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An Intelligent Reliability Assessment technique for Bipolar Junction Transistor using Artificial Intelligence Techniques

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ABSTRACT

The need for high speed, low cost and smaller area has increased the integration of electronic devices. As the number of components increases, the reliability of system becomes a major challenge. The bipolar junction transistor is an immensely used passive component in the various electronics industry. Reliability and failure prediction are the major constraints for the estimation of the residual life of the component. In this paper, Artificial intelligence techniques are employed on bipolar junction transistor which provides knowledge of failure mechanism of a component in actual operating conditions such that if it deviates from the actual output, a preventive measure to be taken before serious failure occurs. The end of life has been explored using the design of experiments approach. After calculating lifetime, an expert system has been modeled which predicts the sudden crash of transistor before it actual fails, using various statistical and analytical techniques. The comparison of accuracy has been conducted on all techniques of artificial intelligence and statistical method. The comparison shows that ANFIS is the most accurate technique with an accuracy of 96.65%. A graphical user interface is created which indicates the failure of bipolar junction transistor at various level of inputs.

Keywords: Artificial intelligence, design of experiments, Regression analysis, reliability prediction, Taguchi method

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INTRODUCTION

Reliability assessment is the degree which tells how reliably a particular electronic system or component will work as it is expected to, in the specific or desired duration(Varde, Tian, & Pecht, 2014). The remaining useful life relies on the failure rate of a component and on the operating

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conditions of a device. The importance of life estimation is to evaluate the remaining useful life (RUL) of a specific component under the different stress parameters (Özel & Karpat, 2005). As an increasing number of components are integrated on to a chip, the chances of failure increase, as the different parts have their own stress factors and different working conditions. So the condition monitoring strategies are utilized which enhances the reliability of a component and a suitable move to be made before any harmful breakdown happens (Kwong & Bai, 2002). The electronic circuits need a failure estimation technique to protect the system from unavoidable failures. Residual life estimation of electronic components is an important fact these days as electronic components and devices become a great need for society. Residual life prediction is predicting the remaining useful life of a component or device based on various failure factors of any component and it also depends on the operating conditions (Al-Zubaidi, Ghani, & Haron, 2013). Various methods for predicting the life of electronic components have been developed. The life of electronic components can be predicted by creating an intelligent system for the failure analysis. The capability to predict the life of electronic components is a key to prevent the sudden costly failure and it will increase the overall performance and reliability of a system (Gokulachandran & Mohandas, 2012). So, remaining useful life prediction is an important factor for every active and passive electronic component (Mamlook, Badran, & Abdulhadi, 2009).

Bipolar Junction Transistor

A transistor is an electronic gadget that controls current or voltage flow and acts as a switch or gate for electronic signals (Jang, 1993). Transistor is made up of three layers of a semiconductor material, each capable of carrying a current (Tsividis & McAndrew, 2011). It is sandwiching one semiconductor between two other semiconductors (Ramey et al., 2013). A transistor is composed of two words transfer-resistor. Mainly, there are two types of bipolar junction transistors; PNP and NPN transistor, based on doping level, as shown in Figure 1. The standard BC547 is represented as Figure 2.

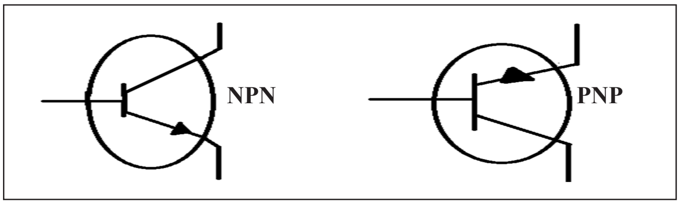

Figure 1. Symbol of bipolar junction transistor

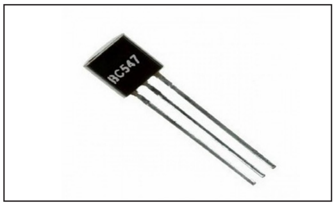

Figure 2. Bipolar junction transistor BC547

MATERIALS AND METHODS

Methods for Residual Life Prediction

Reliability assessment of electronic components is a great need of electronic society as the electronic devices are becoming integrated and high speed (Choi & Seong, 2009). The remaining useful life of electronic components, gadgets and equipment's depends on various failure factors of any component and on the operating conditions (Di Giacomo & Di Giacomo, 1997). A bipolar junction transistor using various techniques such as experimental method, statistical techniques and artificial intelligence techniques such as Regression, ANN, Fuzzy and ANFIS (Chinnam & Baruah, 2004).

