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Polynomial Modeling of Transformer Hazard Using Artificial Neural Network

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ABSTRACT. The conventional way of forming the hazard lifetime function of transformers applies the best modeling based on the history data using Hazard Plotting Approach (HPA) under different functions: Normal Distribution, Lognormal Distribution, Weibull Distribution and Smallest Extreme Value Distribution. In this paper will propose a new method to develop best modeling using Artificial Neural Network- based polynomial model with minimum error to represent the hazard function for transformer. The procedure of applying the proposed methodology is simple. The quality of the obtained results ensures the adequacy of applying of this methodology for expecting the failure time of the transformer.

KEYWORDS: Polynomial Model, Artificial Neural Network, Transformer Hazard Plotting Approach, Observed Hazard.

1. INTRODUCTION

Electric power systems should operate at the highest efficiency to ensure continuity of supply and reliability of serving end-customers. In order to maintain these sound operating conditions, power systems' assets should be managed optimally. Transformers are the highest investment in the transmission utility and its failure considered a potential risk as when the service stop, the transmission utility will pay penalty to both energy investors and consumers. Therefore, the importance of asset management represented in monitoring transformer lifetime is clear. The expected lifetime of a power transformer is up to 40 years with reliable operation based on the manufactures and utilities common expectation [1-4]. Normally, a transformer reaches its end-of-life when it does not meet the operation requirements anymore [3, 5]. The classification of transformer failure factors, i.e. the root cause, differ from one place to another as shown in Figures 1 and 2 in Hartford, US [1] and Netherlands [6] respectively. Figure 1 and 2 describe the different concept analysis results may change if the study parameter depends on operating conditions' temperature, environmental conditions, and load characteristics.

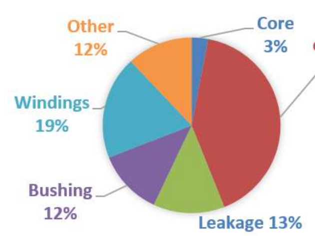

FIGURE 1. Transformer failure factors, Hartford, US [1].

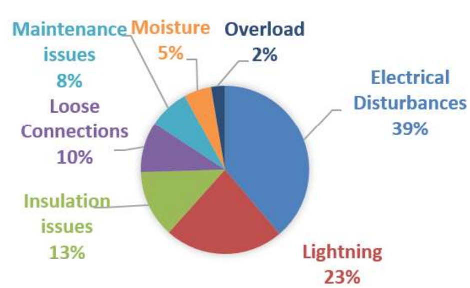

FIGURE 2. Transformer failure factors, Netherlands [6].

Transformer failures occur due to either excessive overloading or system transients. System transients are caused by lightning surge, short-circuit faults, switching surge, and temporary over-voltages [2]. Figure 3 shows that at early years of transformer operation, the operation stress caused by normal operation is much lower than the insulation withstand strength. By time, due to the transformer aging, the insulation withstand gradually reduces [7]. Thus, the effect of systems' transients increase on the transformer lifetime. Finally, if the operating stress or systems' transients exceed the isolation withstand strength, i.e. the intersection point in Figure 3, the transformer will fail earlier than the designed lifetime [8].

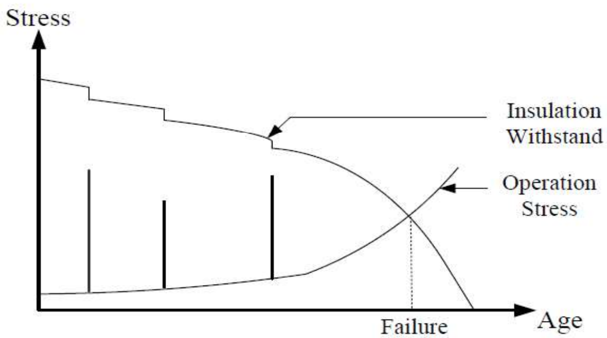

FIGURE 3. Transformer's stress and aging relation [7].

Data history can be analyzed to expect the failure rate of the utilities' transformers. Statistics science started and developed since 1940's, to help the modern technologies to grow [9-12]. It was implemented to suggest advanced analysis methods, to develop engineering products design and manufacturing [13]. The following steps are used to statistically analyze the transformers' lifetimes: Collect data, Select the proper suitable distribution models, Apply curve fitting and estimate the model's parameters values, and Test the goodness-of-fit to select the best models. Finally, a decision support is taken based on the obtained ages, reliability, and failure expectation in Figure 4 [6].

