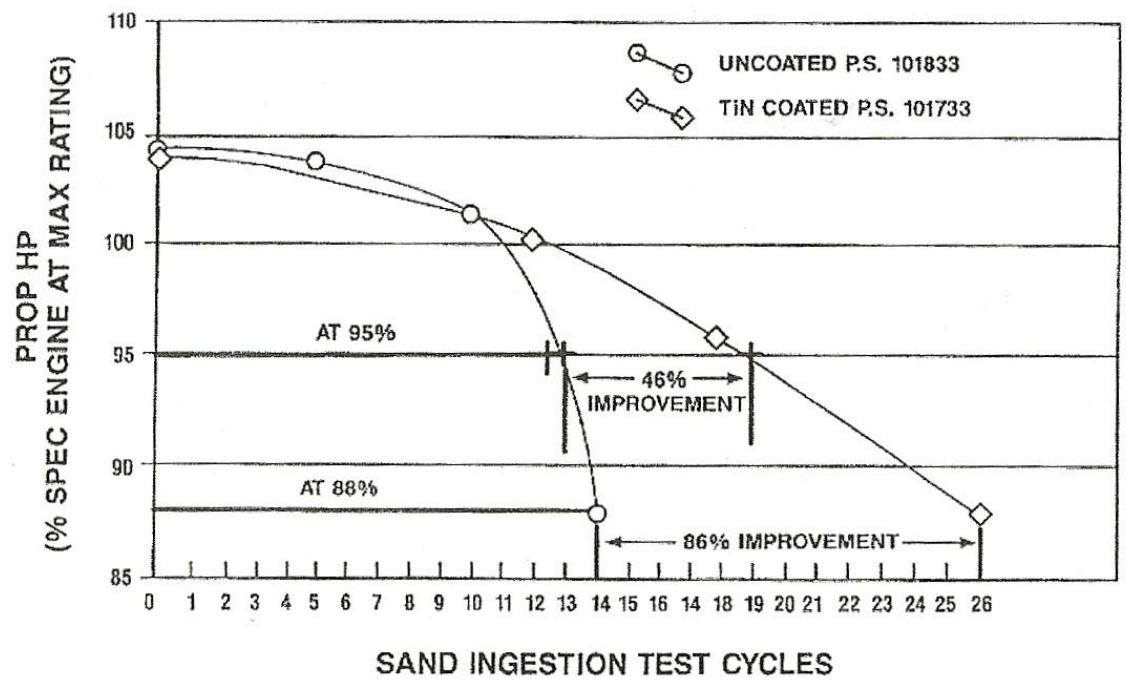


Figure 5-1 Erosion Evaluation of TiN coating turbine airfoils

To further utilize this work and to better adapt it to support maintenance strategies, there are several points that can be investigated:

- The application of this work could be extended into many areas where failure prediction becomes a dilemma. The prediction of failure rate for any component can be calculated using the same approach mentioned in this work. The key is to have an accurate failure history in order to come up with reliable calculations.

- Analyzing the effect of environmental factors in the reliability of the engine turbine, by categorizing the failure data gathered from the field by the season. As it is well known that cold season has major effects in leaks failures, and hot season has a major effects in performance reduction failures.

- Investigating and comparing different ANN schemes would yield to valuable information on the best scheme for a particular failure type. As example using Probabilistic (PNN) and General Regression Neural Networks (GRNN).

- Using hybrid approaches, which are a combination of ANN with other techniques like expert systems, Fuzzy logic and Genetic Algorithm (GA) to make such analysis.

- Based on the results presented in this work, an optimization procedure could be developed for an efficient preventive maintenance plan, taking into account the preventive maintenance time, as well as repair time. Based on the manufacturer acceptable reliability values, the downtime for maintenance could be minimized without compromising the safety of the flight.

- The optimum replacement age in flight hours can be calculated for various (cost of in-service failure to cost of planned replacement) ratios. If the cost for an unplanned failure is very high compared to a planned replacement, then beta greater than 1 is easy to handle on a predictive replacement basis. However, if the cost of an unplanned failure is approximately equal to a planned replacement then it is advised to run the component to failure. If the failures modes are due to chance failure (β=1) or infant mortality (β<1), then the component should run to failure for any ratio of costs.

- This study can be a great tool for spare part inventory planning. Having accurate failure predictions figures will reduce cost and enhance aircraft availability. The other benefit is to avoid over stocking which in turns decreases the warehouse storage capability.

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Appendix A

Table A- 1 Weibull analysis for C-130 general turbine failure data (T.T)

Turbine (T.T) "hours"	Rank (i)	Median Ranks $F(t)$	1/(1-$F(t)$)	ln(ln(1/(1-$F(t)$)))	ln(Turbine(T.T))	Predicted ln(ln(1/(1-$F(t)$)))	CDF
562.9	1	0.00734	1.00739	-4.91107	6.33310	-4.97018	0.00692
1088.20	2	0.01782	1.01814	-4.01847	6.99228	-3.70274	0.02435
1169.70	3	0.02830	1.02913	-3.55051	7.06450	-3.56388	0.02793
1261.50	4	0.03878	1.04035	-3.23003	7.14006	-3.41860	0.03223
1310.90	5	0.04927	1.05182	-2.98536	7.17847	-3.34474	0.03465
1343.50	6	0.05975	1.06355	-2.78697	7.20303	-3.29751	0.03630
1511.70	7	0.07023	1.07554	-2.61978	7.32099	-3.07071	0.04533
1915.3	8	0.08071	1.08780	-2.47507	7.55763	-2.61571	0.07051
1942.6	9	0.09119	1.10035	-2.34732	7.57178	-2.58850	0.07238
2088.6	10	0.10168	1.11319	-2.23282	7.64425	-2.44916	0.08274
2347.70	11	0.11216	1.12633	-2.12894	7.76119	-2.22431	0.10250
2586.30	12	0.12264	1.13978	-2.03378	7.85798	-2.03820	0.12214
2901.80	13	0.13312	1.15357	-1.94590	7.97309	-1.81689	0.15001
2973.6	14	0.14361	1.16769	-1.86417	7.99753	-1.76989	0.15663
3173.60	15	0.15409	1.18216	-1.78773	8.06262	-1.64473	0.17557
3206.10	16	0.16457	1.19699	-1.71586	8.07281	-1.62514	0.17871
3332.40	17	0.17505	1.21220	-1.64799	8.11145	-1.55085	0.19109
3427.20	18	0.18553	1.22780	-1.58366	8.13950	-1.49692	0.20054
3650.60	19	0.19602	1.24381	-1.52245	8.20265	-1.37550	0.22331
3730.20	20	0.20650	1.26024	-1.46404	8.22422	-1.33402	0.23158
3732.9	21	0.21698	1.27711	-1.40814	8.22494	-1.33263	0.23186
3749.90	22	0.22746	1.29444	-1.35450	8.22948	-1.32390	0.23364
3751.50	23	0.23795	1.31224	-1.30292	8.22991	-1.32307	0.23380
3969.10	24	0.24843	1.33054	-1.25321	8.28629	-1.21466	0.25681
4055.40	25	0.25891	1.34936	-1.20520	8.30780	-1.17330	0.26607
4066.60	26	0.26939	1.36872	-1.15875	8.31056	-1.16800	0.26728
4116.70	27	0.27987	1.38865	-1.11374	8.32281	-1.14446	0.27269
4222.20	28	0.29036	1.40916	-1.07005	8.34811	-1.09580	0.28414
4615.70	29	0.30084	1.43028	-1.02758	8.43722	-0.92447	0.32749

