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Remaining useful life estimation of a Product

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Abstract— A sudden failure of a product or a component may result in loss of valuable data or interruption in the task being carried out. In order to eliminate these kind of scenarios and to avoid unnecessary investments on the used products, the remaining life need to be predicted/estimated. In this work, a comprehensive two-phase approach is proposed. In the first stage phase, statistically analyzing the behavior of components for reuse, a well-known reliability assessment method, the Weibull analysis, is applied to the time-to-failure data to assess the mean life of components. In the second phase, the degradation and condition monitoring data are analyzed by developing an Artificial Neural Network model (ANN model). This project is aimed on estimating the remaining useful life of washing machine and LED bulb

Keywords: *Weibull analysis, reliability, mean- life, Artificial Neural Networks*

1. Introduction

Management of products and materials during the end of lifecycle stage is one of the important tasks in integral part of product life cycle. Primary goal is to minimize the wasted resources and reduce the costs associated with methods of reuse, recycling and disposal [1]. Analyzing the deteriorating pattern of the functional parameters of a product under realistic operation conditions would give a true and actual estimation of remaining useful life [2]. The proposed methodology in this paper uses two types of the data, namely maintenance data and lifetime monitoring data, maintenance data is usually recorded by manufacturing companies over period of several years, lifetime monitoring data is collected during operation of particular product. In the case of a strong trend data, regression analysis is an useful technique because of its ability to provide a result that how each parameter contributes towards the estimation of response variable [3]. The proposed model is based on reliability evaluation through data analysis of the life cycle, and suggested approach considers both statistical and condition monitoring data for decision making on further use.

2. Literature Survey

2.1 Remaining useful life estimation

The remaining useful life is a function of the component's overall life and the actual (used) life under the operating conditions of use. Mathematically, $L_R = L_M - L_A$ where L_R is the remaining useful life, L_M the mean-life and L_A represents the actual life of components under given conditions of use. L_M and L_A represent two distinct perspectives – static and dynamic – and therefore they need to be addressed accordingly [1]. L_M basically represents the component's total functional life under stated conditions of use, and it is estimated by analyzing time-to-failure data of a family of components operated under the same conditions of use. The accuracy and authenticity of the L_M estimation becomes better with increasing amounts of available statistical data. On the other hand, L_A is dynamic in the sense that it mainly depends upon the real conditions of use.



2.2 Life Data Analysis (Weibull analysis)

In life data analysis, the user attempts to make predictions about the life of all products in the population by fitting a statistical distribution to life data from a representative sample of units. The parameterized distribution for the data set can then be used to estimate important life characteristics of the product such as reliability or probability of failure at a specific time, the mean life and the failure rate. Life data analysis requires the analyzer to gather life data for the product, select a lifetime distribution that will fit the data and model the life of the product. Estimate the parameters that will fit the distribution to the data. Plots and results need to be generated to estimate the life characteristics of the product, such as the reliability or mean life [7].

2.3 Artificial Neural Networks

Neural networks are becoming more popular among researchers because of their proven ability to recognize complex relationships between input and output variables. Artificial neural networks are adaptive and have parallel information-processing structures that have the ability to build functional relationships between data and provide a powerful toolbox for nonlinear, multi-dimensional interpolations. This facet of neural networks makes it possible to capture and interpret the existing highly complex nonlinear relationships between input and output parameters that are most of the time not well understood [4].

3. Methodology and Implementation

This research work started with literature survey on Weibull analysis and ANN, next phase involved in calculation of mean and actual used life and in the final phase, ANN model is developed and integrated with Weibull analysis to estimate the remaining useful life.