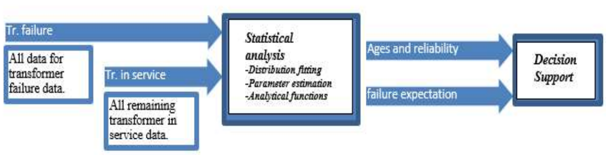

FIGURE 4. Transformer's lifetime estimation.

Literature review showed that the Homogeneous Poisson Process (HPP) is used to estimate failure rate between groups of transformers to prepare a suitable spare leading to continuity of service. The process divides transformer population into groups have the same voltage but different MVA. Historical field data is applied to mathematical models. Results show that the shape of hazard at early ages varies significantly according to different transformer operation practice. In the meanwhile, the quality of the process can be estimated numerically using the x^2 test [14]. The mathematical model applies various distributions; three parameter Lognormal Distribution, Weibull Distribution, and Smallest Extreme Value Distribution, to generate practical model representation. In [15], the probability of life distributions for a different set of equipment were examined. An appropriate choice was investigated to expresses the rate of failure based on the evidence recorded for these equipment. This failure was converted into mathematical equations (model) that almost reflect failure rates. The model was able to describe the method of allocating failure not only to material considerations but to the ability of the distribution to explain the recorded failure data. However, the model is not accurate because it did not use the test procedure to accept or reject the model. In [1], two ways (Normal Distribution and Weibull Distribution) were examined to estimate the average age and standard deviation of a set of power equipment. The used distribution provided better than the traditional medium-sample technique, which uses only the age of the deceased. As both distributions results were based on both the age of the deceased and the survivors which are more accurate. However, the authors failed to compare between these distributions and the error between the actual value and calculated value. Also, the authors did not identify the criteria for accepting or rejecting these [1].

The main objective of this paper is to develop a new methodology for life cycle hazard function modeling for transmission utility transformers. Artificial Neural Network (ANN) is implemented to obtain goodness of Fit. The obtained results will be compared with the conventional modeling using Normal Distribution, Lognormal Distribution, Weibull Distribution, and Smallest Extreme Value Distribution. The performance of the proposed modeling compared to the conventional modeling using various mentioned distributions will be evaluated. The obtained results are reported, evaluated, and discussed.

2. MODELING HAZARD FUNCTION

Figure 5. Shows the modeling steps of a hazard function using conventional Hazard Plotting Approach (HPA) [7], The following paragraphs describe the formulation of each step.

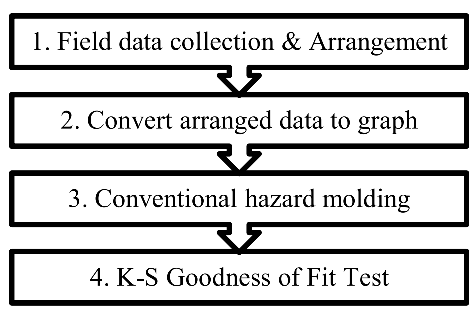

FIGURE 5. The conventional hazard function modeling steps.

2.1. Field Data Collection and Arrangement

The field data of equipment under study is collected over a long time period; from the equipment installation date till the end of the study period, as shown in Figure 6.

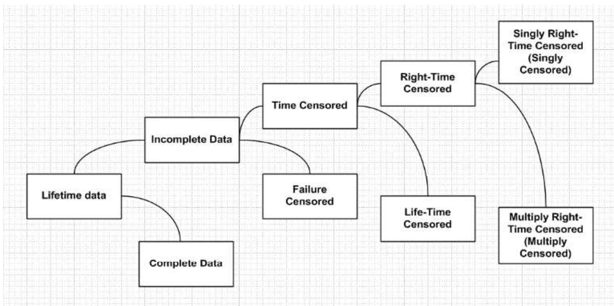

FIGURE 6. Collected field data history categorization

The following equations, (1) to (3), are used to calculate various equipment ages based on the collected field data:

$$Eq_{\text{in-service age}}\ (A) = \text{final year} - \text{Eq\_ins.} \quad (1)$$

$$Eq_{\text{Failure age}}\ (F) = \text{failure year} - \text{Eq\_ins.} \quad (2)$$

$$Eq_{\text{Scrapped age}}\ (X) = \text{failure year} - \text{Eq\_ins.} \quad (3)$$

Where;

Eq_ins is the equipment installation year,

$Eq_{\text{Failure age}}$ is the equipment failure age, and

$Eq_{\text{Scrapped age}}$ is the equipment salvage age.

The results obtained from (1) to (3) are arranged as shown in Figure 7 to prepare data to plot the hazard function, form which Table 1 is created, where:

Column 1: order the equipment based on its age in an ascending order (from smallest to largest).