Need For Failure Prediction and Life Estimation

From daily life applications to military applications and from toys to satellites, the use of electronic components is in extensive. In critical applications like aviation industry, if a component fails before its actual life, it can cost lives of many human beings. So, prediction before failure, can save the entire system and data to be lost. The user can replace faulty component with the accurate one, and system will be saved from complete shutdown (Agarwal, Paul, Zhang, & Mitra, 2007).

During manufacturing process of electronic components/devices, different tests are conducted on these components/devices to check its performance and capabilities. Then data sheets of those components have been framed, which signifies minimum and maximum range of all electrical parameters as well as environmental stress. Then components/devices are released to real market with a warranty period depending on the qualification testing (Vichare & Pecht, 2006). Before purchasing the specific component, user needs assurance about the long life, reliable and satisfactory performance throughout the operation. Moreover, quality assurance cells are becoming strict towards protection of user rights. So, the product manufacturers reacted to these constraints by offering extended warranties and guarantees. The warranty may be in the shape of lifetime i.e. the specific component will work successfully for specific duration of time, that is called lifetime. This document is generally endorsed with datasheet. The manufacturer has to replace or rectify the component free of cost, if it falls under warranty period. If the component under warranty time, could not perform the specified task, it will incur an extra cost on manufacturer to replace it or compensate the user. Replacement will not only become extra financial burden on manufacturer, but also, it will degrade the reputation of manufacturer in competitive market. The warranty service or replacement cost may vary from 2-10%, depending on sale price of that component (Murthy, 2007). The decision on warranty period is directly connected with reliability of the system or component.

The performance of next generation U.S. Army operations such as miniature driver-less ground vehicles and driver-less Arial vehicles are intensely dependent on electronics (Habtour, Drake, & Davies, 2011). Due to vibration and shocking environment, these electronic systems may experience variation in their performance. This will lead major damage to packaging and soldering of joints. Nowadays, failure rate prediction is not just a domain for the military. As electronics is used in almost every area of human life, and as a result all of these areas being "safety critical", the prediction of the lifetime of electronic modules becomes an ever-increasing necessity (Jánó & Pitică, 2011). This is especially true for aeronautics and automotive applications, where temperatures can sometimes well exceed the maximum guaranteed operating temperature for a particular component. Performance parameters as well as failure prediction, reliability and safety need to be built in during design and development and retained during operation and production of item.

Selection of Components for Life Estimation

There are many electronic components used in high-speed electronic devices nowadays. All these components have some residual life that depends on the operating conditions of a component (Debnath, Roychowdhury, & Kundu, 2016). In this paper, basic components

