

Article

Sustainability Analysis of a ZnO-NaCl-Based Capacitor Using Accelerated Life Testing and an Intelligent Modeling Approach

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Abstract: From small toys to satellites, capacitors play a vital role as an energy storage element, filtering or controlling other critical tasks. This research paper focuses on estimating the remaining useful life of a nanocomposite-based fabricated capacitor using various experimental and artificial intelligence techniques. Accelerated life testing is used to explore the sustainability and remaining useful life of the fabricated capacitor. The acceleration factors affecting the health of capacitors are investigated, and experiments are designed using Taguchi's approach. The remaining useful lifetime of the fabricated capacitor is calculated using a statistical technique, i.e., regression analysis using Minitab 18.1 software. An expert model is designed using artificial neural networks (ANN), which warns the user of any upcoming faults and failures. The average remaining useful life of the fabricated capacitor, using accelerated life testing, regression, and artificial neural network, is reported as 13,724.3 h, 14,515.9 h, and 14,247.1 h, respectively. A comparison analysis is conducted, and performance metrics are analyzed to opt for the most efficient technique for the prediction of the remaining useful life of the fabricated capacitor, which confirms 93.83% accuracy using the statistical method and 95.82% accuracy using artificial neural networks. The root mean square error (RMSE) of regression and artificial neural networks is found to be 0.102 and 0.167, respectively, which validates the consistency of the reliability methods.

Keywords: artificial intelligence techniques; accelerated life testing; artificial neural network; regression analysis; remaining useful life; sustainability; Taguchi's approach



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1. Introduction

Energy is the most concerning topic for the world now because the world is developing at a very fast rate. In countries such as China, India, Russia, Indonesia, and Brazil, the rate of industrialization is increasing at a very fast rate, and these countries are consuming lots of conventional energy sources, which is causing problems such as global warming. In the era of integration, thousands of electronic components are installed on smaller devices. Due to the stressed environment, sometimes, the component and devices experience sudden failure. The reliable method of device or component prognosis and diagnosis will diminish the unnecessary maintenance charges and replacement cost [1]. Further, the failure of a single component can destroy the whole device [2]. As the problem of electronic waste is enhancing at an accelerating rate, using remaining useful life prediction, the e-waste problem can be minimized due to the remaining useful life emphasis on the reuse potential of the component. The user can reuse the component, rather than throwing it away as waste, if its remaining useful life can be estimated [3]. Customer satisfaction is closely associated with component reliability [4]. Moreover, if the product fails during the warranty period, the unnecessary replacement cost and dubious market reputation of the manufacturer are setbacks for the vendor or consumer. The untimely failure of a component or device

can diminish the reputation of the seller, and the replacement or repair cost during the warranty period burdens the manufacturer [2].

Nanomaterial also shows a very high aspect ratio, which enables the fabrication of devices in a very compact size; they also show very high porosity due to the fact that they can store more and more charges [5]. A capacitor is an example of a passive electronic component and stores energy in the form of an electrostatic field. It consists of two conducting plates, which are separated by a dielectric. Nanocomposite-based capacitors are easy to fabricate and show an effective charging–discharging pattern. The synthesis and characterization techniques such as Scanning Electron Microscope (SEM), Transmission Electron Microscopy (TEM), Ultra-Violet microscopy, etc., confirm the capacitive behavior of the component. Reliability is the major constraint for successful operation when the fabricated capacitor is used in equipment in a real-time environment [6]. Thus, this research article focuses on the remaining useful lifetime estimation of a fabricated capacitor using various tools and techniques. Various empirical, experimental, or software-based reliability assessment techniques are available for failure analysis. Intelligent techniques using artificial intelligence or deep learning assist the user in assessing its health condition, and necessary preventive actions can be taken [7].

This research paper is divided into three major sections. In the first section, the synthesis and characterization of the fabricated capacitor are discussed, along with its charging and discharging capacity. The second section of the paper discusses the remaining useful life prediction of a fabricated capacitor using accelerated life testing and statistical and intelligent techniques. The design of experiments (DOE) is designed and conducted using Taguchi's approach. The statistical analysis and intelligent prediction of remaining useful life using artificial neural networks are explained. The last section is reserved for the performance matrices, accuracy analysis, and experimental technique validation of the fabricated capacitor.

2. Fabrication of the Capacitor

Nanomaterial Zinc-oxide, which has a 3.3 eV bandgap, can help to store charges due to its high band gap nature. Zinc-oxide, which is chemically represented as ZnO, is a semiconductor material, but this can be used to accumulate charges. If ZnO is mixed with aqueous NaCl in a 1:1 concentration, then the dielectric constant can be enhanced further [8]. Here, dielectric material shows a very high capacitance value, because when we apply an electric field, the NaCl undergoes ionization due to the fact that Na^+ migrates to the positive terminal and Cl^- migrates to the negative terminal. The nanoparticles of ZnO were prepared by the sol-gel method [9] (Figure 1a), using Zinc Nitrate ($\text{Zn}(\text{NO}_3)_2$) as a precursor solution, Sodium Hydroxide (NaOH) as a reducing agent, and thioglycerol ($\text{C}_3\text{H}_8\text{O}_2\text{S}$) as a capping agent. An Eppendorf was used, in which NaCl (0.3 g) and then 1 mL of distilled water were added. Then, the solution was stirred, and ZnO (0.1 g) was added. A gel forms, and in the gel form, NaCl was an insulating compound. ZnO and distilled water were in a ratio of 1:1. The concentration of NaCl was varied in order to study the highest capacitance value of the fabricated capacitor, i.e., 0.1 g, 0.2 g, 0.3 g, 0.4 g, and 0.5 g, but the capacitance value for the ZnO mixed aq. NaCl water with NaCl 30% by weight showed the highest mean NaCl (0.3 g) in 1 mL distilled water, and 0.1 g ZnO was the highest. After that, the gel was coated on the 12 mm diameter copper (Cu) plates. The thickness was 1 mm, and another Cu plate was placed on it with some mechanical force to distribute the gel between the plates equally and smoothly. Since ZnO has a band gap of 3.3 eV and has high porosity, it stored these charges. Hence, NaCl behaving as an insulator in gel form caused an increase in the positivity of ZnO [10]. Moreover, at 0.8 V, the water also broke down into ions, as more charges were available to store.

