Parameter Estimation in Software Reliability

Meenakshi Malik[1], Garima Garg[2]

[1]Research Scholar, NNSS SGI Samalkha

[2]Assistant Professor NNSS SGI Samalkha

Abstract: ***All through the procedure of software engineering, software reliability investigation is expert at various stages as a try for the estimation of whether the software necessities have been experienced or not. Amid the underlying periods of software advancement, software reliability expectation methods were exceptionally testing. Various software reliability models have been advanced amid the antiquated couple of years keeping in mind the end goal to quantify the software reliability. Reliability of each software relic is a quantifiable trademark which is exceptionally crucial for predicting the level of reliability of any software with the goal that it can work accurately for an unmistakable interim of time. Besides there must not be nearness of a disappointment. In this paper, I have quickly talked about some key parametric estimation systems in software reliability models. This paper exceptionally concentrates on how diverse sorts of strategies can be used for assessing the different parameters.***

Keywords: Software reliability, Software reliability growth models, parameter estimation, maximum likelihood estimation, least square estimation, particle swarm optimization, ant colony optimization, cuckoo search

1. Introduction

In cutting edge time, effective frameworks having complex software's and hardware in this way are improving our everyday life. Software reliability is key software normal for any unpredictable framework. All through the procedure of building software, reliability can be executed at its different stages so as to gauge whether the software prerequisites have been experienced or not. The principle difference between these two central models i.e. black box and white box testing is that, dissimilar to black box testing, white box testing considers the structure of the software for reliability estimation. Not at all like hardware items, are software items not bound by the limitations of the physical world, so they are scholarly in nature. The most extreme fundamental parameter of software quality and framework steadfastness is software reliability. Software reliability can be cited as "inside a distinguished situation and amid an unmistakable range of time, what will be software operation likelihood which is without disappointment in nature" [1].

The software likelihood investigation not just gives criticism to the planners of software additionally it likewise gives data about the nature of software. While examining the software reliability, the two important parameters which must be contemplated via estimation and prediction. In both the parameters, factual deduction methods are connected to the disappointment information keeping in mind the end goal to measure software reliability. [1] There are different software reliability estimation and forecast models which consider diverse software development lifecycle elements, for example, requirement, design, implementation, testing and validation. Few reliability models use combination of these attributes. The classification of software reliability models based on these elements is as follows [2]:
1) Early prediction model.
2) Architecture based model.
3) Hybrid White box model.
4) Hybrid black box model.
5) Software reliability growth model.
6) Input domain based model.

In the course of the past 2 decades, a huge aggregation of SRGMs has been handled for the estimation of software reliability methods. These methods include total sum of faults left behind, proportion of software failure rate, and software reliability. The most important decision to be taken in the arena of software reliability is picking up of the most optimal SRGM for use in a specific situation [2].

2. Literature Survey

2.1 Various Parameter Estimation Techniques

Amid the advancement of software methods, writing review is the most generally held earth shattering stage. In the wake of contrasting the significance of the software reliability to the software engineering, its "property of probability" changes into an attribute that is astoundingly vital. With a specific end goal to foresee programming reliability hybrid intelligent frameworks were the most extreme crisp exploration work. [3]. Software reliability can be anticipated by method for various methods. A portion of the methods incorporate "genetic programming and bunch method of data handling (GMDH)", hybrid models and so forth [4]. By making utilization of the machine learning methods we can decisively anticipate the software reliability. In the wake of looking over, in countless neural networks recommends various favorable tactics so as to predict the software reliability. [5]. Karunanithi et al. [5, 6] were the main to put on Neural Networks for the forecast of software reliability. Here encryption of both input and output was done into the binary bit strings in which the execution time was actualized Neural Networks was used for the forecast of aggregate number of system faults present furthermore expressed that the models were produced by the neural with enhanced features of fitting and prognosticquality. For the modeling of the software reliability, the neural networks utilized can be sorted into two sorts of groups. The principal group used aggregate execution time as the contribution alongside the analogous assembled calamities as the favored yields. Additionally, this gathering makes accentuations on software reliability modeling by faltering disparate assortments of neural networks like intermittent neural network [7]. .The second classification/gathering of class models is developed on the attributes of both input and output. The input is various deferred inputs and the yield is single yield neural network. A model was built up by RajKiran and Ravi [8]. This model was a gathering model, whose fundamental capacity was to precisely anticipate software reliability. For the improvement of gathering, MLR, MARS, dynamic evolving neuron-fuzzy inference systems (DENFIS) and Tree Net were utilized. Three sorts of straight troupe and one kind of nonlinear outfit were composed and after that tested. Toward the end of the last testing stage it was chosen that, non-direct gathering surpassed all different sorts of group, constituent's statistical and intelligent techniques. The use of wavelet Neural Networks were proposed by RajKiran and Ravi [9] with the idea that Morley wavelet and Gaussian wavelet transfer functions keeping in mind the end goal to evaluate the software reliability.