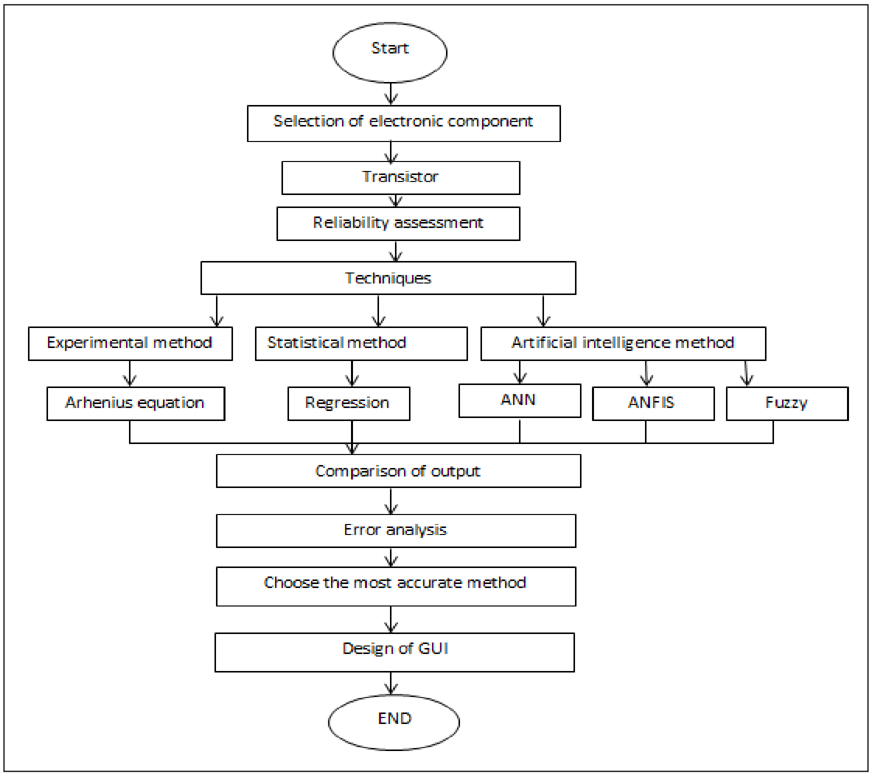

Figure 3. Methodology of the proposed work

such as a bipolar junction transistor are selected as these components are the part of many high-speed electronic devices (Novak et al., 2015). So, life estimation of these components is necessary in order to prevent the complete device from a serious breakdown and costly failures (Lu & Christou, 2017).

Methods to Exploring the Remaining Useful Life of Electronic Devices

The life estimation model is developed using various methods such as experimental method, regression and artificial intelligent model. The experimental method is the working method that predict the remaining useful life of any electronic devices(Pecht & Nash, 1994).

Experimental Method

In this method, lifetime was estimated using the ALT (Acceleration life testing). ALT is the process of testing the component under the stress factor temperature in order to find the failure rate and life of a component. This method is mainly used by big manufacturing unit where many samples or electrical units are subjected to tests (Zhao, Makis, Chen, & Li, 2018). These tests can be environmental, electrical, thermal and so on. One of the examples of such testing is Accelerated Life Testing (ALT) using temperature.

In the first step, the components were placed on the hotplate, the value of each component was measured, and the desired temperature level was set on the hot plate. The temperature was allowed to achieve the maximum rated temperature.

(a) The trial was executed for 20 hours. This time length was chosen according to various temperature ranges. Time interval must be shorter at a higher temperature as chances of failure of components are more as compared to lower temperature limit.

(b) The value of every component was measured and noted after few hours and checked on how many components got failed after few hours and calculation of the output life was done.

(c) After collection of failure data, life had been calculated using Arrhenius equation given below:

Life = 1/TDH * A_F

Where, A_F is failure rate which is given by:

$$A_F = e^{\frac{Ea}{K}\left[\frac{1}{Tm} - \frac{1}{Ta}\right]}$$

Where, T_m is maximum temperature

T_a is applied temperature

E_a is activation energy of transistor

K is Boltzmann's constant

TDH is Total no. of devices * Hours of operation

In order to develop the life prediction model, the input parameters to be selected process

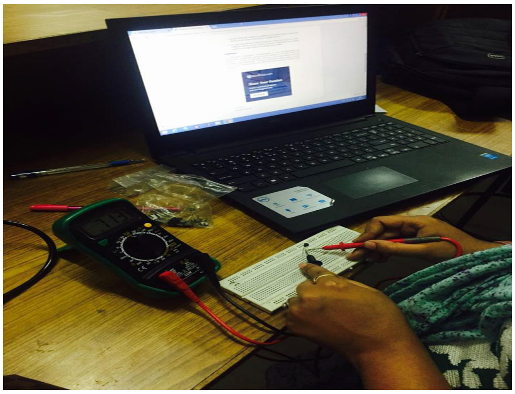

Figure 4. Experimental setup of bipolar junction transistor

Figure 5. Accelerated life testing of bipolar junction transistor

Table 1
Specification of NPN BC547

PARAMETER	VALUE
Collector-emitter voltage	45 V
Collector base voltage	50 V
Emitter-base voltage	6 V
Temperature	-55°C to 150°C
Pins	3
Collector current	100 mA