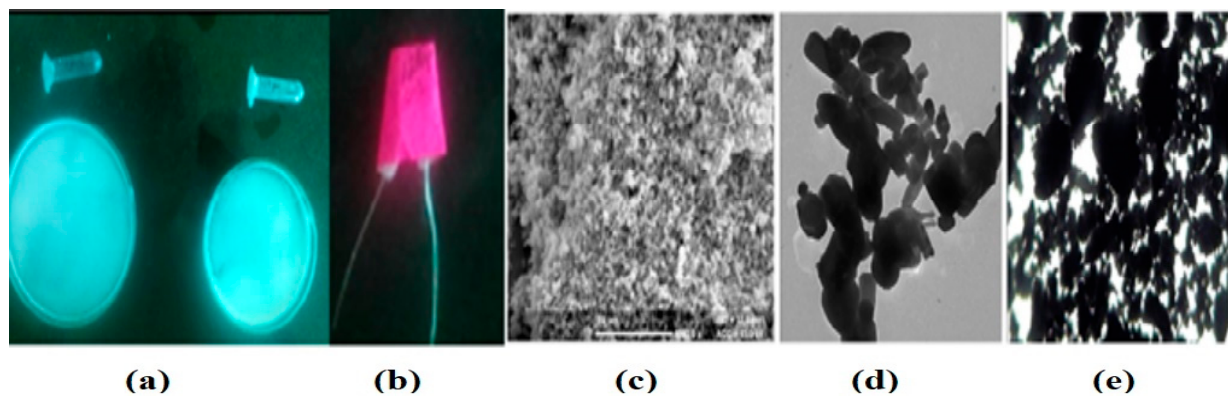


Figure 1. (a) Sol-gel method; (b) fabricated capacitor; (c) SEM image; (d) TEM image; (e) optical microscopy.

The nanocomposite-based fabricated capacitor is shown in Figure 1b. The capacitance of the fabricated capacitor was confirmed using circuit and Arduino interfacing, which showed 143.9 microfarad capacitance, and a charging–discharging pattern was recorded. Various characterization techniques, such as scanning electron microscope SEM (Figure 1c), transmission electron microscopy (TEM) (Figure 1d), and optical microscopy of a composite gel (Figure 1e), confirm its capacitive behavior.

The various characterization results prove its capacitive functionality. This fabricated capacitor is cost-effective and environmentally friendly. Before releasing it to the actual market, it is necessary to evaluate its performance and reliability. Thus, various types of reliability analysis methods were used to find the remaining useful lifetime, with an extreme level of input parameters. The results were statistically verified and intelligently modeled, which assists users in performing desired operations successfully.

3. Remaining Useful Life Prediction of the Fabricated Capacitor

The lifetime prediction of the fabricated capacitor is the critical parameter for its reliable and successful operation [11]. Due to electrical parameters and environmental condition variations, the faults and failures may disturb the component as well as the whole system [12]. The sudden failure of the component not only degrades the overall performance of the equipment but also deteriorates the market reputation of the component manufacturer [13,14]. The design flow of the remaining useful life prediction of the fabricated capacitor is as per Figure 2, starting from the selection of capacitors to exploring the remaining useful lifetime of capacitors using various experimental, statistical, and intelligent prediction techniques.

A hundred samples of fabricated capacitors were selected in equal proportion of NaCl and ZnO. The critical parameters were explored, those which influence the condition of capacitors under various electrical and environmental conditions. Figure 3 shows various influential parameters for the health prognostics and condition monitoring of fabricated capacitors. The five parameters are taken as acceleration factors, which play a vital role in health prognostics, i.e., temperature, voltage, current, humidity, and vibration [11]. The design of experiments (DOE) was prepared using Taguchi's approach. Minitab 18.0 software is used for designing the L16 matrix of the orthogonal array [15]. The five parameters were assigned four levels. The process parameters are depicted in Table 1. The level of input parameters was divided into four sub-levels, starting from low to extreme.