There are three classifications of methodology present in natural computing. These are: (1) the principal classification creates novel critical thinking techniques by taking inspiration from the nature; (2) the second class manufacture natural facts with the assistance of PCs; (3) the third classification figures the natural resources. These three fundamental categories depend on artificial neural network, evolutionary algorithms, swarm intelligence, artificial immune systems, fractal geometry, artificial life, DNA computing, and quantum computing. The relationship of computational aptitude and aggregate knowledge offers ascend to box inspired computing. The above two computational methodologies are utilized to accommodate complex issues. The primary motivation behind the box inspired computing is to fabricate computational apparatuses having the properties of more prominent quality, versatility, adaptability furthermore build up those devices which can undoubtedly and effectively connect with people. This box inspired computing component gives biological scientists, with an IT-arranged learning so they can watch how cells compute or prepare data. This instrument likewise bolsters PC researchers in building the calculations built up on normal structures like transformative and hereditary calculations.

2.2 Maximum Likelihood Estimation And Least Square Estimation Method

In statistics, MLE is a powerful technique used for the estimation of parameters of a statistical model. When we will try to implement the estimation technique to a predefined facts and figures, maximum possibility estimation offers approximations for the model constraints. In statistics the process of maximum likelihood matches to a various number of eminent estimation methods. In case of MLE the estimates are attained by taking into consideration the mean and the variance as parameters and then locating the particular parametric values that formulate the pragmatic results the most feasible. Having a lesser number failures biasing of the MLE's can be done very deeply. Moreover the outsized sample optimality properties do not apply. For the computation of MLE's, it needs specific software's for the explanation of complex nonlinear equations. While making use of the maximum likelihood estimation technique for the parameter estimation, it is in need of solving the sets of instantaneous equations in order to maximize the possibility of fault data which approaches from a given function(at times from the model equation) in order to estimate the parameters. MLE has been considered as the best estimator for huge amount of data as it achieves a number of significant statistical properties of the optimal estimator. But at the same time the set of equations which are used to evaluate the parameters by making use of MLE are highly complex and they need to be solved numerically [18] [19] [20]. This is a real world issue that confines the use of MLE by industrial practitioners. They may not be well skilled to use the statistical modeling techniques which are required to use MLE. The difficulty for estimating the parameters via MLE is further compounded either due to the SRGM models having functions which are complex log likelihood and moreover in the situations where unidentified parameters of MLE does not congregate to give unique estimations. Estimating the parameters of Goel-Okumoto, Yamada S-shaped and Inflection S– shaped models can be evaluated by making use of the MLE technique. Due to the absence of viable tools in manufacturing industries the use of MLE is limited which in turn offers consistent MLE parameter estimation for different SRGMs.

Least square estimation method is used for determining the set of parameters having the highest likelihood being accurate for a given set of experimental data. In this technique, in order to estimate the parameters least squares are taken into account by minimizing the squared inconsistencies between experimental data and their predictable values. In comparison with the conventional random sample plans, the first failure expurgated sampling plan, has an important property of saving both test time and the resources [21]. Moreover least square estimation technique makes use of the curve fitting to the experimental data in order to estimate the unidentified parameters. For the curve the parameter values are estimated that results in minimum sum of square of errors. For estimating the unidentified parameters, LSE makes use of the nonlinear regression. Nonlinear regression is accessible as a standard routine in most of the commercially available statistical packages, so LSE is very easy to apply. MLE and LSE were implemented by Wood [21] and it was concluded that least square predictions are more steady and better, though MLE results were practical. He also concluded that in between confidence intervals, least square estimations were unsatisfactory where as in MLE confidence interval estimates were realistic and too comprehensive to make practical conclusions. LSE offers steady outcomes in broader data sets and is a highly preferred method used by the organizational practitioners. The situation where MLE cannot provide the parameter estimations, least square method is the most natural one. Hence least square estimator is being used more than MLE, evaluating different SRGMS over larger data sets [12], [13].

2.3 Parameter Estimation of SRGM's And Techniques

During the testing phase of software, there is an increase in the software reliability by eliminating the failures identified. In the recent decades a lot of SRGMs have been projected. A number of researchers established the legitimacy of these models. There are two features which are common in traditional SRGMs. Earlier they have some norms for the representation of a specified environment. For instance, an assumption was made that recognition of failures is independent of one another. We can also say that, there arises no failure, whenever a developer corrects a failure. As soon as the failure is detected, it is removed instantaneously and after this no new failure takes place. On the other hand, other models makes an assumption that the failures are never removed completely, and moreover the fresh ones can be presented under consideration of inadequate debugging and error generation. As per these assumptions, we can categorize the traditional conventions and then can be applied to each definite environment. Also SRGMs consist of a few parameters possessing physical interpretation like the total number of failures or the failure detection rate. In case of SRGM, a mean value function is demonstrated for the failure detection which is denoted by m (t). It signifies the expected number of failures in time (0, t]. The GO model equation can be written as:

$$M(t) = a(1 - e{-}but),\ a > 0,\ b > 0 \quad (1)$$

Where the variable a indicates the total number of failures and the variable b indicates the detection rate of failures.