4780.00	30	0.31132	1.45205	-0.98623	8.47220	-0.85722	0.34580
4902.90	31	0.32180	1.47450	-0.94593	8.49758	-0.80841	0.35954
4912.70	32	0.33229	1.49765	-0.90660	8.49958	-0.80457	0.36064
4948.10	33	0.34277	1.52153	-0.86817	8.50676	-0.79076	0.36460
5074.00	34	0.35325	1.54619	-0.83058	8.53188	-0.74245	0.37870
5160.30	35	0.36373	1.57166	-0.79377	8.54875	-0.71002	0.38837
5218.50	36	0.37421	1.59799	-0.75769	8.55997	-0.68846	0.39489
5289.90	37	0.38470	1.62521	-0.72229	8.57355	-0.66233	0.40289
5342.10	38	0.39518	1.65338	-0.68752	8.58337	-0.64345	0.40873
5351.10	39	0.40566	1.68254	-0.65334	8.58506	-0.64021	0.40973
5661.60	40	0.41614	1.71275	-0.61971	8.64146	-0.53176	0.44432
5839.8	41	0.42662	1.74406	-0.58660	8.67245	-0.47218	0.46401
6167.9	42	0.43711	1.77654	-0.55397	8.72711	-0.36707	0.49981
6205.00	43	0.44759	1.81025	-0.52178	8.73311	-0.35554	0.50381
6222.90	44	0.45807	1.84526	-0.49001	8.73599	-0.35000	0.50574
6606.80	45	0.46855	1.88166	-0.45862	8.79585	-0.23490	0.54645
6612.90	46	0.47904	1.91952	-0.42760	8.79678	-0.23313	0.54709
6910.30	47	0.48952	1.95893	-0.39690	8.84077	-0.14854	0.57767
6927.7	48	0.50000	2.00000	-0.36651	8.84328	-0.14371	0.57943
6956.90	49	0.51048	2.04283	-0.33640	8.84749	-0.13562	0.58238
6996.6	50	0.52096	2.08753	-0.30655	8.85318	-0.12468	0.58637
7019.10	51	0.53145	2.13423	-0.27693	8.85639	-0.11851	0.58862
7290.10	52	0.54193	2.18307	-0.24753	8.89427	-0.04567	0.61533
7392.70	53	0.55241	2.23419	-0.21831	8.90825	-0.01880	0.62521
7449.60	54	0.56289	2.28777	-0.18925	8.91592	-0.00405	0.63063
7453.20	55	0.57338	2.34398	-0.16034	8.91640	-0.00312	0.63097
7475.10	56	0.58386	2.40302	-0.13156	8.91933	0.00252	0.63305
7538.5	57	0.59434	2.46512	-0.10288	8.92778	0.01876	0.63902
7642.20	58	0.60482	2.53050	-0.07427	8.94144	0.04503	0.64868
7654.30	59	0.61530	2.59946	-0.04573	8.94302	0.04807	0.64980
7781.50	60	0.62579	2.67227	-0.01722	8.95950	0.07976	0.66143
8141.60	61	0.63627	2.74928	0.01128	9.00474	0.16674	0.69317
8226.90	62	0.64675	2.83086	0.03978	9.01516	0.18678	0.70042

8368.8	63	0.65723	2.91743	0.06832	9.03227	0.21966	0.71225
8448.70	64	0.66771	3.00946	0.09691	9.04177	0.23793	0.71878
8453.60	65	0.67820	3.10749	0.12559	9.04235	0.23905	0.71918
8472.00	66	0.68868	3.21212	0.15438	9.04452	0.24323	0.72067
8477.60	67	0.69916	3.32404	0.18331	9.04518	0.24450	0.72112
8596.80	68	0.70964	3.44404	0.21240	9.05915	0.27134	0.73064
8792.20	69	0.72013	3.57303	0.24170	9.08162	0.31456	0.74580
8828.40	70	0.73061	3.71206	0.27124	9.08573	0.32246	0.74855
8843.30	71	0.74109	3.86235	0.30105	9.08742	0.32570	0.74968
8844.5	72	0.75157	4.02532	0.33118	9.08755	0.32596	0.74977
8985.70	73	0.76205	4.20264	0.36166	9.10339	0.35641	0.76026
9104.70	74	0.77254	4.39631	0.39256	9.11655	0.38171	0.76887
9162.90	75	0.78302	4.60870	0.42392	9.12292	0.39396	0.77301
9183.3	76	0.79350	4.84264	0.45582	9.12514	0.39824	0.77445
9311.70	77	0.80398	5.10160	0.48831	9.13903	0.42494	0.78335
9406.20	78	0.81447	5.38983	0.52148	9.14912	0.44435	0.78975
9476.70	79	0.82495	5.71257	0.55542	9.15659	0.45871	0.79444
9540.4	80	0.83543	6.07643	0.59024	9.16329	0.47159	0.79862
9654.20	81	0.84591	6.48980	0.62606	9.17515	0.49439	0.80592
9699.30	82	0.85639	6.96350	0.66304	9.17981	0.50335	0.80877
9757.30	83	0.86688	7.51181	0.70135	9.18577	0.51481	0.81238
10004.7	84	0.87736	8.15385	0.74122	9.21081	0.56296	0.82724
10155.30	85	0.88784	8.91589	0.78291	9.22575	0.59169	0.83586
10330.2	86	0.89832	9.83505	0.82678	9.24283	0.62452	0.84547
10388.50	87	0.90881	10.96552	0.87328	9.24845	0.63534	0.84857
10618.60	88	0.91929	12.38961	0.92301	9.27036	0.67746	0.86039
10761.00	89	0.92977	14.23881	0.97681	9.28368	0.70308	0.86734
10791.90	90	0.94025	16.73684	1.03589	9.28655	0.70859	0.86881
11787.30	91	0.95073	20.29787	1.10211	9.37478	0.87823	0.90988
11895.5	92	0.96122	25.78378	1.17858	9.38392	0.89580	0.91365
11956.20	93	0.97170	35.33333	1.27112	9.38901	0.90558	0.91570
12270.40	94	0.98218	56.11765	1.39313	9.41495	0.95546	0.92572
12873.50	95	0.99266	136.28571	1.59224	9.46293	1.04772	0.94222

Table A- 2 KS GOF test for general turbine failure data (T.T)

ROW	Hours	F_0	F_n	F_{n-1}	D+	D-
1	562.9	0.00692	0.01042	0.00000	0.00350	0.00692
2	1088.2	0.02435	0.02083	0.01053	-0.00352	0.01383
3	1169.7	0.02793	0.03125	0.02105	0.00332	0.00688
4	1261.5	0.03223	0.04167	0.03158	0.00944	0.00065
5	1310.9	0.03465	0.05208	0.04211	0.01743	-0.00745
6	1343.5	0.03630	0.06250	0.05263	0.02620	-0.01633
7	1511.7	0.04533	0.07292	0.06316	0.02759	-0.01783
8	1915.3	0.07051	0.08333	0.07368	0.01283	-0.00318
9	1942.6	0.07238	0.09375	0.08421	0.02137	-0.01183
10	2088.6	0.08274	0.10417	0.09474	0.02143	-0.01200
11	2347.7	0.10250	0.11458	0.10526	0.01208	-0.00276
12	2586.3	0.12214	0.12500	0.11579	0.00286	0.00635
13	2901.8	0.15001	0.13542	0.12632	-0.01459	0.02369
14	2973.6	0.15663	0.14583	0.13684	-0.01080	0.01979
15	3173.6	0.17557	0.15625	0.14737	-0.01932	0.02820
16	3206.1	0.17871	0.16667	0.15789	-0.01205	0.02082
17	3332.4	0.19109	0.17708	0.16842	-0.01401	0.02267
18	3427.2	0.20054	0.18750	0.17895	-0.01304	0.02159
19	3650.6	0.22331	0.19792	0.18947	-0.02539	0.03384
20	3730.2	0.23158	0.20833	0.20000	-0.02324	0.03158
21	3732.9	0.23186	0.21875	0.21053	-0.01311	0.02133
22	3749.9	0.23364	0.22917	0.22105	-0.00447	0.01258
23	3751.5	0.23380	0.23958	0.23158	0.00578	0.00222
24	3969.1	0.25681	0.25000	0.24211	-0.00681	0.01471
25	4055.4	0.26607	0.26042	0.25263	-0.00565	0.01344
26	4066.6	0.26728	0.27083	0.26316	0.00356	0.00412
27	4116.7	0.27269	0.28125	0.27368	0.00856	-0.00100
28	4222.2	0.28414	0.29167	0.28421	0.00753	-0.00007
29	4615.7	0.32749	0.30208	0.29474	-0.02541	0.03275
30	4780	0.34580	0.31250	0.30526	-0.03330	0.04054