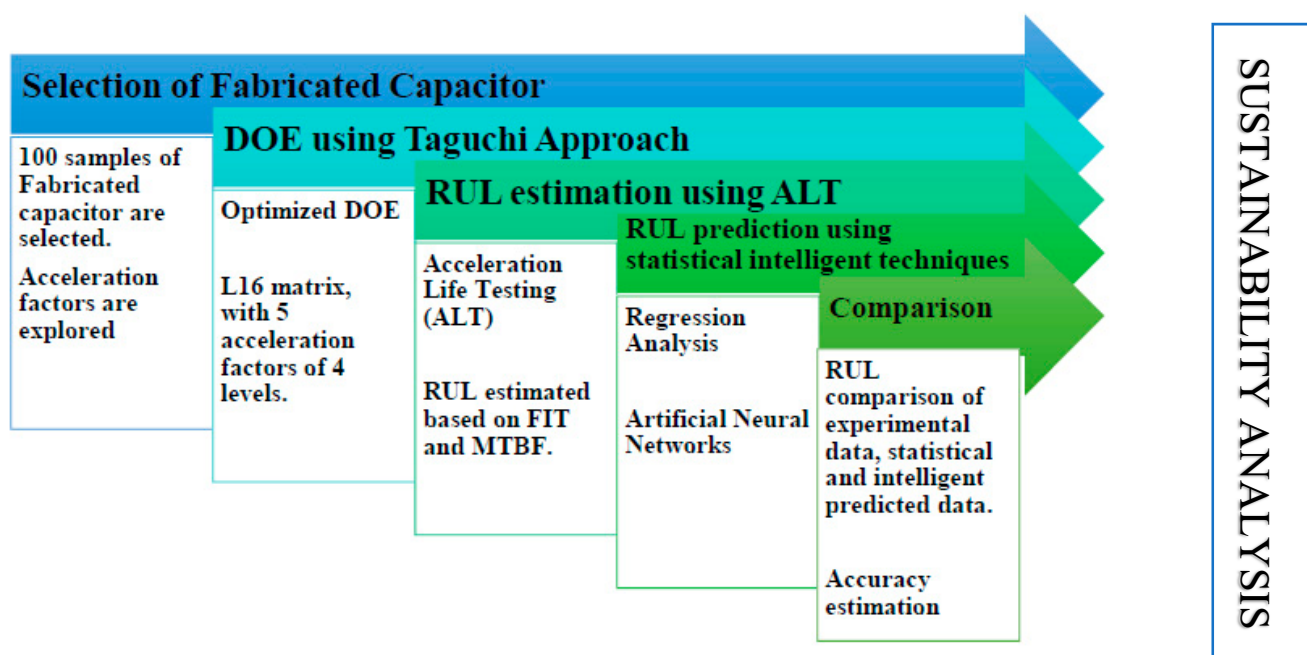


Figure 2. Design flow of remaining useful life estimation of fabricated capacitor.

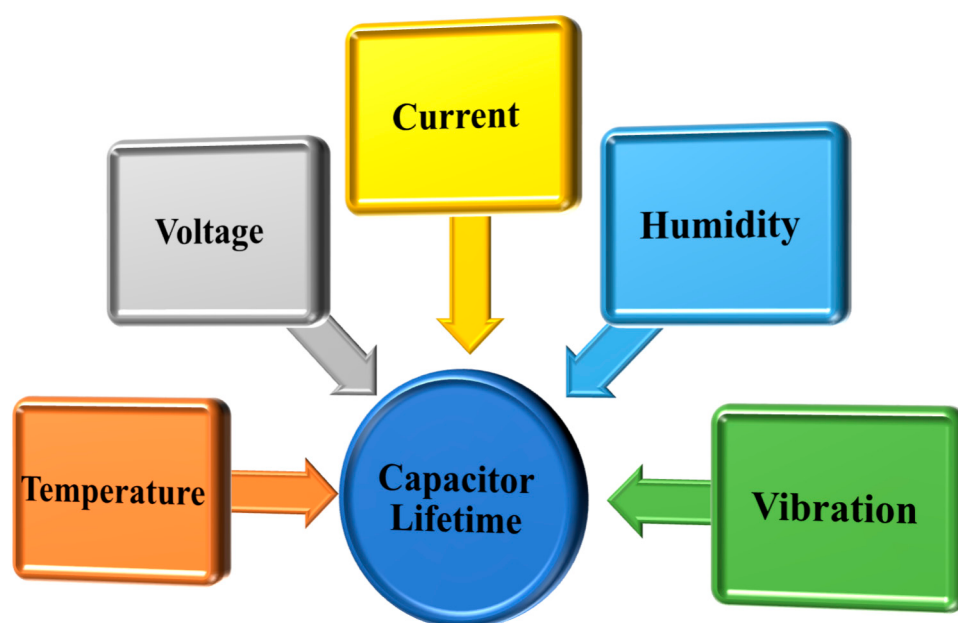


Figure 3. Factors affecting capacitor lifetime.

Table 1. Process parameters and levels.

Parameters	Units	Notation	Level			
			Low (1)	Medium (2)	High (3)	Extreme (4)
Temperature	°C	t	75	85	95	105
Voltage	V	v	4.2	4.8	5.4	6.0
Current	Ma	i	24	26	28	30
Humidity	Rh	r	77	80	83	86
Vibration	Hz	vb	23	26	29	32

After deciding the process parameters and levels, an orthogonal array was prepared using Taguchi's approach, which is the L16 matrix. The values of process parameters have been assigned to the respective column of Taguchi's approach [16]. After assigning the values to the L16 matrix, the experiment was conducted in a controlled manner. The experimental technique for the reliability estimation of the fabricated capacitor is discussed in the following section. For designing experiments (DOE), Taguchi's approach was used [17].

The various factors affecting the health of fabricated capacitors are explored and shown in Figure 3.

The process parameters and level of optimization are discussed in Table 1, which range from low to extreme.

3.1. Remaining Useful Life Estimation Using Accelerated Life Testing (ALT)

To identify the potential failures or its withstanding capability, the product or component is tested in extreme conditions, a process which is known as accelerated life testing (ALT). Accelerated life testing represents a technique for exploring product reliability in a short span of time as compared to standard life testing. The selection of stresses, acceleration factors, and Design of Experiments (DOE) should be performed with utmost care. The characteristics of the product under test will be the basis for the actual acceleration factors. Due to increased stress levels, the duration of accelerated life testing is reduced, which is one of the prominent benefits. As the testing duration is decreased, more tests are initiated, which run for a specific duration of time. In such a way, accelerated life testing is a fast way to bring a product to market and cost-effective, which evolved it as one of the extensive methods available for reliability testing.

The fabricated capacitor lifetime was assessed using accelerated life testing [18]. Stress parameters were explored for the health prognostics and condition monitoring of the component. The process for conducting the experimental technique, i.e., accelerated life testing, has the following steps, as shown in Figure 4.