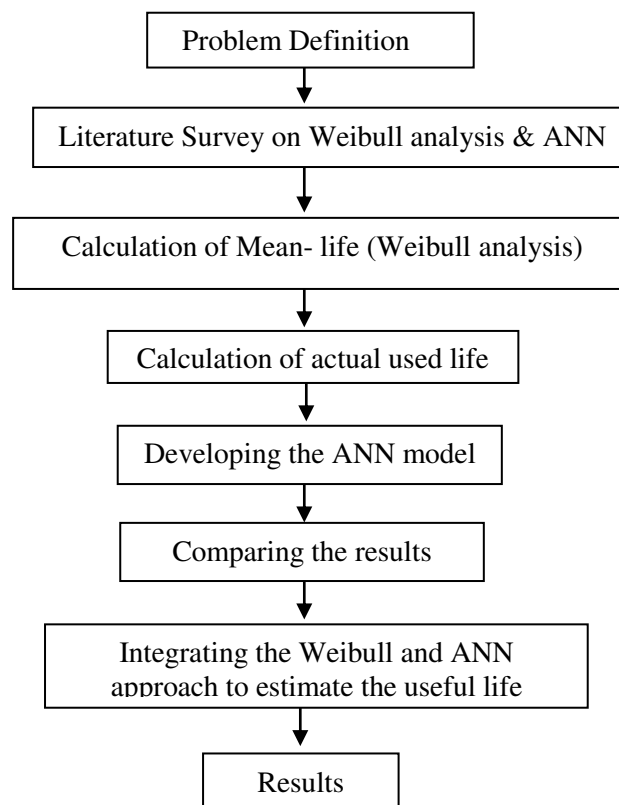


Figure 1. Flowchart of methodology followed

3.1 Estimating the remaining useful life (Washing Machine)

The mean- life is calculated under the same conditions of use through the calculation of time-to-failure data for the same categories of components. Time to failure data for the electric motor and gearbox of a top-load washing machine have been considered for the earlier studies.

Weibull analysis is an effective technique for reliability testing used to identify failures and model failure behavior, which is widely used in maintenance procedures [1]. The methods are used to assess an appropriate re-placement repair intervals for wear-out parts, in the broad range of industries such as military, automotive, electronics, composites, aerospace, electrical power, nuclear power, dental science etc.

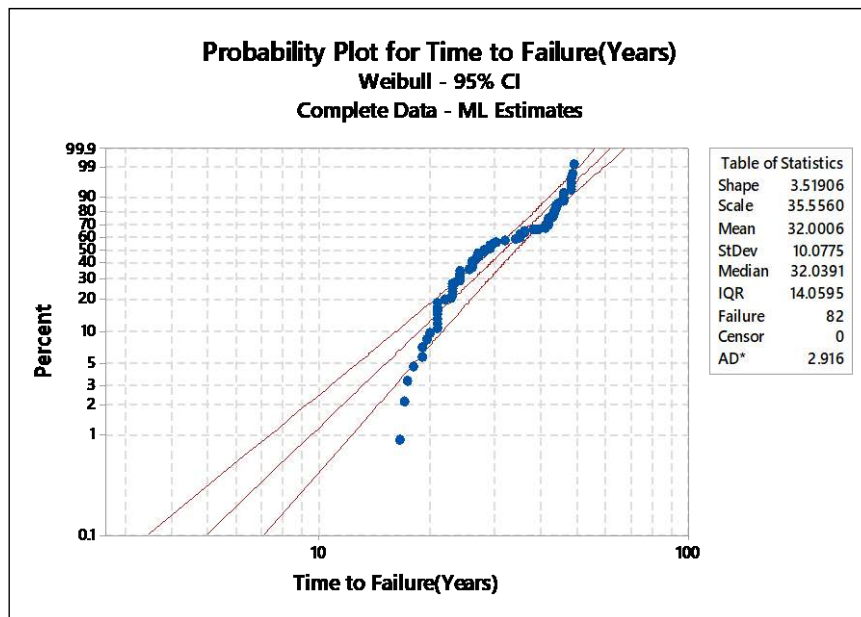


Figure 2. Weibull Plot for life data of washing machine

Table 1. Weibull analysis results for washing machine data

	Calculated Results	Results from Minitab	Percentage Variation
Shape Parameter	3.26	3.519	7%
Scale Parameter	35.44	35.556	0.32%
Mean Life	31.74	32.006	0.8%

Weibull plot for life data of washing machine obtained through Minitab tool is presented in Fig.1. Finally regression analysis is carried out to find out the used life of components at particular conditions of use. Regression analysis provides fairly reasonable results in circumstances where the input variables obey a well-defined positive pattern over the computer age. But this approach has been found struggling to retain its prediction accuracy when the input variables show a complex pattern. This is demonstrated by a study of regression in different data pieces, as the behavior of functional Parameters shifts during the washing machine's entire life as shown in Table 1.