31	4902.9	0.35954	0.32292	0.31579	-0.03662	0.04375
32	4912.7	0.36064	0.33333	0.32632	-0.02730	0.03432
33	4948.1	0.36460	0.34375	0.33684	-0.02085	0.02776
34	5074	0.37870	0.35417	0.34737	-0.02454	0.03133
35	5160.3	0.38837	0.36458	0.35789	-0.02379	0.03048
36	5218.5	0.39489	0.37500	0.36842	-0.01989	0.02647
37	5289.9	0.40289	0.38542	0.37895	-0.01747	0.02394
38	5342.1	0.40873	0.39583	0.38947	-0.01289	0.01925
39	5351.1	0.40973	0.40625	0.40000	-0.00348	0.00973
40	5661.6	0.44432	0.41667	0.41053	-0.02766	0.03380
41	5839.8	0.46401	0.42708	0.42105	-0.03693	0.04296
42	6167.9	0.49981	0.43750	0.43158	-0.06231	0.06823
43	6205	0.50381	0.44792	0.44211	-0.05589	0.06170
44	6222.9	0.50574	0.45833	0.45263	-0.04740	0.05310
45	6606.8	0.54645	0.46875	0.46316	-0.07770	0.08329
46	6612.9	0.54709	0.47917	0.47368	-0.06792	0.07340
47	6910.3	0.57767	0.48958	0.48421	-0.08808	0.09346
48	6927.7	0.57943	0.50000	0.49474	-0.07943	0.08469
49	6956.9	0.58238	0.51042	0.50526	-0.07196	0.07711
50	6996.6	0.58637	0.52083	0.51579	-0.06554	0.07058
51	7019.1	0.58862	0.53125	0.52632	-0.05737	0.06231
52	7290.1	0.61533	0.54167	0.53684	-0.07366	0.07848
53	7392.7	0.62521	0.55208	0.54737	-0.07312	0.07784
54	7449.6	0.63063	0.56250	0.55789	-0.06813	0.07273
55	7453.2	0.63097	0.57292	0.56842	-0.05805	0.06255
56	7475.1	0.63305	0.58333	0.57895	-0.04971	0.05410
57	7538.5	0.63902	0.59375	0.58947	-0.04527	0.04955
58	7642.2	0.64868	0.60417	0.60000	-0.04451	0.04868
59	7654.3	0.64980	0.61458	0.61053	-0.03521	0.03927
60	7781.5	0.66143	0.62500	0.62105	-0.03643	0.04038
61	8141.6	0.69317	0.63542	0.63158	-0.05775	0.06159
62	8226.9	0.70042	0.64583	0.64211	-0.05458	0.05831
63	8368.8	0.71225	0.65625	0.65263	-0.05600	0.05962

64	8448.7	0.71878	0.66667	0.66316	-0.05211	0.05562
65	8453.6	0.71918	0.67708	0.67368	-0.04210	0.04549
66	8472	0.72067	0.68750	0.68421	-0.03317	0.03646
67	8477.6	0.72112	0.69792	0.69474	-0.02320	0.02638
68	8596.8	0.73064	0.70833	0.70526	-0.02231	0.02538
69	8792.2	0.74580	0.71875	0.71579	-0.02705	0.03002
70	8828.4	0.74855	0.72917	0.72632	-0.01938	0.02224
71	8843.3	0.74968	0.73958	0.73684	-0.01009	0.01283
72	8844.5	0.74977	0.75000	0.74737	0.00023	0.00240
73	8985.7	0.76026	0.76042	0.75789	0.00016	0.00237
74	9104.7	0.76887	0.77083	0.76842	0.00196	0.00045
75	9162.9	0.77301	0.78125	0.77895	0.00824	-0.00594
76	9183.3	0.77445	0.79167	0.78947	0.01722	-0.01503
77	9311.7	0.78335	0.80208	0.80000	0.01873	-0.01665
78	9406.2	0.78975	0.81250	0.81053	0.02275	-0.02077
79	9476.7	0.79444	0.82292	0.82105	0.02847	-0.02661
80	9540.4	0.79862	0.83333	0.83158	0.03472	-0.03296
81	9654.2	0.80592	0.84375	0.84211	0.03783	-0.03618
82	9699.3	0.80877	0.85417	0.85263	0.04540	-0.04387
83	9757.3	0.81238	0.86458	0.86316	0.05221	-0.05078
84	10004.7	0.82724	0.87500	0.87368	0.04776	-0.04644
85	10155.3	0.83586	0.88542	0.88421	0.04956	-0.04835
86	10330.2	0.84547	0.89583	0.89474	0.05037	-0.04927
87	10388.5	0.84857	0.90625	0.90526	0.05768	-0.05669
88	10618.6	0.86039	0.91667	0.91579	0.05628	-0.05540
89	10761	0.86734	0.92708	0.92632	0.05974	-0.05898
90	10791.9	0.86881	0.93750	0.93684	0.06869	-0.06803
91	11787.3	0.90988	0.94792	0.94737	0.03803	-0.03749
92	11895.5	0.91365	0.95833	0.95789	0.04469	-0.04425
93	11956.2	0.91570	0.96875	0.96842	0.05305	-0.05272
94	12270.4	0.92572	0.97917	0.97895	0.05345	-0.05323
95	12873.5	0.94222	0.98958	0.98947	0.04736	-0.04725
MAX=					**0.09346**	**0.09346**

Table A- 3 Weibull analysis for C-130 failures required overhaul maintenance (T.S.O)

Turbine (TSO)	Rank (*i*)	Median Ranks *F(t)*	1/(1-*F(t)*)	ln(ln(1/(1-*F(t)*)))	ln(Turbine(T.T))	Predicted ln(ln(1/(1-*F(t)*)))	CDF
100.9	1	0.00734	1.00739	-4.91107	4.61413	-5.13711	0.00586
177.20	2	0.01782	1.01814	-4.01847	5.17728	-4.21280	0.01470
277.10	3	0.02830	1.02913	-3.55051	5.62438	-3.47896	0.03037
301.50	4	0.03878	1.04035	-3.23003	5.70877	-3.34044	0.03480
350.80	5	0.04927	1.05182	-2.98536	5.86022	-3.09187	0.04440
368.40	6	0.05975	1.06355	-2.78697	5.90917	-3.01152	0.04803
456.00	7	0.07023	1.07554	-2.61978	6.12249	-2.66138	0.06747
472.3	8	0.08071	1.08780	-2.47507	6.15761	-2.60374	0.07132
475.7	9	0.09119	1.10035	-2.34732	6.16479	-2.59197	0.07214
497.7	10	0.10168	1.11319	-2.23282	6.21000	-2.51776	0.07747
507.90	11	0.11216	1.12633	-2.12894	6.23028	-2.48446	0.07999
562.90	12	0.12264	1.13978	-2.03378	6.33310	-2.31570	0.09398
646.60	13	0.13312	1.15357	-1.94590	6.47173	-2.08817	0.11654
704.8	14	0.14361	1.16769	-1.86417	6.55791	-1.94671	0.13302
846.40	15	0.15409	1.18216	-1.78773	6.74099	-1.64622	0.17533
857.30	16	0.16457	1.19699	-1.71586	6.75379	-1.62522	0.17870
881.60	17	0.17505	1.21220	-1.64799	6.78174	-1.57934	0.18626
984.70	18	0.18553	1.22780	-1.58366	6.89234	-1.39781	0.21897
1026.30	19	0.19602	1.24381	-1.52245	6.93372	-1.32990	0.23241
1029.30	20	0.20650	1.26024	-1.46404	6.93663	-1.32511	0.23339
1085.0	21	0.21698	1.27711	-1.40814	6.98934	-1.23861	0.25158
1088.20	22	0.22746	1.29444	-1.35450	6.99228	-1.23377	0.25263
1117.50	23	0.23795	1.31224	-1.30292	7.01885	-1.19016	0.26227
1131.00	24	0.24843	1.33054	-1.25321	7.03086	-1.17046	0.26672
1142.70	25	0.25891	1.34936	-1.20520	7.04115	-1.15356	0.27058
1169.70	26	0.26939	1.36872	-1.15875	7.06450	-1.11523	0.27952
1249.80	27	0.27987	1.38865	-1.11374	7.13074	-1.00652	0.30614
1261.50	28	0.29036	1.40916	-1.07005	7.14006	-0.99122	0.31004
1310.90	29	0.30084	1.43028	-1.02758	7.17847	-0.92818	0.32650
1343.50	30	0.31132	1.45205	-0.98623	7.20303	-0.88786	0.33737
1427.30	31	0.32180	1.47450	-0.94593	7.26354	-0.78855	0.36524
1511.70	32	0.33229	1.49765	-0.90660	7.32099	-0.69425	0.39313