In Table 2, the L16 orthogonal array design is shown, in which the values of various levels were inserted by considering Table 1. The trials were framed for conducting the experiments for estimating the remaining useful life of the fabricated capacitor. The five acceleration factors were identified, which were further bifurcated in four stress levels. The 100 samples of fabricated capacitors were taken and put on the digital hot plate, where the temperature was a controlled parameter [19]. The capacitors were further covered with sand so that uniform heating could be given to all the capacitors [5,20,21]. Similarly, the acceleration parameters were monitored at various levels, as shown in Figure 4.

Initially, the capacitance of the capacitors was measured through an LCR meter, and then the experiment was started [22]. The literature suggests that the capacitor is considered to be faulty or fail if the capacitance decreases by 20% and its weight is reduced by 50% [19]. The acceleration factors were gradually increased from the range of low to extreme, as per trials framed in Table 2. When the conditions of reduced capacitance and weight were fulfilled, the capacitor was found to be failed or faulty [23]. From Table 1, the values of levels are mapped to Table 2, and the experiment was initiated. The number of failed capacitors is noted along with the time taken. Using the Arrhenius equation (Equation (1)), the remaining useful lifetime of fabricated capacitors is calculated.

$$FIT(\lambda) = \frac{\text{Number of fail/faulty components}}{\text{Total Number of components} \times \text{Testing hours} \times \text{Acceleration factors}} \quad (1)$$

where the acceleration factor (A_f) is calculated as:

$$\text{Acceleration factor } (A_f) = e^{\frac{E_a}{K} \left(\frac{1}{\text{Ambient temp.}} - \frac{1}{\text{Test temp.}} \right)} \quad (2)$$

where E_a is activation energy = 0.7 eV and K = Boltzmann's constant.

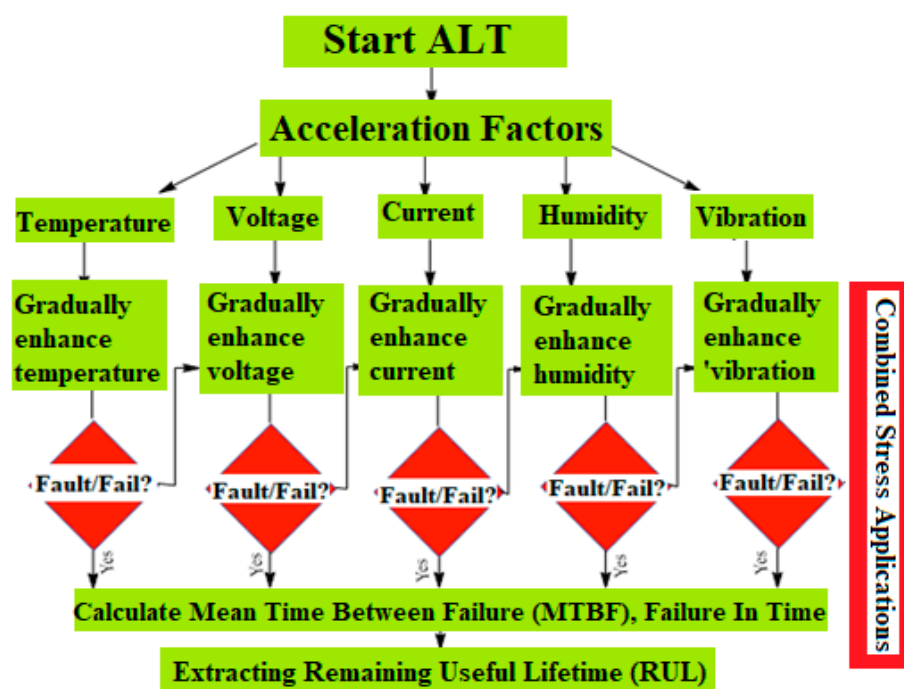


Figure 4. Accelerating life testing (ALT).

Table 2. Taguchi's L16 matrix.

Trials	Process Parameters (Factors)				
	Temperature (°C)	Voltage (V)	Current (mA)	Humidity (Rh)	Vibration (Hz)
1	1	1	1	1	1
2	1	2	2	2	2
3	1	3	3	3	3
4	1	4	4	4	4
5	2	1	2	3	4
6	2	2	1	4	3
7	2	3	4	1	2
8	2	4	3	2	1
9	3	1	3	4	2
10	3	2	4	3	1
11	3	3	1	2	4
12	3	4	2	1	3
13	4	1	4	2	3
14	4	2	3	1	4
15	4	3	2	4	1
16	4	4	1	3	2

Using the accelerated life testing criterion, the failed/faulty components were explored, and failure in time (FIT) was calculated. The number of failed or faulty components further depicts the remaining useful life [24]. The early prediction of remaining useful life guides the user to replace the failure/faulty component.

3.2. Remaining Useful Life Estimation Using Statistical Analysis

The remaining useful life of the fabricated capacitor was also estimated using statistical techniques. Non-linear regression was used to explore the relationship between process parameters and response, i.e., the lifetime of the capacitor. Minitab 18.1 software was used for regression analysis [25]. The following mathematical model establishes a

relation between predictors and response variables, i.e., lifetime and input factors such as temperature, voltage, current, humidity, and vibration.

$$FC(Lifetime) = K(T^a \times V^b \times I^c \times H^d \times Vb^e) \quad (3)$$

where K is the regression constant and T, V, I, H, Vb are the process parameters, and $FC(lifetime)$ is the remaining useful lifetime of the fabricated capacitor. a, b, c, d, e are the model parameters. The values of these model parameters were calculated using Minitab 18.1 software. Equation (3) can be represented in linear form as:

$$\ln FC = a \ln T + b \ln V + c \ln I + d \ln H + e \ln Vb \quad (4)$$

Equation (4) can be further modified as:

$$FC = \alpha_0 + \mu_1 A_1 + \mu_2 A_2 + \mu_3 A_3 + \mu_4 A_4 + \mu_5 A_5 \quad (5)$$

Equation (5) shows capacitor lifetime FC in logarithmic scale; A_1, A_2, A_3, A_4, A_5 are logarithmic process parameters, and $\mu_1, \mu_2, \mu_3, \mu_4, \mu_5$ are logarithmic regression coefficients. The Minitab 18.1 software was used to develop regression equations as well as estimate the regression coefficients.