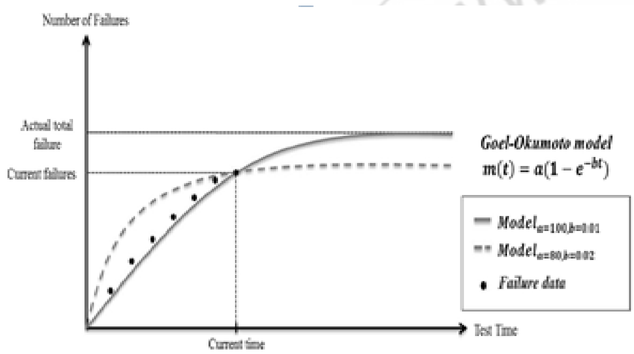

Figure 1: Influence of parameters on the result of SRGMs

It is necessary to estimate the above parameters correctly as there can occur delay of time release and cost overrun for ongoing projects due to the inaccurate estimation of the parameters. The figure shown below shows the impact of the parameters on the results of SRGM. In case of model, a=80 and b=0.02, the estimated total number of failures are smaller than the overall actual failures. For the estimation of SRGM parameters, various numerical methods are used such as MLE or LSE. In most of the research areas, these methods are being widely used for the parameter estimation of a modeling function. For the parameter estimation of a statistical model, a numerical method called as LSE is used. It minimizes the sum of square of residuals between the actual and expected data. One more numerical method called as MLE is also used for the parameter estimation of a statistical method, but it maximizes the value of the likelihood function. While using MLE, there is a necessary need of a statistical model that needs 2 be specified. These methods are applicable only when the mean value function of SRGM is linear. In a number of cases, certain constraints are imposed on the parameter estimation of SRGMs along with the steadiness and actuality of derivatives in the modeling function. In order to find an optimal solution, it is challenging to examine all the candidate areas, as soon as the number of parameters increases which in turn may not solve the local optimization problems. MLE and LSE are unsuitable for parameter estimation as they have two or more parameters at minimum and are nonlinear in nature. This results in a necessity for more operative parameter estimation methods. So due to this disadvantage of MLE and LSE, Meta heuristics are applied, such as GA and PSO for solving this type of problems. It provides precise estimation by attaining an optimal solution as these methods are free from the constraints. Meta heuristics have been widely effective for the parameter estimation of SRGM.

In the next phase of this paper with will discuss different types of parameter estimation techniques.

3. Two Parameter Geometric Distribution

A number of models have been put forward so far in order to represent the lifetime data. In most of these models, lifetime is used as a continuous random variable. Though at times, it becomes troublesome or difficult to estimate the life span of a device on a continuous scale. [15] Practically, we might face circumstances where the random variable lifetime is recorded on a discrete scale. Discrete life distributions were proposed by Barlow and Prochain [16]. Lifetime may be defined as the number of effective cycles or processes of a device before an error/ failure occurs. For instance, whenever a copy is taken from a Xerox machine the bulb present inside it glows. There may occur, spring break down after the completion of a particular number of cycles. These cycles occur in a to and fro motion. The geometric distribution was examined as a failure law in life testing by Yakut and Khan [17]. In order to find out the characteristics/ features of the reliability characteristics they obtained various parametric and non-parametric estimation procedures. In order to estimate the mean life cycle and reliability for this model, Bhattacharya and Kumar [18] proposed the parametric and Bayesian approach for complete and censored sample. Classical and Bayes estimation of reliability were discussed by Krishna and Jain [19] for some basic system configurations. If a manufacturer wants to offer a lowest guarantee life cycle of the items manufactured, then modeling must be accomplished in terms of two parameter geometric and estimation of its parameters along with related functions. The two parameter geometric distribution is mathematically written as below [14]:

$$P(X=x) = (1-\Theta)\ \Theta \text{ expel } (x-r);\ x=r,\ r+1,\ r+2,\ 0<\Theta<1,\ r \in \{0, 1, 2,\}$$