1576.50	33	0.34277	1.52153	-0.86817	7.36296	-0.62536	0.41437
1614.80	34	0.35325	1.54619	-0.83058	7.38697	-0.58596	0.42683
1636.60	35	0.36373	1.57166	-0.79377	7.40038	-0.56395	0.43388
1640.30	36	0.37421	1.59799	-0.75769	7.40263	-0.56025	0.43508
1661.30	37	0.38470	1.62521	-0.72229	7.41536	-0.53937	0.44184
1698.70	38	0.39518	1.65338	-0.68752	7.43762	-0.50282	0.45383
1706.60	39	0.40566	1.68254	-0.65334	7.44226	-0.49521	0.45635
1718.90	40	0.41614	1.71275	-0.61971	7.44944	-0.48342	0.46026
1769	41	0.42662	1.74406	-0.58660	7.47817	-0.43627	0.47610
1790.3	42	0.43711	1.77654	-0.55397	7.49014	-0.41662	0.48277
1870.80	43	0.44759	1.81025	-0.52178	7.53412	-0.34443	0.50768
1915.30	44	0.45807	1.84526	-0.49001	7.55763	-0.30585	0.52121
1942.60	45	0.46855	1.88166	-0.45862	7.57178	-0.28262	0.52943
1968.80	46	0.47904	1.91952	-0.42760	7.58518	-0.26063	0.53725
1991.10	47	0.48952	1.95893	-0.39690	7.59644	-0.24214	0.54386
1992.7	48	0.50000	2.00000	-0.36651	7.59725	-0.24082	0.54433
1993.70	49	0.51048	2.04283	-0.33640	7.59775	-0.24000	0.54462
2007.4	50	0.52096	2.08753	-0.30655	7.60460	-0.22876	0.54865
2088.60	51	0.53145	2.13423	-0.27693	7.64425	-0.16367	0.57217
2107.50	52	0.54193	2.18307	-0.24753	7.65326	-0.14889	0.57754
2112.50	53	0.55241	2.23419	-0.21831	7.65563	-0.14500	0.57896
2115.10	54	0.56289	2.28777	-0.18925	7.65686	-0.14298	0.57969
2200.90	55	0.57338	2.34398	-0.16034	7.69662	-0.07771	0.60356
2248.60	56	0.58386	2.40302	-0.13156	7.71806	-0.04252	0.61648
2292.6	57	0.59434	2.46512	-0.10288	7.73744	-0.01071	0.62818
2314.30	58	0.60482	2.53050	-0.07427	7.74686	0.00475	0.63387
2347.70	59	0.61530	2.59946	-0.04573	7.76119	0.02827	0.64252
2419.30	60	0.62579	2.67227	-0.01722	7.79123	0.07758	0.66063
2432.30	61	0.63627	2.74928	0.01128	7.79659	0.08637	0.66385
2435.00	62	0.64675	2.83086	0.03978	7.79770	0.08819	0.66452
2440.3	63	0.65723	2.91743	0.06832	7.79988	0.09176	0.66583
2458.00	64	0.66771	3.00946	0.09691	7.80710	0.10362	0.67017
2489.80	65	0.67820	3.10749	0.12559	7.81996	0.12472	0.67788
2557.50	66	0.68868	3.21212	0.15438	7.84679	0.16875	0.69390

2569.30	67	0.69916	3.32404	0.18331	7.85139	0.17631	0.69663
2738.20	68	0.70964	3.44404	0.21240	7.91506	0.28081	0.73398
2774.40	69	0.72013	3.57303	0.24170	7.92819	0.30237	0.74155
2780.70	70	0.73061	3.71206	0.27124	7.93046	0.30609	0.74285
2783.50	71	0.74109	3.86235	0.30105	7.93146	0.30774	0.74343
2793.3	72	0.75157	4.02532	0.33118	7.93498	0.31351	0.74544
2799.50	73	0.76205	4.20264	0.36166	7.93720	0.31715	0.74671
2864.30	74	0.77254	4.39631	0.39256	7.96008	0.35471	0.75968
2885.70	75	0.78302	4.60870	0.42392	7.96752	0.36693	0.76385
2973.6	76	0.79350	4.84264	0.45582	7.99753	0.41617	0.78044
3066.60	77	0.80398	5.10160	0.48831	8.02832	0.46672	0.79704
3067.90	78	0.81447	5.38983	0.52148	8.02875	0.46742	0.79727
3086.40	79	0.82495	5.71257	0.55542	8.03476	0.47728	0.80045
3106.6	80	0.83543	6.07643	0.59024	8.04128	0.48799	0.80388
3158.70	81	0.84591	6.48980	0.62606	8.05792	0.51529	0.81253
3181.70	82	0.85639	6.96350	0.66304	8.06517	0.52720	0.81625
3249.30	83	0.86688	7.51181	0.70135	8.08619	0.56171	0.82686
3253.5	84	0.87736	8.15385	0.74122	8.08749	0.56383	0.82750
3267.60	85	0.88784	8.91589	0.78291	8.09181	0.57092	0.82965
3559.4	86	0.89832	9.83505	0.82678	8.17735	0.71132	0.86954
3599.50	87	0.90881	10.96552	0.87328	8.18855	0.72970	0.87438
3650.60	88	0.91929	12.38961	0.92301	8.20265	0.75284	0.88033
3668.60	89	0.92977	14.23881	0.97681	8.20757	0.76092	0.88237
3693.90	90	0.94025	16.73684	1.03589	8.21444	0.77220	0.88519
3775.60	91	0.95073	20.29787	1.10211	8.23631	0.80810	0.89393
3969.1	92	0.96122	25.78378	1.17858	8.28629	0.89014	0.91244
3979.00	93	0.97170	35.33333	1.27112	8.28879	0.89422	0.91331
4072.10	94	0.98218	56.11765	1.39313	8.31191	0.93219	0.92114
4655.60	95	0.992662474	136.2857143	1.592241604	8.445826075	1.15198	0.95776

Table A- 4 KS GOF test for turbine failures required overhaul maintenance (T.S.O)

ROW	Hours	F_0	F_n	F_{n-1}	D+	D-
1	100.9	0.00586	0.01042	0.00000	0.00456	0.00586
2	177.2	0.01470	0.02083	0.01053	0.00614	0.00417
3	277.1	0.03037	0.03125	0.02105	0.00088	0.00932
4	301.5	0.03480	0.04167	0.03158	0.00687	0.00322
5	350.8	0.04440	0.05208	0.04211	0.00768	0.00230
6	368.4	0.04803	0.06250	0.05263	0.01447	-0.00461
7	456	0.06747	0.07292	0.06316	0.00545	0.00431
8	472.3	0.07132	0.08333	0.07368	0.01201	-0.00236
9	475.7	0.07214	0.09375	0.08421	0.02161	-0.01207
10	497.7	0.07747	0.10417	0.09474	0.02669	-0.01726
11	507.9	0.07999	0.11458	0.10526	0.03459	-0.02527
12	562.9	0.09398	0.12500	0.11579	0.03102	-0.02181
13	646.6	0.11654	0.13542	0.12632	0.01887	-0.00977
14	704.8	0.13302	0.14583	0.13684	0.01281	-0.00382
15	846.4	0.17533	0.15625	0.14737	-0.01908	0.02797
16	857.3	0.17870	0.16667	0.15789	-0.01203	0.02081
17	881.6	0.18626	0.17708	0.16842	-0.00917	0.01784
18	984.7	0.21897	0.18750	0.17895	-0.03147	0.04002
19	1026.3	0.23241	0.19792	0.18947	-0.03450	0.04294
20	1029.3	0.23339	0.20833	0.20000	-0.02505	0.03339
21	1085	0.25158	0.21875	0.21053	-0.03283	0.04105
22	1088.2	0.25263	0.22917	0.22105	-0.02346	0.03157
23	1117.5	0.26227	0.23958	0.23158	-0.02268	0.03069
24	1131	0.26672	0.25000	0.24211	-0.01672	0.02461
25	1142.7	0.27058	0.26042	0.25263	-0.01017	0.01795
26	1169.7	0.27952	0.27083	0.26316	-0.00869	0.01636
27	1249.8	0.30614	0.28125	0.27368	-0.02489	0.03246
28	1261.5	0.31004	0.29167	0.28421	-0.01837	0.02583
29	1310.9	0.32650	0.30208	0.29474	-0.02442	0.03177
30	1343.5	0.33737	0.31250	0.30526	-0.02487	0.03211