3.3. Remaining Useful Life Estimation Using Artificial Neural Networks

The application of ANNs has extensively grown in popularity since the last decade because novel and optimized approaches could be represented using neural networks rather than conventional mathematical models and algorithms [26]. Inspired by the human brain's functionality, ANNs have various interconnected elements, such as neurons, that can be utilized for prediction and problem-solving in a similar manner as the human brain. ANNs have refined characteristics of learning adaption, robustness, massive parallelism, spatial-temporal information, etc., which prepare ANNs as one of the finest components of knowledge engineering [27,28].

Figure 5 shows the ANN operational structure, wherein one or more neurons are activated upon applying inputs [11,29]. Implicit knowledge can be built by training supervised or unsupervised neural networks using a back propagation algorithm. Further, the weights are modified to improve the accuracy of the solution. Artificial neural networks have a variety of industrial applications; a few are enlisted in Table 3.

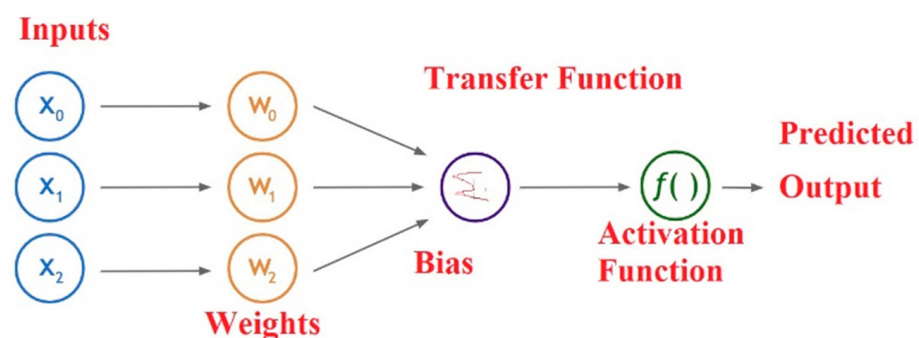


Figure 5. ANN structure.

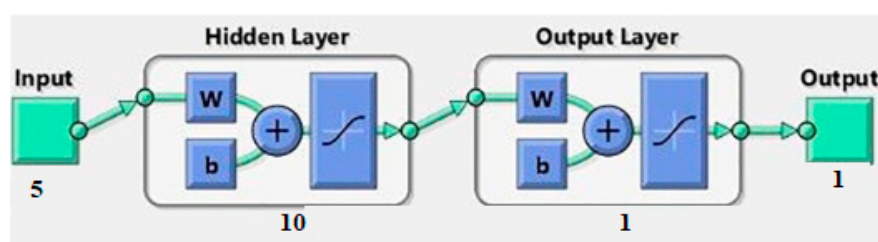
Table 3. ANN industrial applications.

Application Industry	References	Area of Application
Composite science	[30,31]	Selection of suitable composite as per application.
Coal industry	[32,33]	Relate ultimate and proximate analysis data.
Problem-solving in industrial applications	[34–36]	Solve complex and time-consuming problems.
Medical field	[37–40]	Diagnostic tool for tuberculosis, tumors, diabetes, etc.
Mechanical	[41,42]	Leak diagnosis in pipes, recognition of medical tools, etc.

In this research article, ANN-based remaining useful life prediction of a fabricated capacitor was performed before its release to market. Due to various acceleration factors, the mathematical model uses a great number of assumptions, which further decreases the accuracy of the prediction model.

After analyzing the remaining useful lifetime of a fabricated capacitor using the experimental technique, i.e., accelerated life testing and statistical approach (i.e., regression analysis), intelligent prediction models were explored to estimate the remaining useful life [42–44]. An artificial neural network (ANN) was used for developing an expert model for the users. The ANN is a similar system to the human brain. Using training and testing processes, the accuracy of the expert system can be estimated [45]. The activation parameters are used to initialize the process; afterward, the system trains itself, and chances of error are reduced [46].

The number of neurons in the input layer is five, i.e., temperature, voltage, current, humidity, and vibration. A total of 70% of data was used for training purposes, and 30% of data was used for testing purposes [47,48]. As shown in Figure 6, the ANN model is a 5–10–1 model, which shows it has 5 input layers, 10 hidden layers, and 1 output layer. The MATLAB R2017b tool was used for analyzing the output of the ANN (Artificial Neural Network) [49]. After training and testing, the predicted response was analyzed, and a comparison was performed with the response (lifetime) obtained through accelerated life testing [50].

**Figure 6.** ANN Model (5–10–1).

4. Result and Discussion

The remaining useful lifetime of the fabricated capacitor was analyzed by the experimental method (i.e., accelerated life testing (ALT)) and statistical method (i.e., regression analysis), and an expert model was created using an artificial intelligence technique (i.e., Artificial Neural Networks (ANNs)). For the Design of Experiments (DOE), Taguchi's L16 orthogonal array was designed, and trials were formulated [51]. The experiments were conducted as per this set of trials, and faulty/fail components were detected using an LCR meter, which further helps to assess the remaining useful lifetime using the Arrhenius equation [52].

