Analysis of Non-Parametric Bootstrap & Monte Carlo simulation Methods to evaluate MTBF during Faulty Conditions

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Abstract: This paper gives the information about reliability of the system that how long it can be able to withstand during uncertain conditions and these types of uncertainty can be calculated by using two methods which provides a beneficial data to maintain the overall reliability of the system. The two methods are Non-Parametric Bootstrap and Monte Carlo simulation method. Non-Parametric Bootstrap method can be used to evaluate Mean time between failures, samples are taken of a problematical system**.** Where, Monte Carlo simulation method can analysis the samples and provide the information of the occurrence of faulty condition in the system so that we can take a preventive measures to avoid eths types of uncertain conditions and to achieve reliability and accuracy of the system.

Index Terms **- Monte Carlo simulation, Non-parametric bootstrap, faulty system, mean time between failure, reliability.**

I. INTRODUCTION

The assessment of the reliable system is one of the main concerns now days for a smooth running of a normal system because we know that there are many problematic parameters which effect a system, due to this reliability of system is affected. To achieve assessment this there are different methods that can be used to analysis, so that we can easily find out the problems and can be rectified. In this the Non-parametric boot scraping and Monte carol simulation methods are the best for estimation of the faculty network because non-parametric boot scrape provide the numbers of samples and Monte Carlo simulation predicted the probability of faulty conditions due to which we are able to maintain the overall reliability of the system. This type of methods can also be used in distribution system for estimation of system losses. As we know that the transients are the main problem in power system which cannot be denied. The causes of transients are mainly due to device switching, static discharge, arcing, turn on, turn off, load, or unload an inductive device this may bring failure of the system. So by using boot-strap and Monte Carlo which want lesser number of samples that can be used significantly and analyzed to predict a probability of by the system failure and this data is given in CPU that provide the real time data may be achieved. Therefore in this paper boot strapping has been used along with MCS to evaluate MTBF of a complex reliability network. This will enhance the performance to the power system.

II. NON- PARAMETRIC BOOTSTRAP TECHNIQUE

Before going to the non-parametric boot scraping, the term boot scraping is basically used for evaluating throughout data by taking samples of the various parameters of signals using sampling technique. Basically there are three types of boost strapping methods they are parametric bootstrapping, semi bootstrapping and Non- Parametric Bootstrapping method. In which Non-Parametric bootstrapping method is very popular because, it provide the samples from samples are called bootstrap sets or bootstrap samples. By each set of bootstrap sample are used according to the type of measurement. This bootstrap expression provides information regarding sampling locations of sample counts to estimate parameter. So the original base of the method is cleared from its name as “to pull oneself up by one’s own bootstrap,” which implies that a thing is being built by using the thing itself, by drawing samples from the sample, we are building a bootstrap distribution. There are essentially two different types of bootstraps. Without specific assumptions or a particular model for the transient under investigation, the bootstrap is called non-parametric otherwise, it is called parametric.

III. RELIABILITY INDICES AND CRITERIA

The classical index used to assess reliability is probability. However, many other indices are now calculated regularly, the most appropriate being dependent on the system and its requirements. Instead all relevant indices are now generally termed reliability indices and in consequence, the term ‘reliability’ is frequently used as a generic term describing all these indices rather than being solely associated with the term probability. Typical examples of additional indices are as follows:

(i) The expected number of failures that will occur in a specified period of time.
(ii) The average duration or down time of a system or a device.
(iii) The expected loss in revenue due to failures.
(iv) The expected loss of output due to failures.

The need to set criteria for assessing adequate performance is applicable whether probabilistic or deterministic assessments are being used.

IV. Reliability and Availability

The ability of a system to continue functioning without failure, i.e., to complete a mission satisfactorily. Therefore, this measure is suitability for quantifying the adequacy of mission oriented systems and reliability can be interpreted as the probability of a component or device or system staying in the operating state without failure.

It is also evident that this interpretation of the term ‘reliability’ makes it totally unsuitable as a measure for these continuously operated systems that can tolerate failures. The measure used for these systems is ‘availability’.