31	1427.3	0.36524	0.32292	0.31579	-0.04232	0.04945
32	1511.7	0.39313	0.33333	0.32632	-0.05980	0.06682
33	1576.5	0.41437	0.34375	0.33684	-0.07062	0.07753
34	1614.8	0.42683	0.35417	0.34737	-0.07266	0.07946
35	1636.6	0.43388	0.36458	0.35789	-0.06930	0.07599
36	1640.3	0.43508	0.37500	0.36842	-0.06008	0.06666
37	1661.3	0.44184	0.38542	0.37895	-0.05643	0.06290
38	1698.7	0.45383	0.39583	0.38947	-0.05799	0.06435
39	1706.6	0.45635	0.40625	0.40000	-0.05010	0.05635
40	1718.9	0.46026	0.41667	0.41053	-0.04359	0.04973
41	1769	0.47610	0.42708	0.42105	-0.04901	0.05504
42	1790.3	0.48277	0.43750	0.43158	-0.04527	0.05119
43	1870.8	0.50768	0.44792	0.44211	-0.05976	0.06557
44	1915.3	0.52121	0.45833	0.45263	-0.06288	0.06858
45	1942.6	0.52943	0.46875	0.46316	-0.06068	0.06627
46	1968.8	0.53725	0.47917	0.47368	-0.05808	0.06357
47	1991.1	0.54386	0.48958	0.48421	-0.05427	0.05964
48	1992.7	0.54433	0.50000	0.49474	-0.04433	0.04959
49	1993.7	0.54462	0.51042	0.50526	-0.03421	0.03936
50	2007.4	0.54865	0.52083	0.51579	-0.02782	0.03286
51	2088.6	0.57217	0.53125	0.52632	-0.04092	0.04585
52	2107.5	0.57754	0.54167	0.53684	-0.03588	0.04070
53	2112.5	0.57896	0.55208	0.54737	-0.02687	0.03159
54	2115.1	0.57969	0.56250	0.55789	-0.01719	0.02180
55	2200.9	0.60356	0.57292	0.56842	-0.03064	0.03514
56	2248.6	0.61648	0.58333	0.57895	-0.03315	0.03754
57	2292.6	0.62818	0.59375	0.58947	-0.03443	0.03871
58	2314.3	0.63387	0.60417	0.60000	-0.02970	0.03387
59	2347.7	0.64252	0.61458	0.61053	-0.02793	0.03199
60	2419.3	0.66063	0.62500	0.62105	-0.03563	0.03958
61	2432.3	0.66385	0.63542	0.63158	-0.02844	0.03228
62	2435	0.66452	0.64583	0.64211	-0.01869	0.02242
63	2440.3	0.66583	0.65625	0.65263	-0.00958	0.01320

64	2458	0.67017	0.66667	0.66316	-0.00350	0.00701
65	2489.8	0.67788	0.67708	0.67368	-0.00080	0.00420
66	2557.5	0.69390	0.68750	0.68421	-0.00640	0.00969
67	2569.3	0.69663	0.69792	0.69474	0.00128	0.00190
68	2738.2	0.73398	0.70833	0.70526	-0.02565	0.02872
69	2774.4	0.74155	0.71875	0.71579	-0.02280	0.02576
70	2780.7	0.74285	0.72917	0.72632	-0.01369	0.01654
71	2783.5	0.74343	0.73958	0.73684	-0.00385	0.00659
72	2793.3	0.74544	0.75000	0.74737	0.00456	-0.00193
73	2799.5	0.74671	0.76042	0.75789	0.01371	-0.01119
74	2864.3	0.75968	0.77083	0.76842	0.01116	-0.00875
75	2885.7	0.76385	0.78125	0.77895	0.01740	-0.01510
76	2973.6	0.78044	0.79167	0.78947	0.01122	-0.00903
77	3066.6	0.79704	0.80208	0.80000	0.00504	-0.00296
78	3067.9	0.79727	0.81250	0.81053	0.01523	-0.01326
79	3086.4	0.80045	0.82292	0.82105	0.02247	-0.02060
80	3106.6	0.80388	0.83333	0.83158	0.02945	-0.02770
81	3158.7	0.81253	0.84375	0.84211	0.03122	-0.02958
82	3181.7	0.81625	0.85417	0.85263	0.03792	-0.03638
83	3249.3	0.82686	0.86458	0.86316	0.03772	-0.03630
84	3253.5	0.82750	0.87500	0.87368	0.04750	-0.04618
85	3267.6	0.82965	0.88542	0.88421	0.05577	-0.05456
86	3559.4	0.86954	0.89583	0.89474	0.02630	-0.02520
87	3599.5	0.87438	0.90625	0.90526	0.03187	-0.03089
88	3650.6	0.88033	0.91667	0.91579	0.03634	-0.03546
89	3668.6	0.88237	0.92708	0.92632	0.04471	-0.04394
90	3693.9	0.88519	0.93750	0.93684	0.05231	-0.05165
91	3775.6	0.89393	0.94792	0.94737	0.05399	-0.05344
92	3969.1	0.91244	0.95833	0.95789	0.04589	-0.04545
93	3979	0.91331	0.96875	0.96842	0.05544	-0.05511
94	4072.1	0.92114	0.97917	0.97895	0.05803	-0.05781
95	4655.6	0.95776	0.98958	0.98947	0.03182	-0.03171
MAX=					**0.07946**	**0.07946**

Appendix B

Table B- 1 ANN analysis for C-130 general turbine failure data (T.T) with different BP ANN structures, RB ANN and Weibull regression

Turbine (T.T)	Rank (*i*)	Median Ranks F(*t*)	Normalize T.T (Hours)	ANN (2,4,1)	ANN (3,6,1)	ANN (4,8,1)	ANN (4,10,1)	ANN (4,20,1)	Weibull	Radial Based ANN
562.9	1	0.00734	0.00000	-0.06171	0.00534	0.01061	0.00336	-0.00301	0.00692	0.00734
1088.20	2	0.01782	0.04267	-0.00369	0.02022	0.02693	0.02368	0.01916	0.02435	0.01782
1169.70	3	0.02830	0.04929	0.00387	0.02527	0.03501	0.0335	0.02911	0.02793	0.0283
1261.50	4	0.03878	0.05675	0.01159	0.03221	0.04468	0.04338	0.03916	0.03223	0.03878
1310.90	5	0.04927	0.06076	0.01538	0.03646	0.05346	0.05192	0.04833	0.03465	0.04927
1343.50	6	0.05975	0.06341	0.01774	0.03944	0.06194	0.0597	0.05721	0.03630	0.05975
1511.70	7	0.07023	0.07707	0.02817	0.0564	0.07667	0.07031	0.06795	0.04533	0.07023
1915.3	8	0.08071	0.10986	0.0451	0.09533	0.09951	0.08592	0.08097	0.07051	0.08071
1942.6	9	0.09119	0.11207	0.04614	0.09726	0.10605	0.09238	0.08922	0.07238	0.09119
2088.6	10	0.10168	0.12393	0.05227	0.10526	0.11494	0.10135	0.09868	0.08274	0.10168
2347.70	11	0.11216	0.14498	0.06751	0.1099	0.12395	0.11278	0.10942	0.10250	0.11216
2586.30	12	0.12264	0.16436	0.08828	0.11044	0.13068	0.12382	0.12028	0.12214	0.12264
2901.80	13	0.13312	0.18999	0.1239	0.11619	0.13917	0.13686	0.13309	0.15001	0.13312
2973.6	14	0.14361	0.19582	0.13258	0.12038	0.14457	0.14487	0.1422	0.15663	0.14361
3173.60	15	0.15409	0.21207	0.1563	0.13879	0.15525	0.15629	0.15416	0.17557	0.15409
3206.10	16	0.16457	0.21471	0.15998	0.14269	0.1621	0.16433	0.1626	0.17871	0.16457
3332.40	17	0.17505	0.22497	0.17362	0.15988	0.17403	0.17509	0.17337	0.19109	0.17505
3427.20	18	0.18553	0.23267	0.18306	0.17448	0.18591	0.18556	0.18349	0.20054	0.18553
3650.60	19	0.19602	0.25082	0.20277	0.21123	0.20575	0.19965	0.19769	0.22331	0.19602
3730.20	20	0.20650	0.25728	0.20918	0.22402	0.21801	0.21047	0.2077	0.23158	0.2065
3732.9	21	0.21698	0.25750	0.20939	0.22444	0.22584	0.21954	0.21505	0.23186	0.21698
3749.90	22	0.22746	0.25888	0.21074	0.22709	0.23416	0.22907	0.22273	0.23364	0.22746
3751.50	23	0.23795	0.25901	0.21087	0.22734	0.24133	0.23823	0.22973	0.23380	0.23795
3969.10	24	0.24843	0.27669	0.22838	0.25743	0.25742	0.25258	0.24458	0.25681	0.24843
4055.40	25	0.25891	0.28370	0.23593	0.267	0.26618	0.26347	0.25467	0.26607	0.25891
4066.60	26	0.26939	0.28461	0.23695	0.26813	0.27155	0.27223	0.26182	0.26728	0.26939
4116.70	27	0.27987	0.28868	0.24166	0.27292	0.27775	0.28161	0.27041	0.27269	0.27987
4222.20	28	0.29036	0.29725	0.25243	0.2815	0.28511	0.29197	0.28116	0.28414	0.29036
4615.70	29	0.30084	0.32921	0.30413	0.30322	0.3003	0.30935	0.30313	0.32749	0.30084
4780.00	30	0.31132	0.34256	0.32968	0.31321	0.31087	0.32082	0.31591	0.34580	0.31132