4.1. Remaining Useful Life Assessment Using the Experimental Technique

The 16 various trials were formulated for the five process parameters with four levels, as shown in Table 2. The values and levels of process parameters were assigned to Taguchi's L16 orthogonal array matrix [53]. The experiments were conducted for all 16 trials, and the remaining useful life was calculated using Equations (1) and (2). Table 4 shows the remaining useful lifetime of fabricated capacitors, as per accelerated life testing (ALT) and Arrhenius' law.

Table 4. Remaining useful life estimation using experimental method.

Trials	Process Parameters (Factors)					Output
	Temperature (°C)	Voltage (V)	Current (mA)	Humidity (Rh)	Vibration (Hz)	ALT Remaining Useful Life (Hours)
1	75	4.2	24	77	23	9875.4
2	75	4.8	26	80	26	13,012.4
3	75	5.4	28	83	29	17,811.8
4	75	6	30	86	32	21,887.6
5	85	4.2	26	83	32	14,818.1
6	85	4.8	24	86	29	15,161.5
7	85	5.4	30	77	26	13,714.5
8	85	6	28	80	23	14,317.9
9	95	4.2	28	86	26	14,513.2
10	95	4.8	30	83	23	13,887.3
11	95	5.4	24	80	32	13,450.5
12	95	6	26	77	29	11,966.3
13	105	4.2	30	80	29	11,600.4
14	105	4.8	28	77	32	10,190.3
15	105	5.4	26	86	23	12,047.9
16	105	6	24	83	26	11,335.2

4.2. Remaining Useful Life Assessment Using the Statistical Technique

Using Minitab 18.1 software, the statistical analysis of the remaining useful lifetime of fabricated capacitors was performed [54]. The regression equation was formulated, and as per this equation, the lifetime was estimated for all 16 trials. Conclusively, R-squared and other regression parameters validate its statistical analysis well [55].

$$FC(Lifetime) = -41276 - 141.1(temperature) + 1286(voltage) + 484.9(current) + 492.2(humidity) + 288.5(vibration) \quad (6)$$

In regression analysis, R-squared is a measure that tells us what proportion of the total variability is explained by the model. In analyzing the remaining useful lifetime data using Minitab 18.0, 98.10% and 97.16% R-sq value and R-sq (adj) values were achieved. The regression model parameters prove that the experimental model is statistically validated.

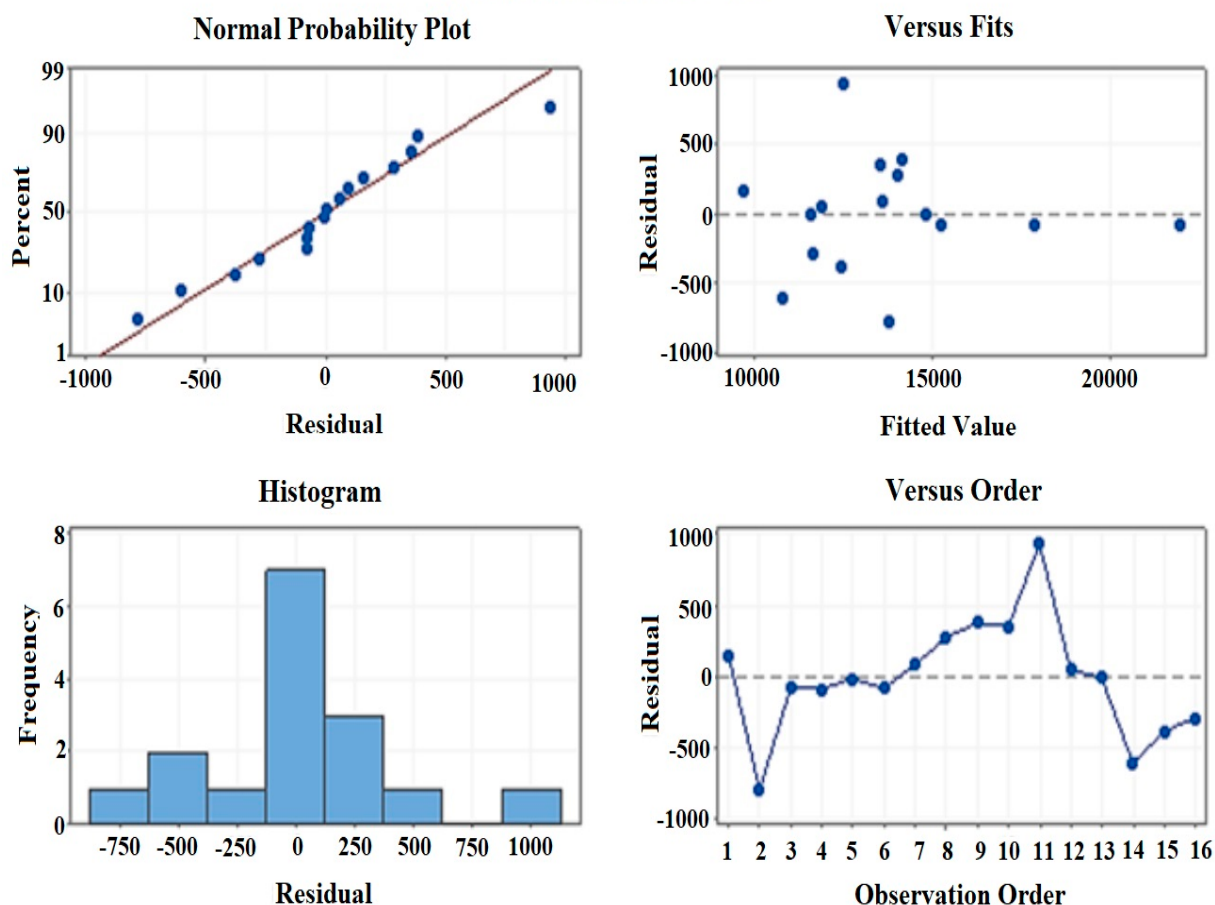
Table 5 summarizes the performance parameters of the reliability analysis methods, which govern the accuracy of all the reliability models. The root mean squared error of the regression and artificial neural networks is 0.102 and 0.167, respectively, whereas the mean absolute error is 0.092 and 0.13, respectively, and correlation coefficients are 0.989 and 0.898 for regression and ANN, respectively.