The following regression equation gives the Actual used life of washing machine

$$L_A = a + b (\text{rpm}) + c (\text{temp}) + d (\text{pow}) + e (\text{cur}) + f (\text{vol}) \quad (1)$$

$$L_{A=} -1152.9 + 0.81 (\text{rpm}) + 0.095 (\text{temp}) + 0.06 (\text{pow}) + 0.1 (\text{cur}) - 0.11 (\text{Vol}) \quad (2)$$

3.2 Remaining useful life (LED Bulb)

Lighting using LEDs has increased dramatically in recent years due to its critical benefits such as lower consumption, smaller size and longer lifespan. Tests of LEDs failure modes, catastrophic failures (open circuit) and degradation failures were studied in this study. Hence the lifetime models are proposed for catastrophic and degradation failures.

3.2.1 Failure Criteria

The LEDs posed two types of failures: catastrophic, which could be either the short or the open circuit conditions; in observed tests, only the open circuit failures occurred and all of them were triggered by humidity penetration into the anode, resulting in bonding oxidation between the lead frame and the cathode wire and failures in degradation, in catastrophic failure analysis mainly three types of tests were carried out, they are Temperature tests, Current tests, Humidity tests, and these three parameters observed to be mainly affecting the life span of LEDs. Weibull plot for life data of LED obtained through Minitab tool is presented in Fig.2.

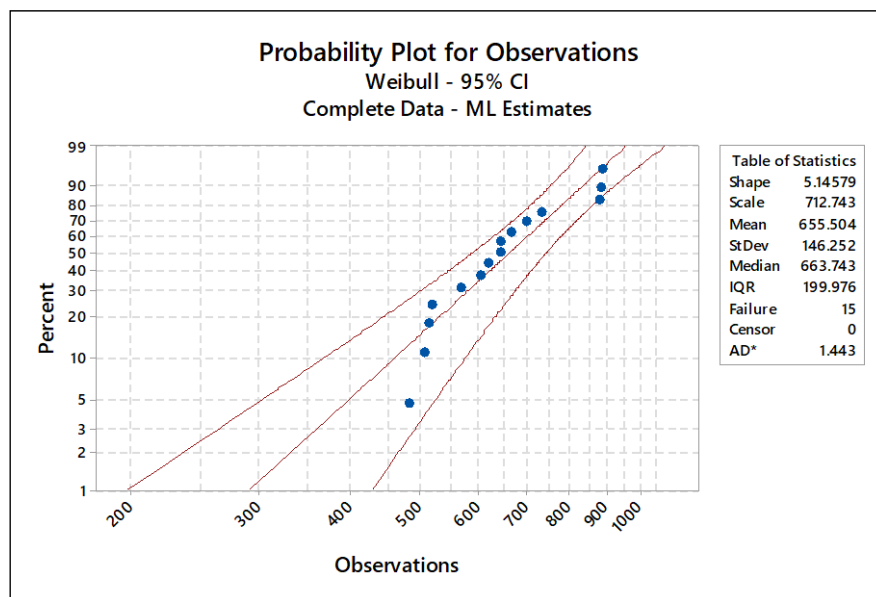


Figure 3. Weibull plot for Life data of LED bulb

Table 2. Weibull analysis results comparison for LED data

	Calculated Results	Results from Minitab	Percentage Variation
Shape Parameter	4.98	5.145	3.2
Scale Parameter	717.56	712.74	0.6
Mean Life	656.68	655.5	0.17