4902.90	31	0.32180	0.35254	0.34892	0.32311	0.32187	0.33102	0.32695	0.35954	0.3218
4912.70	32	0.33229	0.35334	0.35043	0.32401	0.32962	0.33797	0.33375	0.36064	0.33229
4948.10	33	0.34277	0.35621	0.35584	0.32739	0.33927	0.3455	0.34149	0.36460	0.34277
5074.00	34	0.35325	0.36644	0.37413	0.34124	0.35431	0.35555	0.3524	0.37870	0.35325
5160.30	35	0.36373	0.37345	0.38552	0.35224	0.36825	0.36456	0.36185	0.38837	0.36373
5218.50	36	0.37421	0.37818	0.39254	0.36025	0.381	0.37288	0.37034	0.39489	0.37421
5289.90	37	0.38470	0.38398	0.40033	0.37058	0.39433	0.38174	0.37928	0.40289	0.3847
5342.10	38	0.39518	0.38822	0.40541	0.37838	0.4062	0.39025	0.38764	0.40873	0.39518
5351.10	39	0.40566	0.38895	0.40624	0.37974	0.41545	0.3978	0.39476	0.40973	0.40566
5661.60	40	0.41614	0.41417	0.42547	0.42528	0.43479	0.41361	0.41069	0.44432	0.41614
5839.8	41	0.42662	0.42865	0.4303	0.44602	0.44532	0.42568	0.42254	0.46401	0.42662
6167.9	42	0.43711	0.45530	0.43772	0.46713	0.45475	0.44082	0.43828	0.49981	0.43711
6205.00	43	0.44759	0.45831	0.43908	0.46827	0.45891	0.44949	0.44628	0.50381	0.44759
6222.90	44	0.45807	0.45977	0.43981	0.46875	0.46283	0.4579	0.4539	0.50574	0.45807
6606.80	45	0.46855	0.49095	0.46806	0.47609	0.47134	0.47351	0.47114	0.54645	0.46855
6612.90	46	0.47904	0.49145	0.46871	0.47627	0.47672	0.48177	0.47865	0.54709	0.47904
6910.30	47	0.48952	0.51560	0.50578	0.49357	0.49087	0.49593	0.49397	0.57767	0.48952
6927.7	48	0.50000	0.51702	0.50814	0.49519	0.49945	0.50455	0.502	0.57943	0.5
6956.90	49	0.51048	0.51939	0.51211	0.49806	0.50935	0.51339	0.51041	0.58238	0.51048
6996.6	50	0.52096	0.52261	0.5175	0.50229	0.52052	0.52242	0.51918	0.58637	0.52096
7019.10	51	0.53145	0.52444	0.52055	0.50485	0.53155	0.53098	0.52751	0.58862	0.53145
7290.10	52	0.54193	0.54646	0.55442	0.54347	0.55478	0.54599	0.54295	0.61533	0.54193
7392.70	53	0.55241	0.55479	0.56496	0.56062	0.56966	0.5569	0.55374	0.62521	0.55241
7449.60	54	0.56289	0.55941	0.57012	0.57033	0.58175	0.56651	0.56323	0.63063	0.56289
7453.20	55	0.57338	0.55970	0.57043	0.57094	0.59102	0.57441	0.57113	0.63097	0.57338
7475.10	56	0.58386	0.56148	0.57228	0.57468	0.6003	0.58278	0.57955	0.63305	0.58386
7538.5	57	0.59434	0.56663	0.57722	0.58543	0.6099	0.59244	0.58921	0.63902	0.59434
7642.20	58	0.60482	0.57506	0.58411	0.60243	0.61911	0.60345	0.60013	0.64868	0.60482
7654.30	59	0.61530	0.57604	0.58483	0.60434	0.62535	0.61146	0.60815	0.64980	0.6153
7781.50	60	0.62579	0.58637	0.59159	0.62326	0.63266	0.62332	0.61983	0.66143	0.62579
8141.60	61	0.63627	0.61562	0.61026	0.66261	0.6427	0.6425	0.63924	0.69317	0.63627
8226.90	62	0.64675	0.62255	0.61658	0.66932	0.64947	0.65271	0.6497	0.70042	0.64675
8368.8	63	0.65723	0.63408	0.63011	0.67964	0.6587	0.66444	0.66207	0.71225	0.65723