Figure 7 presents the various residual plots for the lifetime of the fabricated capacitors, such as the normal probability plot, fits curve, histogram, etc. Table 6 shows the remaining useful lifetime values of fabricated capacitors using a statistical method, i.e., regression analysis.

Table 5. Performance metrics of reliability methods.

Methods	Performance Parameters		
	Root Mean Square Error (RMSE)	Mean Absolute Error (MAE)	Correlation Coefficient (CC)
Regression Remaining Useful Life (Years)	0.102	0.092	0.989
ANN Remaining Useful Life (Years)	0.167	0.13	0.898

Residual Plots for Life

**Figure 7.** Regression plots for capacitor lifetime.

Equation (6) is used to estimate the remaining useful lifetime of fabricated capacitors using a statistical method, i.e., regression analysis.

Table 6. Remaining useful life estimation using statistical method.

Trials	Process Parameters (Factors)					Output
	Temperature (°C)	Voltage (V)	Current (mA)	Humidity (Rh)	Vibration (Hz)	Regression Remaining Useful Life (Hours)
1	75	4.2	24	77	23	10,375.2
2	75	4.8	26	80	26	14,458.7
3	75	5.4	28	83	29	18,542.2
4	75	6	30	86	32	22,625.7
5	85	4.2	26	83	32	15,571.7
6	85	4.8	24	86	29	15,984.6
7	85	5.4	30	77	26	14,370.3
8	85	6	28	80	23	14,783.2
9	95	4.2	28	86	26	14,964.1
10	95	4.8	30	83	23	14,363.4
11	95	5.4	24	80	32	13,345.5
12	95	6	26	77	29	12,744.8
13	105	4.2	30	80	29	12,523.2
14	105	4.8	28	77	32	11,713.9
15	105	5.4	26	86	23	13,349
16	105	6	24	83	26	125,39.7

4.3. Remaining Useful Life Prediction Using an Intelligent Technique

The remaining useful lifetime of fabricated capacitors was estimated using accelerated life testing and analyzed using regression analysis. An intelligent expert model was designed using artificial neural networks, which warn the user about the failure well before it actually occurs. The MATLAB R2017b (Santa Clara, CA, USA) tool was used for this purpose [2,56]. The ANN 5–10–1 model was used, with five input layers, 10 hidden layers, and 1 output layer. This expert model was trained and tested for the 16 sets of trials, and lifetime was estimated, as shown in Table 7. A total of 70% of data was used for training and 30% was used for testing purposes. The comparative analysis of all the techniques is discussed in the following section.

Table 7. Remaining useful life estimation using ANN.

Trials	Process Parameters (Factors)					Output
	Temperature (°C)	Voltage (V)	Current (mA)	Humidity (Rh)	Vibration (Hz)	ANN Remaining Useful Life (Hours)
1	75	4.2	24	77	23	11,188.1
2	75	4.8	26	80	26	14,799.1
3	75	5.4	28	83	29	21,150.2
4	75	6	30	86	32	22,181.1
5	85	4.2	26	83	32	13,454.5
6	85	4.8	24	86	29	14,130.7
7	85	5.4	30	77	26	12,557.8
8	85	6	28	80	23	13,932.8
9	95	4.2	28	86	26	14,007.6
10	95	4.8	30	83	23	13,919.9
11	95	5.4	24	80	32	16,121.8
12	95	6	26	77	29	11,507.9
13	105	4.2	30	80	29	13,787.5
14	105	4.8	28	77	32	11,216.7
15	105	5.4	26	86	23	12,432.9
16	105	6	24	83	26	11,565.2

5. Comparative Analysis of Lifetime Calculated by Experimental, Statistical, and Intelligent Techniques

The remaining useful lifetime of fabricated capacitors was calculated using three techniques, i.e., experimental (accelerated life testing), statistical (regression analysis), and intelligent (Artificial Neural Networks). A comparative analysis was carried out to estimate the accuracy of all the techniques.

$$Error(\%) = \frac{(Experimental - Statistical)}{Experimental} \times 100 \quad (7)$$

$$Error(\%) = \frac{(Experimental - Intelligent)}{Experimental} \times 100 \quad (8)$$

Using Equations (7) and (8), the error analysis of all the techniques was processed and accuracy was estimated, as shown in Table 8. The graphical analysis of the remaining useful lifetime calculated using ALT, regression, and ANNs is shown in Figure 8. The remaining useful lifetime estimated using ALT was validated, and the statistical technique has an average of 6.17% error, whereas the ANN has a 4.18% average error.

Table 8. Error analysis of ALT, statistical, and ANN techniques.