Column 2: categorize each equipment ("1" for failed equipment and "0" for censored equipment).

Column 3: identify each equipment in reverse rank (krr) (the rank of the newest equipment is N) and (the rank of the oldest equipment is 1).

Column 4: recognize each failed equipment "i" (i = 1,2,3,4,……n) (n is the total number of failed equipment). Calculate the observed instantaneous hazard h (i)=1/krr (i), where krr (i) is the reversed rank for the $i^{th.}$ failed equipment.

Column 5: calculate the cumulative hazard function H (i) for each failed equipment "i". The cumulative hazard function is the sum of all of the previously observed instantaneous hazard.

Table 1. Format of Transformer Failures Data and Hazard Function

age (t)	Censored or Failed	Reversed Rank (Krr)	Hazard h(i)	Cumulative Hazard H(i)

The procedure of developing the transformer hazard model based on conventional methods of Hazard Plotting Approach (HPA) is shown in the Figure 7.

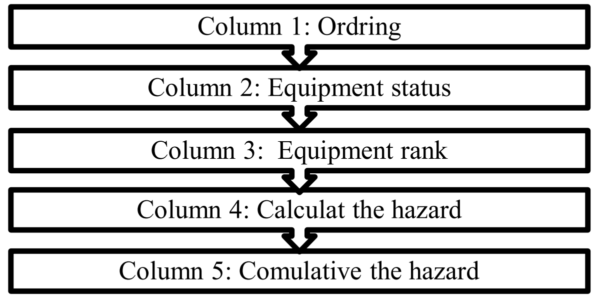

FIGURE 7. Steps of Developing Hazard Model Using Conventional Methods.

2.2. Convert the Arranged Data to Graph

Plot the relation between the failed equipment age(t) (in years) and the cumulative hazard function H(i) according to the relevant equation, under the various distribution models.

2.3. Conventional Hazard Modeling

Four distribution functions can be applied to calculate hazard functions:

A. Normal Distribution

Normal Distribution (Gaussian Distribution) has wide applications in describing product lifetime data. Its Probability Distribution Function (PDF), which describes the instantaneous function, is expressed by:

$$f(t) = \frac{1}{\sqrt{2\pi\sigma}} \exp\left[-\frac{t-\mu}{2\sigma^2}\right] \quad (4)$$

Where;

t is the time, and

μ, σ Are the mean and the standard deviation respectively.

The normal distribution Cumulative Distribution Function (CDF) is expressed by:

$$F(t) = \int_0^t \frac{1}{\sqrt{2\pi\sigma}} \exp\left[-\frac{t-\mu}{2\sigma^2}\right] dy = \varphi\left[\frac{t-\mu}{\sigma}\right] = \varphi[Z] \quad (5)$$

Where;

Φ (Z) is the CDF for the Standard Normal Distribution (with μ=0 and σ=1)

$Z= \frac{t-\mu}{\sigma}$ is the Standard Normal Distribution transfer factor, which transfers a general Normal Distribution to the Standard Normal Distribution.

The normal distribution hazard function is described by:

$$h(t) = \frac{f(t)}{1-F(t)} \quad (6)$$

Substituting (1) and (2) into (3), the Normal Distribution hazard function can be written as:

$$h(t) = \frac{1}{\sqrt{2\pi\sigma}} \exp\left[-\frac{t-\mu}{2\sigma^2}\right] / \left(1 - \varphi\left[\frac{t-\mu}{\sigma}\right]\right) \quad (7)$$

B. Lognormal Distribution

The Lognormal Distribution is an extension of the Normal Distribution, as the logarithm of the Lognormal Distribution variable distributes normally. The PDF of the Lognormal Distribution is expressed by:

$$f(t) = \frac{1}{\sqrt{2\pi t \delta}} \exp[\frac{-[\ln(t)-\lambda]^2}{2\delta^2}] \quad (8)$$

Where;

ln (t) is the symbol of natural exponential logarithm,

λ is the mean value of ln(t) and is called the "log mean" of the Lognormal Distribution, and

δ is the shape of a Normal Distribution.

Therefore, according to the definition, if the variable t follows a Lognormal Distribution with parameters λ and δ, ln(t) follows a Normal Distribution with mean of λ (μ=λ) and standard deviation of δ (σ=δ). In other words, the plot of a Lognormal Distribution is a log scale. The lognormal CDF is expressed by:

$$\mathrm{F(t)} = \varphi\left[\frac{[\ln(t)-\lambda]}{\delta}\right] \quad (9)$$

The Lognormal Distribution hazard function is shown in the following equation:

$$\mathrm{h(t)} = \frac{1}{\sqrt{2\pi t\delta}} \exp\left[\frac{-[\ln(t)-\lambda]^2}{2\delta^2}\right] / [1-\varphi[\frac{[\ln(t)-\lambda]}{\delta}]] \quad (10)$$

The shape of Lognormal Distribution hazard varies depending on the value of δ as follow:

- When δ is less than 0.2, h (t) increases against age t,
- When δ is around 0.5, h (t) is roughly constant over age, and
- When δ is larger than 0.8, h (t) decreases over the most age.