8448.70	64	0.66771	0.64057	0.6396	0.68552	0.66782	0.67434	0.67237	0.71878	0.66771
8453.60	65	0.67820	0.64097	0.64023	0.68589	0.6753	0.68238	0.6801	0.71918	0.6782
8472.00	66	0.68868	0.64246	0.64263	0.6873	0.68386	0.69092	0.68827	0.72067	0.68868
8477.60	67	0.69916	0.64292	0.64338	0.68774	0.6924	0.69933	0.69599	0.72112	0.69916
8596.80	68	0.70964	0.65260	0.66079	0.69776	0.7071	0.71053	0.70767	0.73064	0.70964
8792.20	69	0.72013	0.66847	0.69467	0.71869	0.72691	0.7234	0.72206	0.74580	0.72013
8828.40	70	0.73061	0.67141	0.70145	0.72331	0.73836	0.73282	0.73092	0.74855	0.73061
8843.30	71	0.74109	0.67262	0.70426	0.72528	0.74849	0.74187	0.73907	0.74968	0.74109
8844.5	72	0.75157	0.67272	0.70449	0.72544	0.75762	0.75066	0.74677	0.74977	0.75157
8985.70	73	0.76205	0.68419	0.73145	0.74609	0.77314	0.7626	0.75941	0.76026	0.76205
9104.70	74	0.77254	0.69386	0.75355	0.76578	0.78614	0.77415	0.77128	0.76887	0.77254
9162.90	75	0.78302	0.69858	0.76377	0.77594	0.79548	0.7843	0.78107	0.77301	0.78302
9183.3	76	0.79350	0.70024	0.76722	0.77955	0.80274	0.79344	0.78958	0.77445	0.7935
9311.70	77	0.80398	0.71067	0.78709	0.80245	0.81281	0.80527	0.80178	0.78335	0.80398
9406.20	78	0.81447	0.71835	0.79929	0.81888	0.82115	0.8162	0.81277	0.78975	0.81447
9476.70	79	0.82495	0.72408	0.80687	0.83052	0.82861	0.82638	0.82292	0.79444	0.82495
9540.4	80	0.83543	0.72925	0.81259	0.84036	0.83601	0.83621	0.8328	0.79862	0.83543
9654.20	81	0.84591	0.73849	0.82017	0.85587	0.84537	0.84733	0.84416	0.80592	0.84591
9699.30	82	0.85639	0.74216	0.8223	0.86117	0.85316	0.85625	0.85327	0.80877	0.85639
9757.30	83	0.86688	0.74687	0.82441	0.86722	0.86197	0.86534	0.86266	0.81238	0.86688
10004.7	84	0.87736	0.76697	0.82782	0.88298	0.87946	0.87969	0.87723	0.82724	0.87736
10155.30	85	0.88784	0.77920	0.82863	0.88314	0.89392	0.89087	0.88857	0.83586	0.88784
10330.2	86	0.89832	0.79341	0.83222	0.88406	0.90948	0.90229	0.90003	0.84547	0.89832
10388.50	87	0.90881	0.79814	0.83456	0.88472	0.91928	0.91019	0.90836	0.84857	0.90881
10618.60	88	0.91929	0.81683	0.85102	0.8856	0.93442	0.92207	0.92002	0.86039	0.91929
10761.00	89	0.92977	0.82840	0.86699	0.88585	0.94386	0.93127	0.92928	0.86734	0.92977
10791.90	90	0.94025	0.83091	0.87095	0.88688	0.94884	0.93776	0.93617	0.86881	0.94025
11787.30	91	0.95073	0.91177	0.97942	0.95403	0.96164	0.96071	0.95592	0.90988	0.95073
11895.5	92	0.96122	0.92056	0.98161	0.95627	0.96539	0.9676	0.963	0.91365	0.96122
11956.20	93	0.97170	0.92549	0.98243	0.95687	0.96977	0.97392	0.96947	0.91570	0.9717
12270.40	94	0.98218	0.95101	0.98902	0.95724	0.98235	0.98367	0.97888	0.92572	0.98218
12873.50	95	0.99266	1.00000	1.06258	0.99894	1.01531	0.99799	0.99352	0.94222	0.99266
Average Error (%) =				**25.64%**	**5.22%**	**4.01%**	**1.53%**	**0.96%**	**18.20 %**	**7.54E-16**

Table B- 2 ANN analysis for C-130 failures required overhaul maintenance (T.S.O) with different BP ANN structures, RB ANN and Weibull regression

Turbine (T.T)	Rank (*i*)	Median Ranks *F(t)*	Normalize T.T (Hours)	ANN (2,4,1)	ANN (3,6,1)	ANN (4,8,1)	ANN (4,10,1)	ANN (4,20,1)	Weibull	Radial Based ANN
100.9	1	0.00734	0.00000	0.00318	0.00829	0.00734	0.00734	0.00734	0.00586	0.00734
177.20	2	0.01782	0.01675	0.00644	0.01472	0.01782	0.01782	0.01782	0.01470	0.01782
277.10	3	0.02830	0.03869	0.01149	0.03493	0.02830	0.02830	0.02830	0.03037	0.02830
301.50	4	0.03878	0.04404	0.01714	0.04166	0.03878	0.03878	0.03878	0.03480	0.03878
350.80	5	0.04927	0.05487	0.03308	0.05673	0.04927	0.04927	0.04927	0.04440	0.04927
368.40	6	0.05975	0.05873	0.04010	0.06245	0.05975	0.05975	0.05975	0.04803	0.05975
456.00	7	0.07023	0.07796	0.08152	0.09145	0.07023	0.07023	0.07023	0.06747	0.07023
472.3	8	0.08071	0.08154	0.08970	0.09666	0.08071	0.08071	0.08071	0.07132	0.08071
475.7	9	0.09119	0.08229	0.09140	0.09774	0.09119	0.09119	0.09119	0.07214	0.09119
497.7	10	0.10168	0.08712	0.10224	0.10452	0.10168	0.10168	0.10168	0.07747	0.10168
507.90	11	0.11216	0.08936	0.10712	0.10757	0.11216	0.11216	0.11216	0.07999	0.11216
562.90	12	0.12264	0.10143	0.13097	0.12269	0.12264	0.12264	0.12264	0.09398	0.12264
646.60	13	0.13312	0.11981	0.15523	0.14118	0.13312	0.13312	0.13312	0.11654	0.13312
704.8	14	0.14361	0.13259	0.16195	0.15129	0.14361	0.14361	0.14361	0.13302	0.14361
846.40	15	0.15409	0.16368	0.16197	0.17336	0.15409	0.15409	0.15409	0.17533	0.15409
857.30	16	0.16457	0.16607	0.16246	0.17526	0.16457	0.16457	0.16457	0.17870	0.16457
881.60	17	0.17505	0.17141	0.16255	0.17973	0.17505	0.17505	0.17505	0.18626	0.17505
984.70	18	0.18553	0.19404	0.17715	0.20297	0.18553	0.18553	0.18553	0.21897	0.18553
1026.30	19	0.19602	0.20317	0.18953	0.21437	0.19602	0.19602	0.19602	0.23241	0.19602
1029.30	20	0.20650	0.20383	0.19056	0.21523	0.20650	0.20650	0.20650	0.23339	0.20650
1085.0	21	0.21698	0.21606	0.21247	0.23201	0.21698	0.21698	0.21698	0.25158	0.21698
1088.20	22	0.22746	0.21677	0.21386	0.23301	0.22746	0.22746	0.22746	0.25263	0.22746
1117.50	23	0.23795	0.22320	0.22703	0.24228	0.23795	0.23795	0.23795	0.26227	0.23795
1131.00	24	0.24843	0.22616	0.23329	0.24660	0.24843	0.24843	0.24843	0.26672	0.24843
1142.70	25	0.25891	0.22873	0.23876	0.25036	0.25891	0.25891	0.25891	0.27058	0.25891
1169.70	26	0.26939	0.23466	0.25137	0.25903	0.26939	0.26939	0.26939	0.27952	0.26939
1249.80	27	0.27987	0.25224	0.28582	0.28396	0.27987	0.27987	0.27987	0.30614	0.27987
1261.50	28	0.29036	0.25481	0.29018	0.28743	0.29036	0.29036	0.29036	0.31004	0.29036
1310.90	29	0.30084	0.26566	0.30604	0.30139	0.30084	0.30084	0.30084	0.32650	0.30084
1343.50	30	0.31132	0.27282	0.31416	0.30998	0.31132	0.31132	0.31132	0.33737	0.31132