The following regression equation gives the time to failure of LED bulb,

$$\text{Time to Failure} = a + b(\text{temp}) + c(\text{current}) + d(\text{humidity}) \quad (3)$$

$$\text{Time to Failure} = 2726 - 14.20(\text{temp}) - 10.47(\text{current}) - 4.93(\text{Humidity}) \quad (4)$$

3.3 Proposed Artificial Neural Network Model

The proposed neural network model is multilayer feed-forward neural network; back-propagation model has the advantages of solving nonlinear learning problems with high accuracy. For backward propagation networks it is necessary to be able to measure the derivatives of any transfer functions used to make the back-propagation neural network more versatile in terms of understanding complex relationships as shown in Fig. 3. Both the transfer functions $tansig$ and $purelin$ used in the proposed network have a corresponding $dtansig$ and $dpurelin$ derivative function, respectively. Both $tansig$ and $purelin$ are transfer functions that calculate a layer's output from its net input.

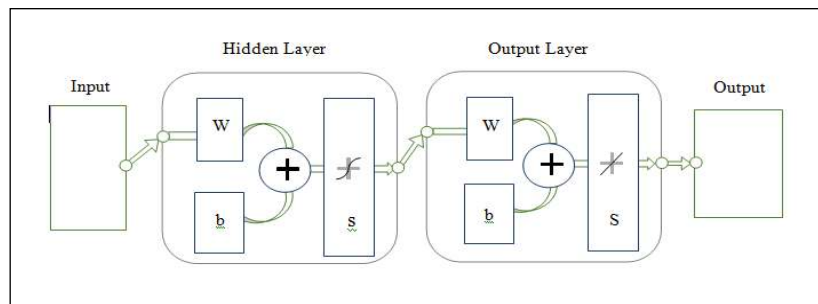


Figure 4. Proposed Network Model

When it comes to structure of proposed network in washing machine, the input parameters are five in number (Temperature, Speed, Power, Voltage, and Current), W indicates training data weights, b indicates testing data weights, S is no. of neurons and the output is actual used life. Whereas in LED input parameters are three in number (Temperature, Current, and Humidity), output is actual used life.

3.3.1 Training and Target Data

Neural network models require a large amount of data for training and simulating the networks to get the sufficient amount of data random data generation is done by statistical data analysis of the life data. Maximum portion of the data is assigned as training data and remaining portion as target data

3.3.2 Training and simulation of network

Training style is the supervised learning in which a series of examples (training series) of proper network behavior are given for the learning law. The training set consists of inputs and the appropriate outputs (targets) for that, the Levenberg – Marquardt algorithm, one of the most efficient learning algorithms, was used to train the network. This algorithm is known to be one that has the fastest convergence on functional approximation problems. One of the issues that arise during the training of neural networks is over fitting or 'over-training.' In this case, the network memorizes the training examples but has not learned to generalize to new scenarios. The MATLAB `trainbr` method, which has been used to train the proposed network, has an integrated process, Bayesian regularization, a technique designed to resolve the over fitting problems. This technique has been reported as a better method for the generalization of approximation function problems.

4. Analysis and Discussion

This research explores the efficacy of neural networks by examining complex and nonlinear life cycle data to estimate the remaining life. The study further discusses and highlights the advantages of using artificial networks for the creation of a reliability evaluation model based on life cycle data analysis over multiple regressions. R^2 value from the Fig.4 and Fig. 5 states that the neural network model produced results very closely related outputs to desired trained outputs for washing machine and LED bulb studies respectively. Remaining useful life estimation with nonlinear inputs is far more complicated than with linear inputs, especially in the case of an intricate mixture of fluctuating and unpredictable trends results provided by the proposed integrated methodology for the remaining life

assessment are correlated with higher rates of certainty due to the fact that known reliability evaluation and statistical analysis techniques were employed at both stages of the study. Additionally, the best available functions and procedures were used to pre-process the inputs, train the network, and post-process the model outputs.