Therefore the Lognormal Distribution can describe different stages of the bathtub curve corresponding to increasing, constant, or decreasing hazard rate [7].

C. Weibull Distribution

The Weibull Distribution PDF is given by:

$$f(t) = \frac{1}{\alpha}\left(\frac{t}{\alpha}\right)^{\beta-1} * \ exp\ [-\left(\frac{t}{\alpha}\right)^{\beta}] \quad (11)$$

Where;

α, β are the scale and shape parameters respectively.

α determines the spread of data and indicates the age corresponding to 63.2% CDF. Thus, it is called the products characteristic life. β implies the shape of the distribution and it is dimensionless. Particularly when 3≤β≤4, the shape of the Weibull Distribution is similar to that of a Normal Distribution. The CDF is describe:

$$F(t) = 1 - exp[-\left(\frac{t}{\alpha}\right)^{\beta}] \quad (12)$$

The Weibull Distribution hazard function is [7]:

$$h(t) = \left(\frac{\beta}{\alpha}\right)\left(\frac{t}{\alpha}\right)^{\beta-1} \quad (13)$$

Where;

When β=1, the Weibull Distribution is equivalent to the Exponential Distribution,

When β>1, h (t) increases against age, and

When β<1, h (t) decreases.

D. Smallest Extreme Value Distribution

An extension of the Weibull Distribution, the Smallest Extreme Value Distribution is used to describe certain extreme phenomena such as the temperature minima, material strength, and the first-failed-component determined product failure [7]. The PDF of the Smallest Extreme Value Distribution is expressed as:

$$f(t) = \frac{1}{\delta} * exp\left(\frac{t-\lambda}{\delta}\right) * exp[-exp\left(\frac{t-\lambda}{\delta}\right)] \quad (14)$$

The CDF is described by :

$$F(t) = 1 - exp[-exp\left(\frac{t-\lambda}{\delta}\right)] \quad (15)$$

Where;

δ, λ are the scale and the location parameters respectively.

λ is the age corresponding to 63.2% of CDF and it is called the population characteristic life. When applied in product lifetime data analysis, λ is always suggested to be at least 4 times as great as δ [7].

The Smallest Extreme Value Distribution hazard function is:

$$h(t) = \frac{1}{\delta} * exp\left(\frac{t-\lambda}{\delta}\right) \quad (16)$$

2.4. K-S Goodness of Fit Test

Kolmogorov-Smirnov test (K-S test) is a method utilized to test the fitting goodness of the implemented distribution model. Based on this test, the implemented distribution model will be rejected or accepted. The following steps describe the K-S test implementation, as shown in Table 2:

Columns 1 to 3 are exactly the same as discussed in Table 1.

Column 4 to 6: Calculate the reliability function R (*i*) based on the following equation.

$$R(i) = \frac{k_{rr(i)-1}}{k_{rr(i)}} * R(i-1) \quad (17)$$

Where;

$R(i)$:is the reliability function, and

$R(i-1)$:is the reliability at the last failure *i*-1.

Column 7: derive the cumulative probability function observed CDF (Fo) at failure i as:

$$Fo(i) = 1 - R(i) \quad (18)$$

Column 8: calculate the CDF at each failure, which is the theoretical CDF (F^0) under Normal Distribution.

$$F^0(i) = \Phi\left[\frac{t(i)-\mu}{\sigma}\right] \quad (19)$$

Column 9: The maximum absolute difference value between the observed $F^0(i)$ and theoretical $F_0(i)$ is obtained by:

$$D_M\ (r) = \max[F^0(i) - F_0(i)], \qquad i=1,\ 2,\ 3,\ \ldots..\ M \qquad (20)$$

From which Calculate:

$$D_M{}^{\gamma}\ (\mathrm{r}) = \frac{y_{1-\gamma}(\mathrm{r})}{\sqrt{M}} \qquad (21)$$

Where;

$r = \frac{M}{N}$ and N is the total number of equipment.

M : Total number of failed equipment

y_1 is the critical value, and

γ is the significance level and also presents the probability that the hypothesized model would be rejected by the test.

If D_M (r) ≤ $D_M{}^{\gamma}$ (r) the distribution model is accepted [16-18].