This is clearly different in concept, since, although failures and down states occur, there is a likelihood of finding the system operating or not operating at all points of time into the future.

4.1 Absolute and Relative Reliability

The terms ‘absolute reliability’ and ‘relative reliability’ are frequently encountered in the practical application of reliability assessment.

Absolute reliability indices are the values one would expect a system to exhibit. They can be monitored for past performance because full knowledge of them is available. However, they are extremely difficult, if not impossible, to predict with a very high degree of confidence.

4.2 Reliability Activities in System Design

As indicated in fig.1 the process culminates in a design review. This programmer is a systematic and disciplined application of the broad engineering knowledge and experience of engineering, manufacturing, construction and operating personnel to the design of a system and equipment. Its basic objective is to provide assurance that the most satisfactory design has been selected to meet the present requirementsThe reliability activity must be synchronized to the project cycle and provide useable input at the decision points concept is extremely important, and reliability personnel must be up to date with their function in order to provide the necessary information.

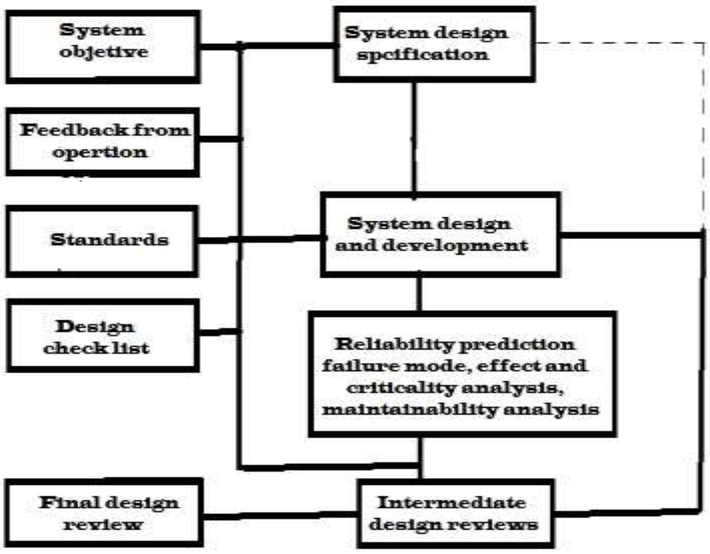

fig.1

4.3 Reliability Economics

The major discussion point in previous sections has centered on reliability. However, as indicated several times, costs and economics play a major role in the application of reliability and its attainment.

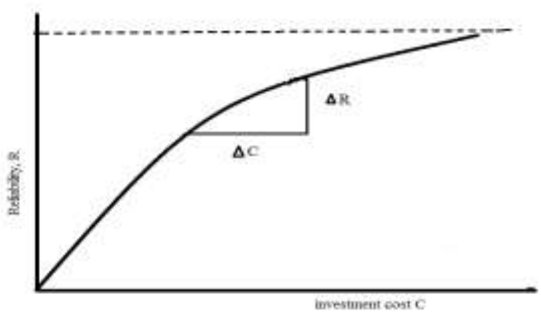

Fig 2 Incremental cost of reliability

V. Monte Carlo simulation technique

Monte Carlo techniques are a wide group of algorithmic system which gives the recurrent odd samples to gives arithmetic results. The basic idea is to use chance to workout on the issues which cannot be unavoidable in this principle. This can be applied on actual and arithmetic problems but this technique is most useful with respect to other techniques where it is difficult to reach on different parameters of the samples. Monte Carlo methods are mostly used in three classes that are optimization, numerical integration, and generating draws from a cumulative distribution.

5.1 Mean time between failures (MTBF)

The Mean time between failures (MTBF) is the forecast of signal to proceed the time between native failure conditions occurs in electrical power system to reliable functioning of the system. MTBF will also calculate as the average time between failures of a system. The MTBF basically cast off for the repairable systems, but on other hand mean time between failure (MTBF) for a non-repairable system and gives the expected time to failure of the non-repairable system.