4.1 Washing Machine

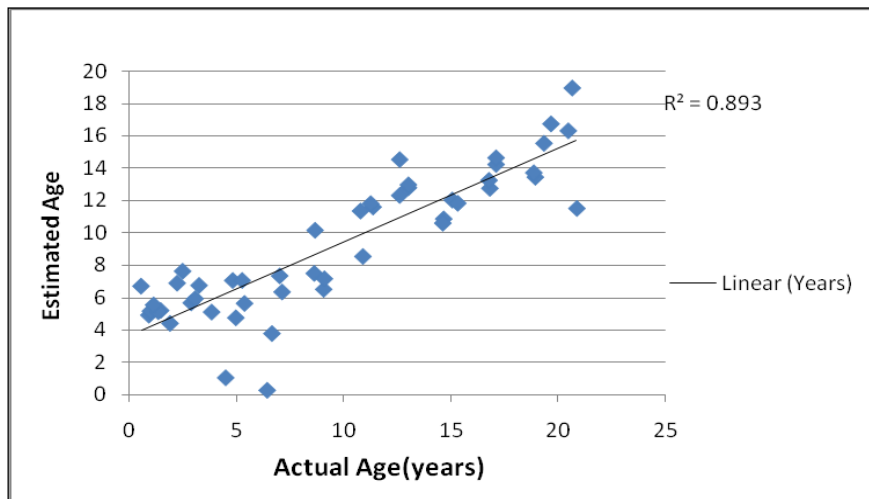


Figure 5. Correlation coefficient for Testing and predicted values of Washing machine

Table 3. Remaining useful life estimates of washing machine

Speed	Temp	Power	Voltage	Current	Mean life	Average life	Reaming Useful life
1420	40	352	240	1.38	42.26	18.81	23.45
1430	32	340	240	1.42	42.26	15.36	26.9
1440	36	345	240	1.41	42.26	16.72	25.54

4.2 LED Bulb

Table 4. Remaining useful life estimates of LED Bulb

Temp	Current	Humidity	Mean life	Average life	Remaining useful life
120	10	55	7189	1698	5491
140	10	70	7727	2473	5254
150	20	85	3316	2970	346

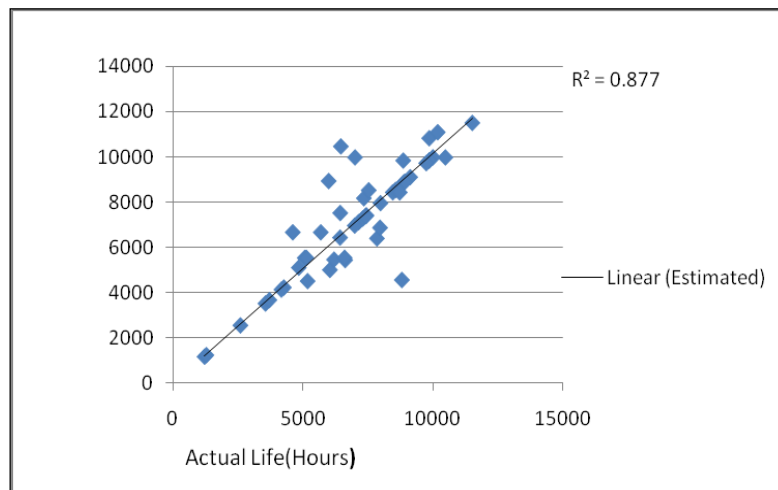


Figure 6. Correlation coefficient for Testing and predicted values of LED Bulb

Remaining useful life estimates of washing machine and LED bulb based on the relevant conditions of use are presented in Table 4 and Table 5 respectively.

5. Conclusion

This paper provides an integrated method for calculating the remaining useful life of the reusable components. The proposed neural network model has been shown to generate life-time estimates with higher rates of certainty once educated. The findings were checked using data on a washing machine's life cycle. It has also been shown that motor speed, winding temperature and power can be used to estimate the residual life of a washing machine and Temperature, Current, Humidity for LEDs. The approach suggested in this paper aimed to address the void currently present in the literature by offering a decision-making tool for achieving closed loop systems. The Integrated approach in this context helps consumers make sound end-of-life decisions over the life cycle of the product.

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