Table 2. HPA using the equipment lifetime data to do K-S Goodness of Fit test.

3. PROPOSED MODELING HAZARD FUNCTION METHODOLOGY

3.1 Motivation

The Historical data of the transformer failures are usually characterized by:

- Small size of recorded failures data.
- Repeated data due to having several transformer failures in the same year.
- High percentage of censored transformers without failure which may lead to having time intervals without failures data.

The application of conventional distribution functions may lead to poor modeling of the hazard function due to the nature of the available historical data as described above.

3.2 Proposed Methodology

The proposed hazard function modeling follows a procedure similar to that of the convention hazard function modeling procedures shown in Figure 5. Therefore, the steps used to implement the conventional hazard plotting functions are replaced by the proposed hazard function modeling using ANN as shown in Figure 8.

Three new steps are added (Steps 3 to 5). Step 3 prepares the data in Table 1 to be used as an input data to the ANN model. This data is split into two-third for training and the rest is for testing. Step 4 is the training and testing of the ANN proposed for the study.

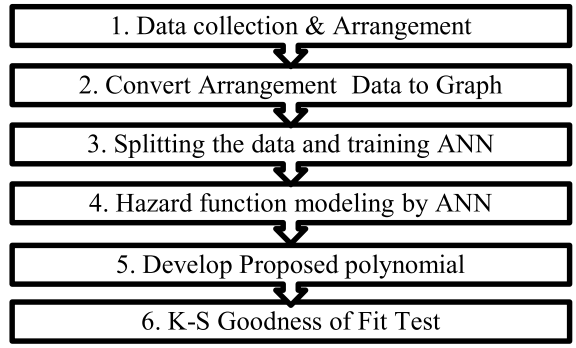

FIGURE 8. Proposed ANN-based Polynomial Hazard Modeling.

3.3 Role of Artificial Neural Network

The artificial neural networks (ANN) inherently incorporate powerful mapping and fitting features enable the handling of the transformer failures data set with having the characteristics mentioned before. Specifically, the ANN can filter any repeated data. Also, it can mitigate the discrete nature of the data set that has extended time intervals without data.

The historical data will be used to develop an ANN model that maps the relation between transformer age and the corresponding hazard rate.

The ANN model, shown in Figure 9, is built as follow: one input, one hidden layer having 10 neurons, and one output. The input to the ANN is the equipment age, while the ANN output is the hazard value.

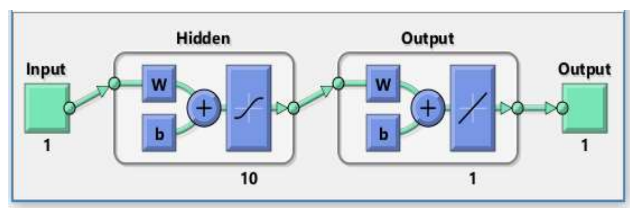

FIGURE 9. ANN fitting using MATLAB model.

3.3 Role of the Polynomial Equation

The ANN model represents the hazard function of the equipment lifetime, however this mathematical model cannot be easily handled. In other words, the hazard function is required to be expressed in a closed form for the purpose of applying mathematical operations; integration, differentiation, …etc. Therefore, the model described by the ANN is to be emulated by a high order polynomial equation.

Step 5 is used to develop the best fitting polynomial equation that describes the ANN equipment model and consequently it is used to fit to the hazard function. The obtained fitting equation error is calculated and compared with those of the conventional distribution models.

The MATLAB's curve fitting toolbox is used to estimate the coefficients of the 8th order Polynomial equation in the form:

$$f(x) = p1 * x^8 + p2 * x^7 + p3 * x^6 + p4 * x^5 + p5 * x^4 + p6 * x^3 + p7 * x^2 + p8 * x + p9 \quad (22)$$

Where; p1 to p9 are the polynomial coefficients to be estimated to fit the ANN-model.

4. CASE STUDY

4.1 System Description and Field Data

The case study selected to evaluate the proposed methodology is extracted from [7]. The study is based on the history of the UK Grid, high-voltage transmission substations (400kV and 275kV) [7]. The transformer status from 1952 to 2008 are classified as follows:

a. Transformers operate and fail.
b. Transformers operate and manually retire.
c. Transformers operate and remain in service but with unknown future.

Figure 10. represents the data collected from UK Grid Power Transformers which describes the number of transformers installed in each year of the study.