Table 2
Units, notations and limits

Process Parameters	Units	Notation	Limit Minimum	Limit Maximum
Time	Hours	T	1	49
Temperature	ºC	T	25	150

Life Estimation of Transistor Using Artificial Intelligence Techniques

The remaining useful life of bipolar junction transistor is also estimated using artificial intelligence techniques such as ANN, Fuzzy and ANFIS. Artificial intelligence techniques are the modern way of estimation as it provides the better results (Recknagel, French, Harkonen, & Yabunaka, 1997) and estimation is done in an intelligent way almost same as the human brain (Bundy, 1997).

Life Estimation using ANN. Artificial Neural Network is an analogous system of the human neural network which tries to mimic the functioning of the actual brain. Input data along with target data has been fed to the network. The system gets the train with the specified number of the epoch. The system will train itself and reduce the error after every epoch and hence, after a specific number of epochs, the best result is achieved. The number of neurons in the input layer consists of input parameters such as temperature and time which are used to obtain the output life of the electronic component.

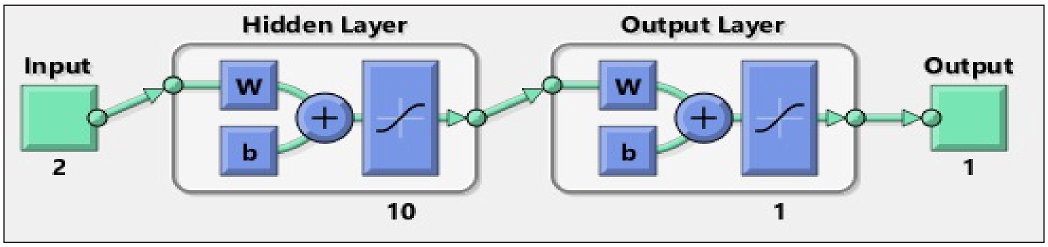

Figure 6. ANN structure (2-10-1)

Life Estimation of Bipolar Junction Transistor using Fuzzy. Fuzzy Inference System is a soft-computing technique to design intelligent model with an advantage that it is user understandable as it involves linguistic variable.