The MTBF for the complicated network, repairable systems, and failures are take that are not taken in account during designing and make system out of working condition and throw on the state for repair. So failures which are out of the box happens are repaired keeping it in unrepaired condition, and during this, system should keeping online condition. But for this definition which includes different units taken down for routine scheduled maintenance in this duration the routine control of system is not considered.

5.2 Problem formulation of parametric signals

The objective is to evaluate Mean Time between Failure (MTBF) & Reliability of a complex network by using Monte Carlo simulation and non parametric bootstrap technique. Algorithm for reliability analysis with boot strapping and Monte Carlo simulation technique for the complex network has been developed.

5.2.1- Computational algorithm for evaluating Mean Time between Failure (MTBF) using non parametric bootstrap techniques is given as follows:

Step1 Obtain data set of time to failures using MCS as explained in previous section.

Step 2 Obtain re –sampled data set as follows :

$$\{t_{fB1}^{(i)}, t_{fB2}^{(i)} \ldots\ldots\ldots t_{fB,NS`}\} \quad (1)$$

Where NS′ is total number of samples ,note that NS′<< NS

Step 3 Calculate mean time to failure as follows:

$$\bar{t}_{fB}^{(i)} = \frac{1}{NS'} \sum_{k=1}^{NS"} t_{fBK}^{(i)} \quad (2)$$

i=1,2………..NB

Over all estimated mean time to failure is calculated as follows:

$$M\hat{T}TF_B = \frac{1}{NB} \sum_{i=1}^{NB} \bar{t}_{fB}^{(i)} \quad (3)$$

$M\hat{T}TF_B$ is estimated mean time to failure obtained using bootstrapping.

Step 4 Obtain coefficient of variation for convergence

$$\beta = s/M\hat{T}TF_B$$

where $s=\hat{\sigma}/\sqrt{NB}$

$$\hat{\sigma}^2 = \frac{1}{NB-1} \sum_{i=1}^{NB} (\bar{t}_{fB_i}^{(i)} - M\hat{T}TF_B)^2$$

Step 5 If $\beta < \zeta$

Then solution has converged, ζ is tolerance specified e.g.0.0010.

Step 6 In each resample calculate reliability for time

$$r_B^{(i)}(t_r) = \frac{n^{(i)}(t_r)}{NS}$$

$n^{(i)}(t_r)$ number of data is for which time to failure is greater than t_r.

i=1.2…..NB

Step 7 Calculate average reliability

$$\bar{r}(t_r)=\frac{1}{NB}\sum_{i=1}^{NB} r_B^{(i)}(t_r)$$

Thus reliability $\bar{r}$ (t_r) is obtained for various time values.

VI. RESULTS AND DISCUSSION

The two technique non-parametric boot strap technique and Monte Carlo simulation technique are used to evaluate Mean Time to Failure (MTTF) and Reliability for bridge network as shown in fig.3.

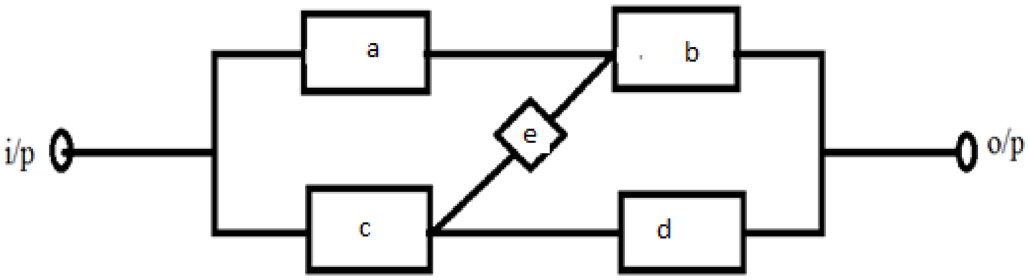

Fig.3 Electrical Bridge Network

Developed algorithms have been implemented by considering failure density function of all components as exponentially distributed. The failure rate of each of component in provided in Table 1.