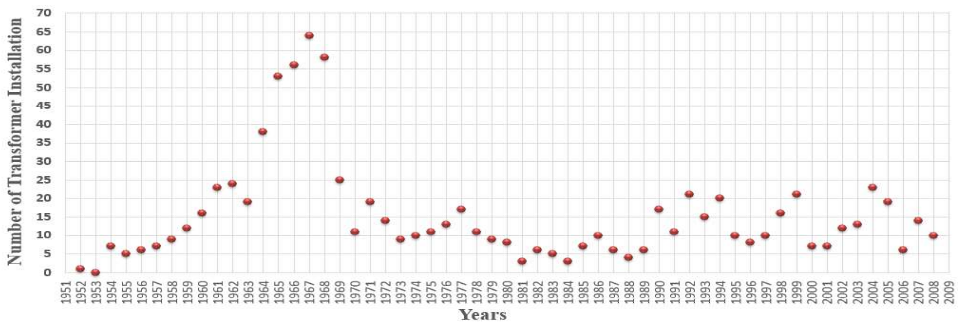

FIGURE 10. The number of transformers installed in UK Grid during 1952 through 2008 [7].

Figure 11. illustrates the number of transformer failures corresponding to each year of the study period.

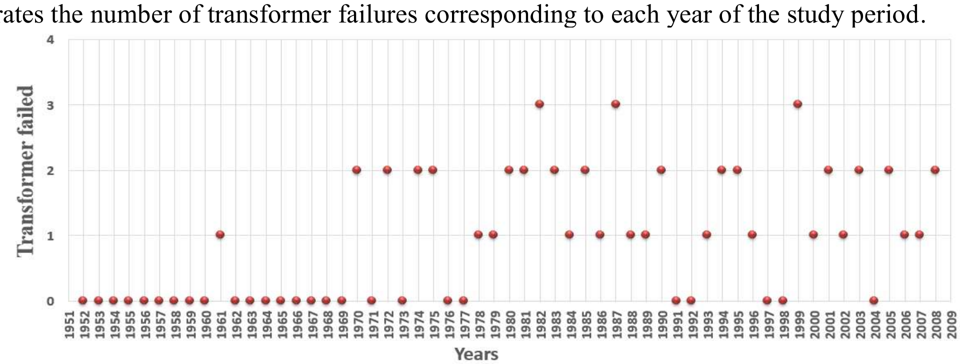

FIGURE 11. Power Transformer Number of Failures in UK Grid during 1952 to 2008 [7]

The in-service transformers in the UK Grid are shown in Figure 12.

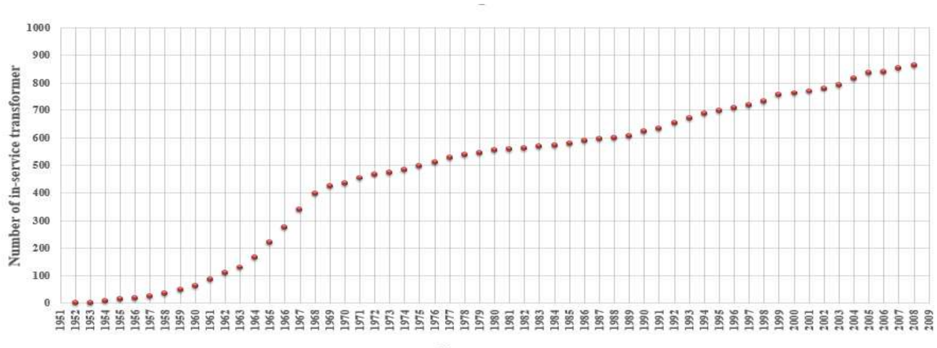

FIGURE 12. Transformer Exposed Number (in-service) during 1952 to 2008 [7]

The conventional HPA methods are applied on the case study to calculate the error in different models by using the K-S Goodness of fit test for each conventional distribution model. Based on the proposed methodology, ANN-based polynomial, exponential, is apply.

Data Preparation

The procedure of forming Table 1 of section 2.1 are applied to calculate the values of the hazard h(i) as shown in the samples of Table 3. The number of failed transformers during the study period is 52 transformers. The observed hazard values are plotted against time in Figure 13.

