

## A NEURAL NETWORK METHODOLOGY FOR SOFTWARE RELIABILITY PREDICTION OF LONG-TERM MTTF

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**Abstract :** Accurate prediction of software MTTF (Mean Time To Failure) is necessary in critical applications. This paper presents the prediction of long-term MTTF using neural network. This proposed method is to learn a sequence of cumulative observation times and the corresponding observed accumulated failures up to the present testing time. The results obtained through proposed method compared with CASRE (Computer-Aided Software Reliability Estimation) tool. It is observed that information provided by the proposed method is more meaningful and relevant as compared to the existing methods.

**Keywords:** CASRE Tool, Software Reliability, Neural Network, Long-Term MTTF.

**Introduction :** In most of the Cases and in Real-Time Applications, Software can be released only after some prescribed reliability conditions had been satisfied at the end of its development and testing processes. In such cases accurate prediction of reliability is necessary.

Neural network [2] has been applied to estimate parameters of the formal model and to learn the process itself in order to predict the future outcomes of the Developed Software. It has been shown that feed forward network can be applied for prediction of the Software Reliability. Back-error propagation is one of the most widely used neural network paradigms and has been applied successfully in application studies in a broad range of areas [1]. We have proposed software reliability prediction method using back propagation neural network using multi-layer neural network. Objectives of the research paper are:

1. To propose Neural Network method for long-term prediction of reliability, MTTF, PPM (Parts Per Million) and software failures.
2. To compare the existing methods using CASRE tool and proposed Neural Network methods on the basis of Kolmogorov-Smirnov test and different error testing methods.

### 2. Long-Term Reliability Prediction

Proposed method has used back-propagation multi-layer neural network algorithm [1] for cumulative execution times as an input and cumulative number of failures as output. We considered one input and one output neural network. The method is used for long-term prediction of MTTF, Software Reliability, Number of Failures and PPM. The reliability indices are defined below, Using Chi-Square distribution, MTTF is defined by

$$MTTF = 2 * T / \chi^2(1-C.L., 2*N+2),$$

Where C.L.=Confidence level,

N= Number of failures

T = Execution time

Reliability after 1 hour of operation =  $\text{Exp}(-1/MTTF)$

PPM (the expected number of failures over the first hour of operation of 1,000,000 Software Systems)

$$= 1000000 * (1 - \text{Exp}(-1/MTTF))$$

The proposed method is compared with meaningful measures [2] in following analytical models using CASRE tool [3].

- NHPP (The Non-Homogeneous Poisson Process)
- S-Shaped Model
- Poisson and Binomial Models

### Results and Discussions

We will see how different software reliability growth models can be compared for their predictive accuracies. We have used software test data [2] as shown in Table 1.

For the test data, we have fitted NHPP, S-Shaped, Poisson and Binomial using CASRE tool and proposed method. We have analyzed these results on the basis of –

1. Root Mean Squared Error (RMSE) =  $(\sqrt{\sum (p-a)^2})/n$ ,  
where n=# of observations,  
p=predicted output,  
a=actual output.
2. Mean Absolute Percent Error (MAPE)  
 $= 1/n * \sum (|pa|/a) * 100$
3. Correlation Coefficient (Cor. Coef.)  
 $= (\sum (p\text{mean}(p))(a\text{mean}(a))) / \sqrt{(\sum (p\text{mean}(p))^2 \sum (a\text{mean}(a))^2)}$
4. Kolmogorov-Smirnov (K-S) test.

The procedure is:

- Tabulate the ranked failure data. Calculate the values of  $|a_i - m_i|$  where  $a_i$  is the  $i$ th actual Cumulative failures and  $m_i$  is the  $i$ th modeled cumulative failures. All  $a_i$  and  $m_i$  must be Normalized [4].
- Determine the highest single value.
- Compare the value with the appropriate K-S value.

The errors and correlation coefficient calculated for the five different models are shown in Table 2.

Smaller the error, higher is the prediction accuracy and higher the correlation coefficient, higher is the prediction accuracy [5, 6, 7]. Thus, the values of errors and correlation coefficient clearly indicate that proposed tool provides better fit than the parametric models. The K-S test is carried out for all five models. The results obtained are presented in Table 2. We have used 10 percent Statistical significance level. We found that critical value from Kolmogorov-Smirnov test table greater than the actual K-S values.

Therefore the null hypothesis, i.e. the data do fit the assumed distribution at 10 percent s-significant level, is rejected. The calculated K-S values indicated that proposed model is the best [8,9]. Figure 1 shows the long-term prediction curve using neural network. We used the cumulative execution time 1512 hours and cumulative failures 194. It is clear from the figure that the predicted failures are 199 up to the execution time of 50,000 hours. MTTF is approximately 223 hours in 95% confidence level as shown in Fig.2.

Table-1  
Time test set

Time Units (Hrs)	Cumulative Number of Failures	Cumulative Execution Time(Hrs)	Cumulative Number of Failures
1	7	16	153
2	8	17	157
3	36	18	174
4	45	19	183
5	60	20	196
6	74	21	200
7	82	22	214
8	98	23	223
9	106	24	246
10	115	25	257
11	120	26	277
12	134	27	283
13	139	28	286
14	142	29	292
15	145	30	297

Table 2  
Summary of errors for different models

Prediction Errors	Model Used				
	NN	NHP P	S-Shaped	Poisson	Bino mial
RRSE	0.483	1.013	1.233	1.288	1.167
MAE	2.00	4.159	5.053	4.522	4.000
MAPE	2.047	6.79	7.13	8.001	7.372
Cor. Coef	0.99884	0.99731	0.99768	0.99844	0.9841
Actual K-S Test					
	0.0206	0.0604	0.0815	0.0868	0.0806
10 percent s-significant level					
0.234					

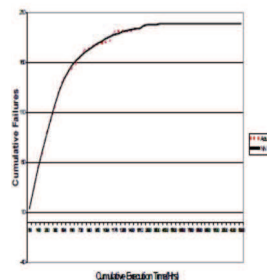


Fig.1: Long-Term Failure Predictions Using Neural Networks.

The Benefits of the Neural Network models for the Prediction of Software Reliability are:

1. Simple construction of models of varying complexity at different points of time for a given data set.
2. Simple adaptation of models of varying complexity to different test data sets.

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