Table 1: Failure rate of components of bridge network

Component	a	b	c	d	e
Failure rate λ/year	0.2	0.3	0.5	0.4	0.2

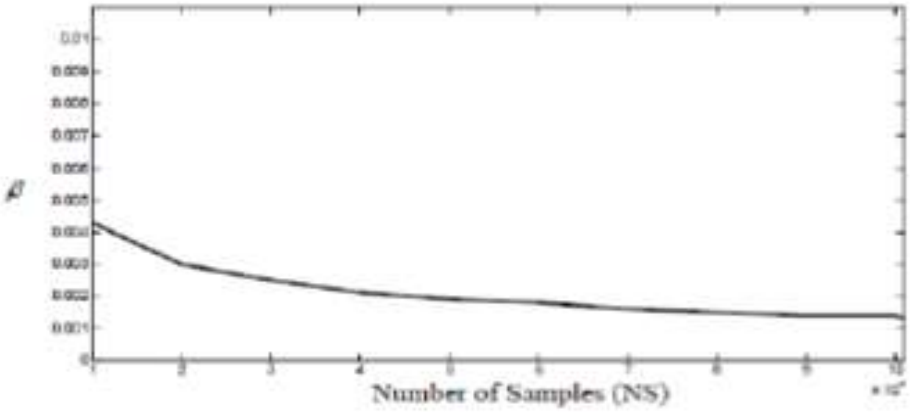

Fig-4 Variation of coefficient of variation with respect to number of samples in MCS

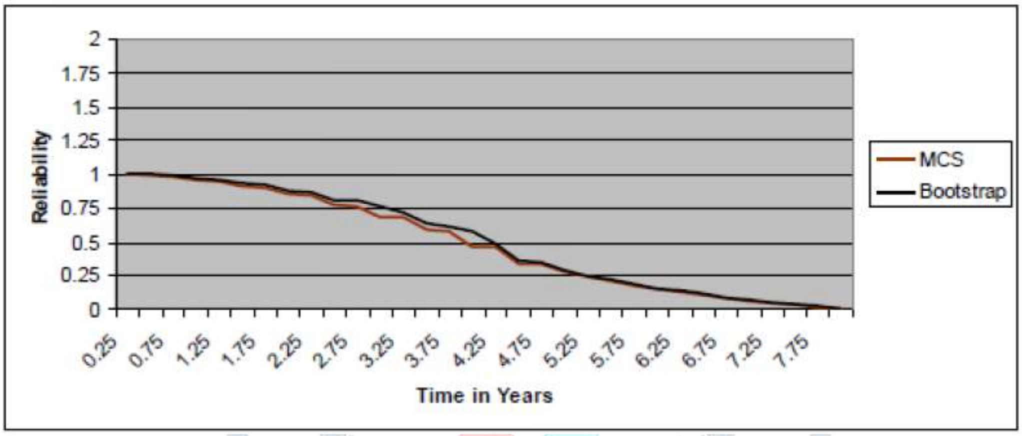

Fig-5 The plot of reliability with respect to time by using Monte Carlo simulation and non parametric bootstrap technique is shown

The error is 2.01% using non-parametric boot strap technique as compare to Monte Carlo simulation. The CPU times required for convergence by using bootstrap technique have reduced by 67%.The plot for coefficient of variation with respect to number of samples by using Monte Carlo simulation and non parametric boot strap technique is shown in fig.4.

Table 2 shows the values of Mean Time to Failure (MTTF) obtained by Monte Carlo simulation.

No. of samples, NS	***MTTF throughout the years***	**Time in CPU in sec.**
100010	4.01609	0.19282

VII. Conclusion

The This thesis describes a methodology for evaluating Mean Time to Failure (MTTF) and Reliability of a complex electrical network by using Monte Carlo simulation and non- parametric bootstrap technique. Each of the components of the bridge network are exponential distributed. The result shows an improvement in the value of Mean Time to Failure (MTTF) with non-parametric bootstrap technique and over Monte Carlo simulation technique.

Reduction in CPU time is observed by non-parametric bootstrap technique over Monte Carlo simulation technique. Improvement in Reliability with respect to time can also be visualized by the reliability versus time plot. The proposed methodology can be implemented on other electrical networks.

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