Table 3. Forming the hazard h(i) and Commulative hazard H(i) Using Transformers' Lifetime historical Data

Age (t)	Censored/ Failed	Reversed Rank krr	Hazard h(i)	Cumulative Hazard H (i)
1	*0*	*865*		
1	*0*	*864*		
1	*0*	*863*		
1	*0*	*862*		
1	*1*	*861*	*0.001161*	*0.001161*
1	*1*	*860*	*0.001163*	*0.002324*
1	*0*	*859*		
2	*0*	*852*		
2	*0*	*851*		
2	*0*	*850*		
2	*0*	*849*		
2	*1*	*848*	*0.001179*	*0.003503*
2	*0*	*847*		
…….	……	……	……	……..
55	*0*	*2*		
57	*0*	*1*		

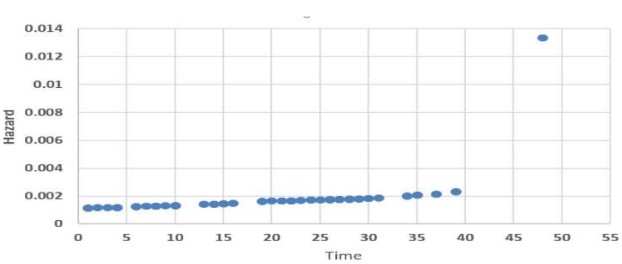

FIGURE 13. The relation between transformer hazard and transformer age

5. RESULTS

5.1 Developing ANN Hazard Model

The available data of hazard h(i) is characterized by having a discrete nature particularly in the range t=39 and t=48 which represents a challenge for the conventional mathematical formulas. It should be noted that most of the data points belong to the constant failure rate part of the bathtub curve. Only one point (at t=48 years) is related to the wear out failures part of the curve. Any credible hazard function must go through this important point.

The data of the observed hazard values "h(i)" against transformer age "t" are used to learn the ANN of Figure 9. The input to the network is the age and the output is the corresponding hazard value. Each pair of the data "h,t" is considered as one pattern. The data are split into two groups: 67% of the data are selected as training patterns and the rest (33%) are considered as testing patterns. The performance of the developed ANN is illustrated by Figure 14 which proves that the errors exhibited during training and testing procedures are relatively very low.

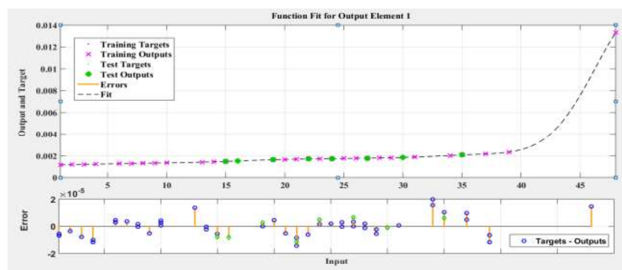

FIGURE 14. Performance of the ANN Hazard Model.

5.2 Emulation of the ANN Model by a Describing Equation

The ANN model is used to generate continuous hazard function; however, its implementation is relatively hard particularly if some mathematical operations are required to be carried out on the hazard function (differentiation, integration, …). Therefore, the generated output from the ANN is used to derive a describing equation that emulates the ANN model through the application of curve fitting techniques. An 8th order polynomial equation is used for this purpose. The application of curve fitting tool gives the following coefficients:

p1	*p2*	*p3*	*p4*	*p5*	*p6*	*p7*	*p8*	*p9*
4.328e-14	-6.23e-12	3.556e-10	-9.98e-09	1.365e-07	-6.64e-07	-1.92e-06	4.213e-05	0.0011 1

The output of the developed polynomial equation is shown in Figure 15, which exhibits a hazard values very close to the target with a maximum absolute error of $4.7 * 10^{-5}$.

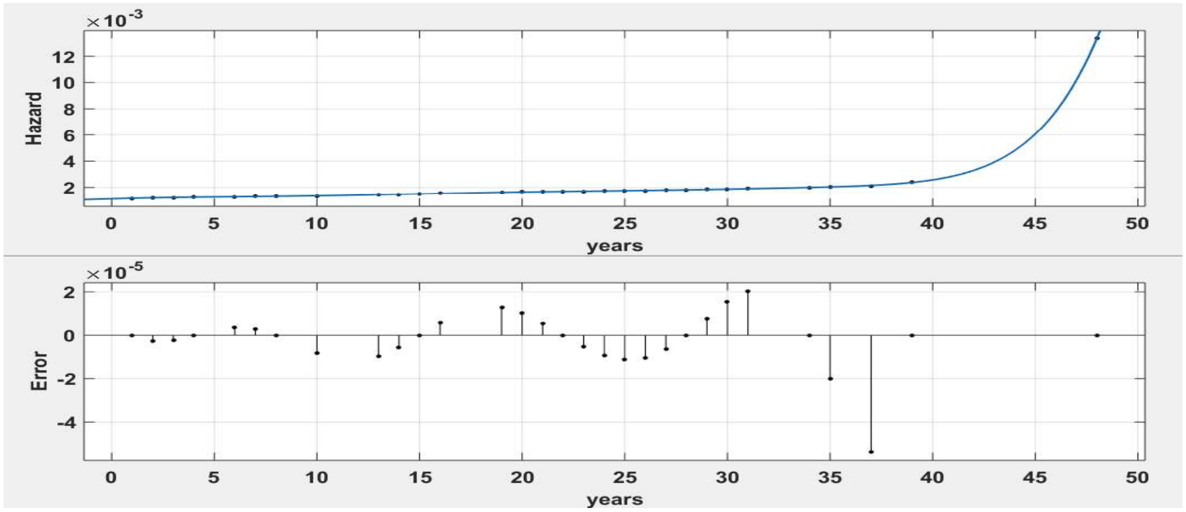

FIGURE 15. Curve fitting under polynomial equation.