1427.30	31	0.32180	0.29122	0.32769	0.33006	0.32180	0.32180	0.32180	0.36524	0.32180
1511.70	32	0.33229	0.30975	0.33631	0.34870	0.33229	0.33229	0.33229	0.39313	0.33229
1576.50	33	0.34277	0.32397	0.34517	0.36338	0.34277	0.34277	0.34277	0.41437	0.34277
1614.80	34	0.35325	0.33238	0.35290	0.37266	0.35325	0.35325	0.35325	0.42683	0.35325
1636.60	35	0.36373	0.33717	0.35833	0.37823	0.36373	0.36373	0.36373	0.43388	0.36373
1640.30	36	0.37421	0.33798	0.35933	0.37919	0.37421	0.37421	0.37421	0.43508	0.37421
1661.30	37	0.38470	0.34259	0.36543	0.38481	0.38470	0.38470	0.38470	0.44184	0.38470
1698.70	38	0.39518	0.35080	0.37804	0.39536	0.39518	0.39518	0.39518	0.45383	0.39518
1706.60	39	0.40566	0.35254	0.38097	0.39768	0.40566	0.40566	0.40566	0.45635	0.40566
1718.90	40	0.41614	0.35524	0.38570	0.40135	0.41614	0.41614	0.41614	0.46026	0.41614
1769	41	0.42662	0.36624	0.40671	0.41706	0.42662	0.42662	0.42662	0.47610	0.42662
1790.3	42	0.43711	0.37091	0.41625	0.42406	0.43711	0.43711	0.43711	0.48277	0.43711
1870.80	43	0.44759	0.38859	0.45279	0.45179	0.44759	0.44759	0.44759	0.50768	0.44759
1915.30	44	0.45807	0.39836	0.47161	0.46761	0.45807	0.45807	0.45807	0.52121	0.45807
1942.60	45	0.46855	0.40435	0.48218	0.47735	0.46855	0.46855	0.46855	0.52943	0.46855
1968.80	46	0.47904	0.41010	0.49150	0.48668	0.47904	0.47904	0.47904	0.53725	0.47904
1991.10	47	0.48952	0.41500	0.49875	0.49458	0.48952	0.48952	0.48952	0.54386	0.48952
1992.7	48	0.50000	0.41535	0.49925	0.49515	0.50000	0.50000	0.50000	0.54433	0.50000
1993.70	49	0.51048	0.41557	0.49955	0.49550	0.51048	0.51048	0.51048	0.54462	0.51048
2007.4	50	0.52096	0.41858	0.50366	0.50034	0.52096	0.52096	0.52096	0.54865	0.52096
2088.60	51	0.53145	0.43641	0.52390	0.52863	0.53145	0.53145	0.53145	0.57217	0.53145
2107.50	52	0.54193	0.44056	0.52787	0.53514	0.54193	0.54193	0.54193	0.57754	0.54193
2112.50	53	0.55241	0.44165	0.52889	0.53686	0.55241	0.55241	0.55241	0.57896	0.55241
2115.10	54	0.56289	0.44222	0.52942	0.53776	0.56289	0.56289	0.56289	0.57969	0.56289
2200.90	55	0.57338	0.46106	0.54672	0.56739	0.57338	0.57338	0.57338	0.60356	0.57338
2248.60	56	0.58386	0.47153	0.55761	0.58419	0.58386	0.58386	0.58386	0.61648	0.58386
2292.6	57	0.59434	0.48120	0.56929	0.60002	0.59434	0.59434	0.59434	0.62818	0.59434
2314.30	58	0.60482	0.48596	0.57570	0.60796	0.60482	0.60482	0.60482	0.63387	0.60482
2347.70	59	0.61530	0.49329	0.58638	0.62032	0.61530	0.61530	0.61530	0.64252	0.61530
2419.30	60	0.62579	0.50901	0.61193	0.64712	0.62579	0.62579	0.62579	0.66063	0.62579
2432.30	61	0.63627	0.51187	0.61681	0.65196	0.63627	0.63627	0.63627	0.66385	0.63627
2435.00	62	0.64675	0.51246	0.61782	0.65297	0.64675	0.64675	0.64675	0.66452	0.64675
2440.3	63	0.65723	0.51362	0.61982	0.65494	0.65723	0.65723	0.65723	0.66583	0.65723

2458.00	64	0.66771	0.51751	0.62650	0.66147	0.66771	0.66771	0.66771	0.67017	0.66771
2489.80	65	0.67820	0.52449	0.63842	0.67298	0.67820	0.67820	0.67820	0.67788	0.67820
2557.50	66	0.68868	0.53935	0.66234	0.69600	0.68868	0.68868	0.68868	0.69390	0.68868
2569.30	67	0.69916	0.54195	0.66619	0.69972	0.69916	0.69916	0.69916	0.69663	0.69916
2738.20	68	0.70964	0.57903	0.70901	0.74056	0.70964	0.70964	0.70964	0.73398	0.70964
2774.40	69	0.72013	0.58698	0.71620	0.74629	0.72013	0.72013	0.72013	0.74155	0.72013
2780.70	70	0.73061	0.58836	0.71744	0.74721	0.73061	0.73061	0.73061	0.74285	0.73061
2783.50	71	0.74109	0.58897	0.71799	0.74761	0.74109	0.74109	0.74109	0.74343	0.74109
2793.3	72	0.75157	0.59113	0.71993	0.74897	0.75157	0.75157	0.75157	0.74544	0.75157
2799.50	73	0.76205	0.59249	0.72116	0.74981	0.76205	0.76205	0.76205	0.74671	0.76205
2864.30	74	0.77254	0.60671	0.73475	0.75787	0.77254	0.77254	0.77254	0.75968	0.77254
2885.70	75	0.78302	0.61141	0.73967	0.76044	0.78302	0.78302	0.78302	0.76385	0.78302
2973.6	76	0.79350	0.63071	0.76270	0.77244	0.79350	0.79350	0.79350	0.78044	0.79350
3066.60	77	0.80398	0.65113	0.79045	0.79098	0.80398	0.80398	0.80398	0.79704	0.80398
3067.90	78	0.81447	0.65142	0.79084	0.79130	0.81447	0.81447	0.81447	0.79727	0.81447
3086.40	79	0.82495	0.65548	0.79637	0.79596	0.82495	0.82495	0.82495	0.80045	0.82495
3106.6	80	0.83543	0.65991	0.80227	0.80143	0.83543	0.83543	0.83543	0.80388	0.83543
3158.70	81	0.84591	0.67135	0.81648	0.81717	0.84591	0.84591	0.84591	0.81253	0.84591
3181.70	82	0.85639	0.67640	0.82214	0.82476	0.85639	0.85639	0.85639	0.81625	0.85639
3249.30	83	0.86688	0.69124	0.83624	0.84844	0.86688	0.86688	0.86688	0.82686	0.86688
3253.5	84	0.87736	0.69216	0.83700	0.84994	0.87736	0.87736	0.87736	0.82750	0.87736
3267.60	85	0.88784	0.69526	0.83943	0.85499	0.88784	0.88784	0.88784	0.82965	0.88784
3559.4	86	0.89832	0.75933	0.89017	0.92738	0.89832	0.89832	0.89832	0.86954	0.89832
3599.50	87	0.90881	0.76813	0.90203	0.93083	0.90881	0.90881	0.90881	0.87438	0.90881
3650.60	88	0.91929	0.77935	0.91885	0.93413	0.91929	0.91929	0.91929	0.88033	0.91929
3668.60	89	0.92977	0.78330	0.92504	0.93521	0.92977	0.92977	0.92977	0.88237	0.92977
3693.90	90	0.94025	0.78886	0.93378	0.93680	0.94025	0.94025	0.94025	0.88519	0.94025
3775.60	91	0.95073	0.80679	0.96049	0.94428	0.95073	0.95073	0.95073	0.89393	0.95073
3969.1	92	0.96122	0.84928	0.99742	0.98931	0.96122	0.96122	0.96122	0.91244	0.96122
3979.00	93	0.97170	0.85145	0.99843	0.99258	0.97170	0.97170	0.97170	0.91331	0.97170
4072.10	94	0.98218	0.87189	1.00858	1.02451	0.98218	0.98218	0.98218	0.92114	0.98218
4655.60	95	0.99266	1.00000	1.19151	1.09364	0.99266	0.99266	0.99266	0.95776	0.99266
Average Error (%) =				**6.85**	**4.51**	**1.51**	**1.00**	**0.84**	**16.55 %**	**1.09E-15**

Vitae

Mr. Nizar Qattan was born in Al-Madīnah Al-Munawarah, Saudi Arabia in 1976. He started his career with Royal Saudi Air Force, by joining King Faisal Air Academy in Riyadh in 1994 for Bachelor Degree in Aero-Science and graduated as Lieutenant Pilot in 1997. Then he joined the operational squadrons as a fighter pilot. In 2005, he graduated from King Abdul Aziz University, Jeddah, Saudi Arabia with a Bachelor of Science Degree in International Business. He joined King Fahd University of Petroleum and Mineral at Dhahran, Saudi Arabia as a part-time graduate student in 2007 for his Master Degree in Aerospace Engineering. During his career, he flown many types of aircrafts starting from a light training aircraft (Cessna-172, PA-28, PA-44, PC-9), fighter aircraft (HAWK, F-15C/D, F-15S), military transport (CN-235), and heavy tanker (KE-3), lately he joined NAS airline as Airbus A320 pilot flying both domestic and international destinations.

He had attended many aviation related courses as:

- Airline Transport Pilot.
- Certified Flight Instructor.
- Flight Safety Officer.
- Operational Risk Management.
- Problem Solving and Decision Making.
- Investigation Data Collection and Processing.
- Conceiving & Steering an Aviation Incident and Accident Prevention program.
- Human Factor in the Prevention and Investigation Process.
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