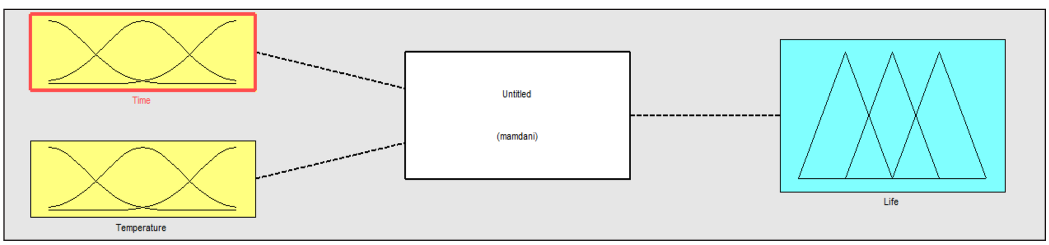

Figure 7. Fuzzy models for bipolar junction transistor

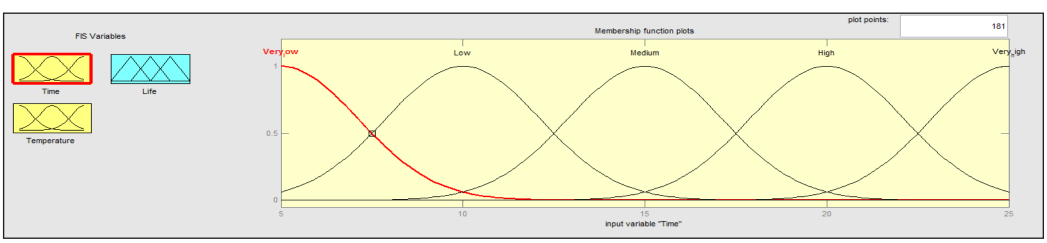

Figure 8. Gaussian membership functions for time

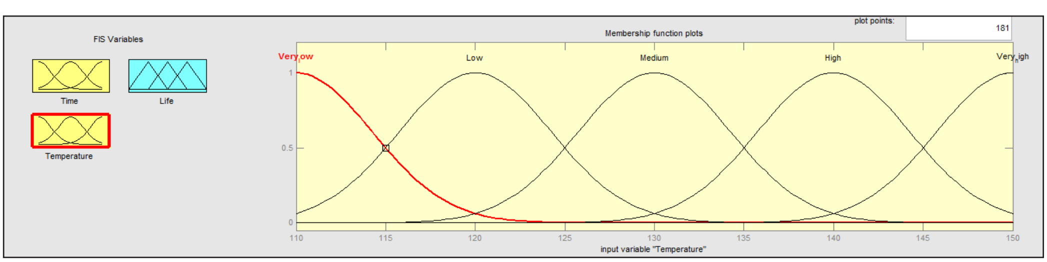

Figure 9. Gaussian membership functions for temperature

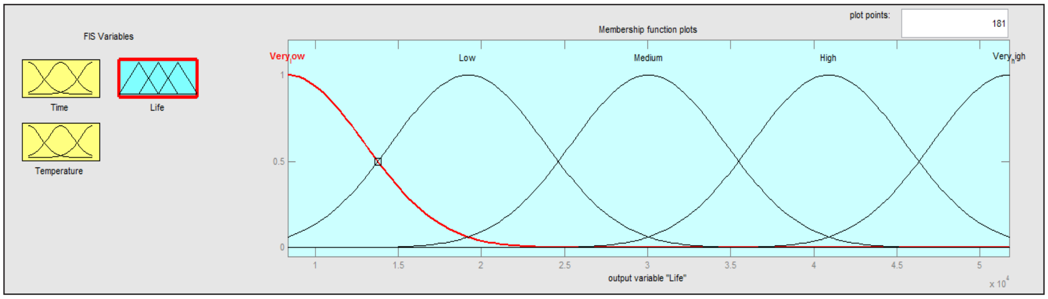

Figure 10. Gaussian membership functions for life

Life Estimation of Bipolar Junction Transistor using ANFIS. The ANFIS is an Adaptive neuro-fuzzy inference system, The ANFIS architecture shown in Figure 11, is a Sugeno fuzzy model where the final fuzzy values optimized by using the artificial neural network training (Chang & Chang, 2006).The linguistic variables very low (VL), low (L), medium (M) and high (H), very high (VH) are used for the inputs as well as for the output (Jang, 1993).