5.3 ANN Model Versus Polynomial Models

The effectiveness of utilizing ANN in modeling the transformer hazard function is tested by comparing its performance with that of two polynomial models. The first polynomial is obtained by applying curve fitting tool directly on the observed hazard data. The second polynomial is that obtained in the previous section through emulating the ANN model. The performance of these three models are compared by calculating the sum of square errors index, described by the following equation:

$$SSE = \sum_{i=1}^{N}(h_m(i) - h(i))^2 \quad (23)$$

Where,

h(i) are the observed hazard values,

h_m(i) are the hazard values calculated from model m at the same time,

i is the number of the data sample,

N is the total number of the observed hazard values,

m is the applied model: Direct ANN, Direct Curve Fitting Polynomial or ANN-based Polynomial

The calculated values of the SSE indices are recorded in Table 4.

Table 4. SSE indices for different models

ANN Model	ANN-based Polynomial	Direct Curve Fitting Polynomial
0.00044378	0.00020057	0.1977

The results show the superiority of the ANN model over the two others. Also, it can be concluded that the direct curve fitting method is not suitable for modeling the hazard function due to its poor performance. Finally, it is shown that the proposed ANN-based polynomial model has a good performance close to that of the ANN model, while providing a simple closed-form model.

5.3 ANN-based Polynomial Model Versus Conventional Models

The historical transformer lifetime data are used to deduce the hazard rate function using 4 conventional distribution methods, namely: Normal Distribution, Lognormal Distribution, Weibull Distribution and Smallest Extreme Value Distribution**.** The procedure of selecting the best fit is described before in Section 2.4. The developed hazard models against the observed patterns are shown in Figure 16. The curves prove that the four distributions fail in connecting the hazard values recorded from the historical data. The models based on the Lognormal and Weibull distributions are very close from the recorded hazard values that represent the normal operation of the transformer where the hazard rate is almost constant. However, these two distributions fail in representing the failure part of the transformer lifetime, particularly the failure at year 48. On the other hand, the two other distributions exhibit hazard functions close to the failure point but still with poor performance. The proposed ANN-based polynomial is plotted on the same figure and shows very good shape. The hazard function produced from the proposed methodology is passing through ALL the historical failure data. It shows a shape very similar to the well-known bathtub function.

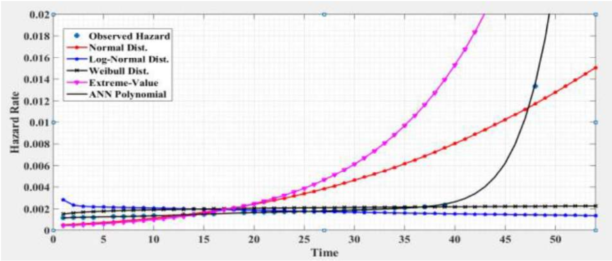

FIGURE 16. Hazard functions developed from conventional methods and proposed method

6. CONCLUSION

The historical transformer lifetime data are used to deduce the hazard rate function using 4 conventional distribution methods, namely: Normal Distribution, Lognormal Distribution, Weibull Distribution and Smallest Extreme Value Distribution. The procedure of selecting the best fit is based on Hazard Plotting Approach (HPA). The results of the transformer hazard models based on these distributions have led to poor results due to the nature of the available historical data. The proposed methodology uses Artificial Neural Network- based polynomial model with minimum error to represent the hazard function for transformer. The results show the superiority of the ANN hazard model. Also, it is shown that the proposed ANN-based polynomial model has a good performance close to that of the ANN model, while providing a simple closed-form model. The hazard function produced from the proposed methodology is passing through ALL the historical failure data. It shows a shape very similar to the well-known bathtub function. This model can be effectively used for expressing the hazard rate of the transformer against its lifetime.

Similar to the well-known bathtub function. Tis model can be effectively used for expressing the hazard rate of the transformer against its lifetime. Similar hazard models may be developed for all other substation components may base on the proposed methodology. Provide that its historical failure data are available**.**

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