Trials	Output			Error Analysis	
	ALT Remaining Useful Life (Hours)	Regression Remaining Useful Life (Hours)	ANN Remaining Useful Life (Hours)	Error between ALT and Statistical	Error between ALT and ANN
1	9875.4	10,375.2	11,188.1	−5.06106	−13.293
2	13,012.4	14,458.7	14,799.1	−11.1148	−13.731
3	17,811.8	18,542.2	21,150.2	−4.10065	−18.743
4	21,887.6	22,625.7	22,181.1	−3.37223	−1.3409
5	14,818.1	15,571.7	13,454.5	−5.08567	9.20226
6	15,161.5	15,984.6	14,130.7	−5.42888	6.7988
7	13,714.5	14,370.3	12,557.8	−4.7818	8.43414
8	14,317.9	14,783.2	13,932.8	−3.24978	2.68964
9	14,513.2	14,964.1	14,007.6	−3.10683	3.48373
10	13,887.3	14,363.4	13,919.9	−3.42831	−0.2347
11	13,450.5	13,345.5	16,121.8	0.78064	−19.86
12	11,966.3	12,744.8	11,507.9	−6.50577	3.83076
13	11,600.4	12,523.2	13,787.5	−7.9549	−18.854
14	10,190.3	11,713.9	11,216.7	−14.9515	−10.072
15	12,047.9	13,349	12,432.9	−10.7994	−3.1956
16	11,335.2	12,539.7	11,565.2	−10.6262	−2.0291
	Average Error (%)			6.17	4.18
	Average Accuracy (%)			93.83	95.82

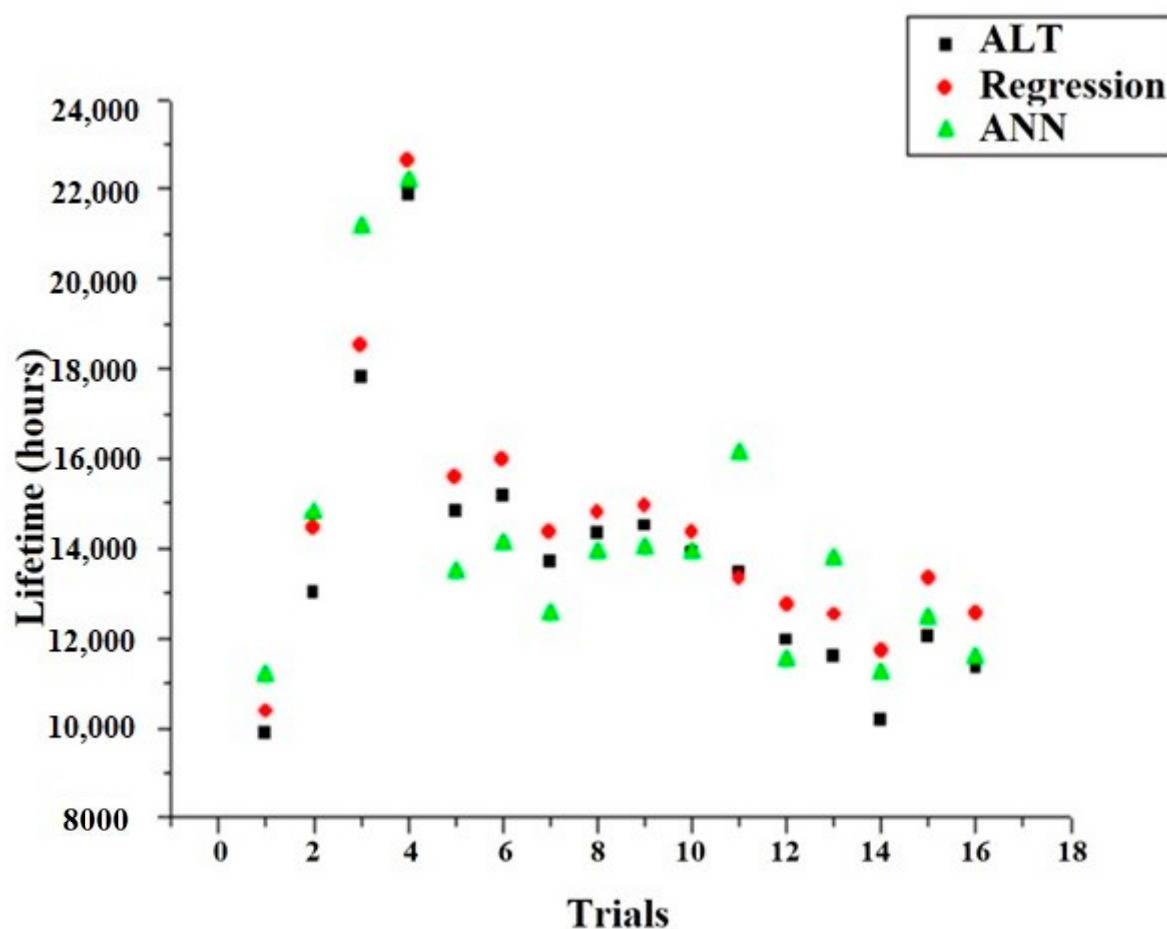


Figure 8. Graphical analysis of remaining useful lifetime.

6. Results, Conclusions, and Scope of Further Research

A nanocomposite-based fabricated capacitor was explored to discover its remaining useful lifetime in successful operation as well as its reusability potential. The timely prediction of faulty and failed components can save the entire device as well as minimize the problem of e-waste.

An experimental method, i.e., accelerated life testing, was conducted for five process parameters at four different levels. The remaining useful lifetime was further analyzed using the regression technique. An intelligent model was framed using artificial neural networks for health prognostics and condition monitoring of the fabricated capacitor. The error analysis confirms that the regression technique has a 6.17% average error, whereas the intelligent technique, i.e., artificial neural network, has a 4.18% error. The RMSE, MAE, and CC values of the regression model and ANN model are extracted as 0.102, 0.167; 0.092, 0.13; 0.989, 0.898, respectively. The average lifetimes of the fabricated capacitor as calculated by experimental, statistical, and intelligent techniques are 13,724.3 h, 14,515.9 h, and 14,247.1 h according to various sets of electrical parameters and environmental conditions. In the future, artificial intelligence can be incorporated during the fabrication and development phases of nanocomposite-based components so that optimized material can be chosen for long-life performance. Convolutional Neural Networks (CNNs) can also be employed as an enhanced intelligent diagnosis technique, and an inspection schedule can be planned. A graphical user interface can also be incorporated using fuzzy logic to track the real-time health status of the capacitor or another component.

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