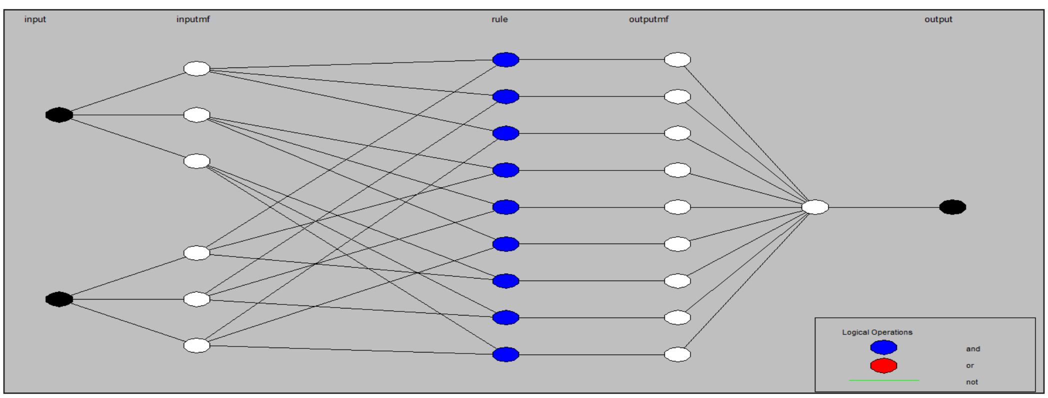

Figure 11. ANFIS structure

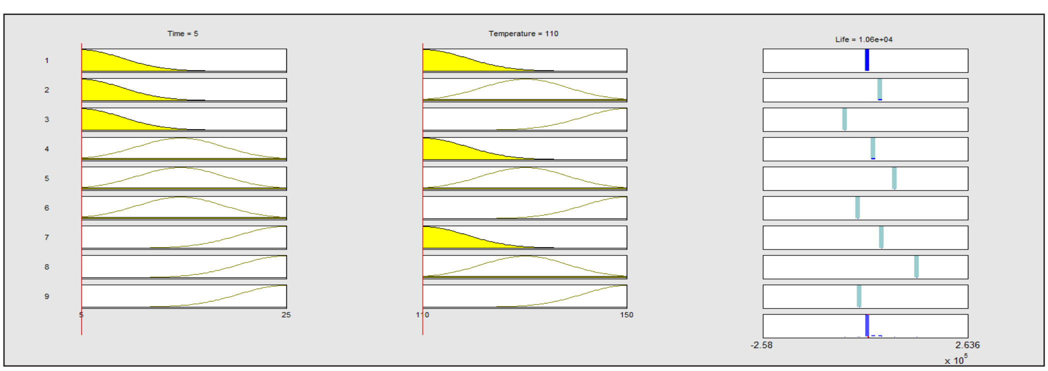

Figure 12. ANFIS rule viewer

Design of Fuzzy based Decision Support System

Designing of graphical user interface (GUI) is the last phase of this method (Aronson, Liang, & Turban, 2005).Using the GUI user can interact with the expert system to check the operating condition of the bipolar junction transistor (Ghodsypour & O'Brien, 1998). The GUI is created using the MATLAB-R2013a. The entire database including rules is designed using the fuzzy logic (Kulak, 2005). The steps to design a fuzzy based decision support system are as follows:

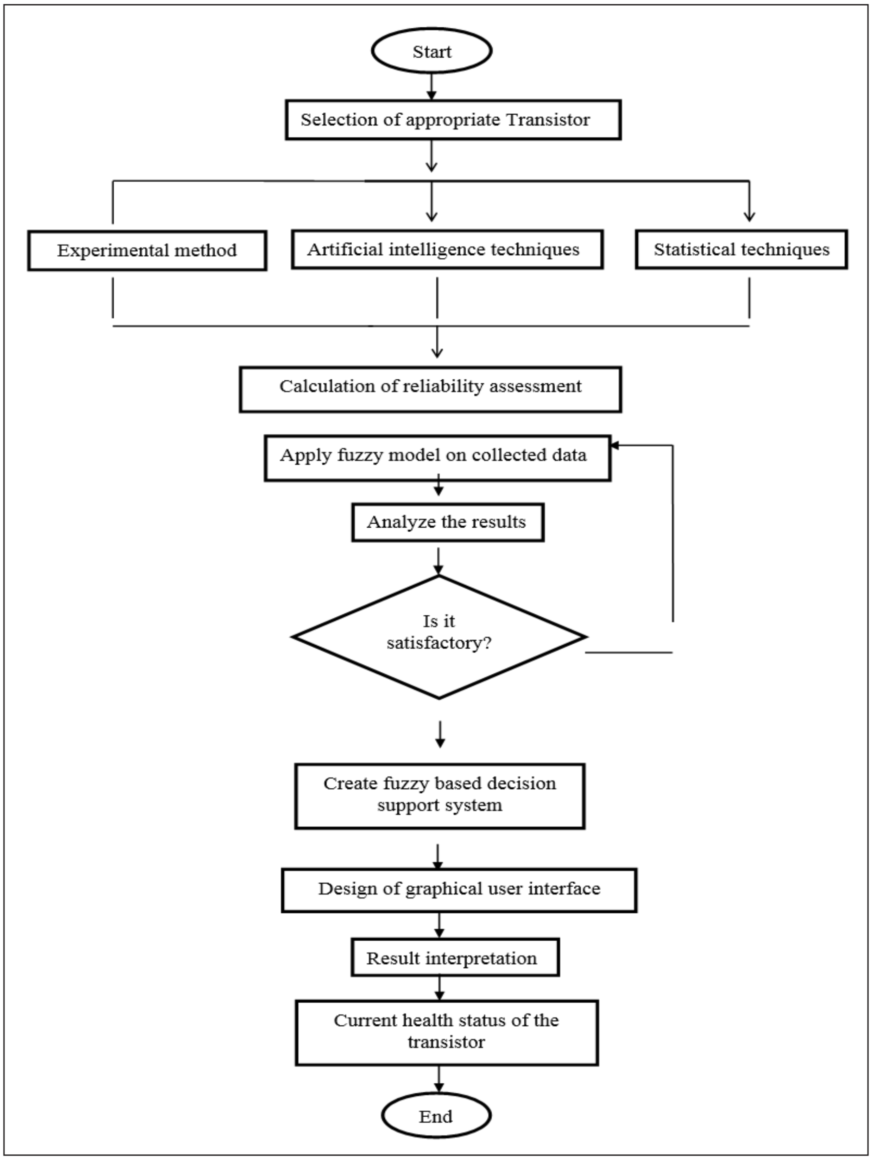

Figure 13. Flowchart of graphical user interface

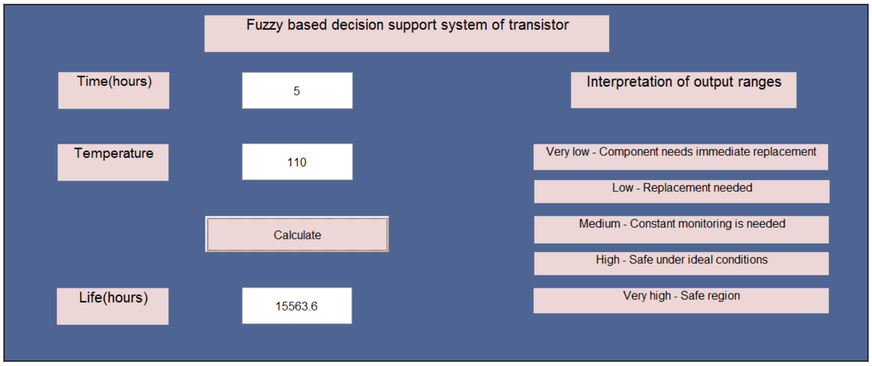

Figure 14. Graphical user interface

RESULTS AND DISCUSSION

This paper is focused particularly on life estimation of the bipolar junction transistor. Various methods have been explored to design critical parameters such as temperature. The comparison is shown as per Table 3.

Table 3
Comparison of life obtained using various methods

Techniques	Life estimation using Regression	Life estimation using ANFIS	Life estimation using ANN	Life estimation using Fuzzy
Estimated lifetime(hours)	27503	27547	26747	30330
Average error %	-15.04	-3.35	4.22	-28.56
Accuracy %	84.96	96.65	95.78	71.44

Different techniques are used for calculating the useful life of bipolar junction transistor. It is found that an Adaptive neuro inference system provides the highest accuracy i.e. 96.65%, to predict the useful life of bipolar junction transistor in comparison with other techniques.

CONCLUSION

As reliability prediction plays a significant role in the successful operation of electronics devices, it is necessary to forecast the useful life of the bipolar junction transistor for making reliable system. Experimental and mathematical analysis has been done on bipolar junction transistor under various operating conditions. It is found that the regression provides less accuracy and ANFIS has the highest accuracy to predict the useful life of electronic components. The reliability assessment of bipolar junction transistor is obtained by the experimental and artificial intelligence models to determine the relative effectiveness of each of the developed. The accuracy of life estimated using artificial intelligence techniques such as using regression is 84.96%; ANN is 95.78%; fuzzy accuracy is 71.44% and it is observed that the adaptive neuro-fuzzy inference (ANFIS) method provides the highest rate of accuracy that is 96.65%.

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