If X tracks a two parameter exponential distribution, then [X], which is an integer part of X, has a two parameter geometric distribution. [22] The reliability of a module when X tracks two parameter geometric distributions is given by;

$$R(t) = \Theta \text{ expel } (t-r);\ t= r,\ r+1,\ r+2,$$

The uniformly minimum variance unbiased estimator (UMVUE) of the reliability function was proposed by Laurent [19] and Tate [19] for the two parameter exponential model. It was explained in Sinhala that dissimilar estimators can be used for this reliability function. If we have a system consisting of m identical components, in which each component follows two parameter geometric distribution, then the reliability of K-out-of-m system is given by;

$$R_s(t) = P(X_{(m-k+1)} \geq t) = \sum_{i=k}^{m} \binom{m}{i} R(t)^i [1 - R(t)]^{m-i}; \quad t = r, r+1, r+2, \ldots$$

When k=m, T_s (t) gives rise to series system and when k=1, T_s (t) gives rise to parallel system. In case of the stress strength setup, R= P(X<Y) which is devised in the framework of reliability of a constituent of strength Y imperiled to a stress X. The constituent may fail, if the stress applied is more than its strength at any interval of time. There occurs no failure if the applied stress is lesser than its strength. Henceforth R is a measure of the reliability of the component/constituent. The two parameter geometric distribution is utilized in case of the discrete life testing problem. Moreover, in discrete life testing problems, a minimum warranty life cycle of the items are offered.

4. EM Algorithms for NHPP based SRMS

By means of the traditional method, like Newton's method or the Fisher's scoring method, we have to take every time the constraints of model parameters into account for parameter estimation. For example, in case of the Goal and Komodo model [15], (ω, β) must always be defined as the non-negative real values. In this manner inside the software reliability models, the model parameters are subjected to an implicit constraint. Moreover, it must also be noted that if the initial values in the Newton's method and Fishers scoring method are far away from the MLE's then they do not congregate to MLEs satisfying the constraints. In other words we can also say that the initial values can also be selected reliant on the accuracy of the estimates. This kind of problem can also be generated by the local convergence property present in the newton's method and the Fisher's scoring method. In order to remove the problem of selecting the initial values, EM algorithm was introduced for the parameter estimation problem present in the software reliability modeling. If we think in terms of convergence speed, the EM algorithm has a tendency to be slower than the Newton's method and the Fisher's scoring method. The likelihood can be made larger by updating the estimates. This characteristic known as the global convergence, results in the decrease in effort while choosing the initial values. In case of the EM algorithms the estimates are given in the form of expected values of MLE's under inadequate data. These estimates under no circumstances disrupt the parameter constraints.

$$\omega = \mathrm{E}[N | \mathcal{D}; \omega', \theta']$$

and

$$\mathrm{E}\left[\sum_{i=1}^{N} \frac{\partial}{\partial \theta} \log f(S_i; \theta) \middle| \mathcal{D}; \omega', \theta' \right] = 0.$$

The EM algorithm is an eye catching parameter estimation methods used in the modeling of software reliability, most importantly in NHPP based SRMs. After examining the efficiency of the EM algorithms, make a comparison with the Newton's method and Fisher's scoring method. This relative study has not been made in the literature [17, 18]. We study the global/ local convergence, and in advance to this, explore the convergence speed along with the arbitrary initial values of the algorithms. Keeping all the numerical problems in mind three types of domain sets were observed in the actual software development projects namely DS1, DS2, DS3 [19]. The overall software faults detected in DS1-DS3 are 86, 136 and 207 respectively. In our illustrations three categories of SRGMs are used with the second degree shape parameter. These are Goel-Okumoto model [15], S-shaped model [10] and Goalmodel [20].

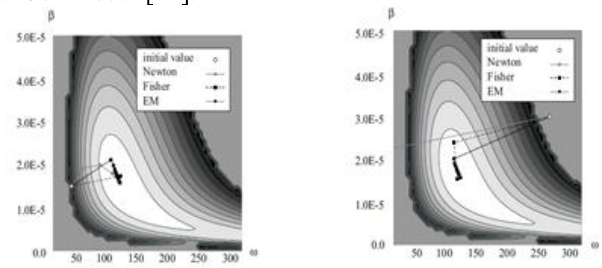

Figure 2: Behavior of estimates in GoalKomodoModel.

Figures 1 and 2[11] demonstrate the performance of estimations calculated by three algorithms with the initial parameter values, (ω, β) = (30, 1.5E-5) and (ω, β) = (250, 3.0E-5), unless and until the approximations congregate to the MLE with DS1 in case of Goel-Okumoto model. [11] LLF for DS1 is specified by the contour lines. In these lines bright colors are present in the figure as soon as the likelihood increases. In case of the figure 1, the experimentally observed estimates calculated by all the algorithms converge to the MLEs. In case of the figure 2, the estimates observed by the Newton's method do not converge to the MLEs. It is because of the fact that they take illegal values. If we try to alter the initial parameter values, we will get the same results. From these experimental observations it has been concluded that the EM algorithms have the global convergence property. At the same time the Newton's method does not function properly. In order to scrutinize the local/global convergence property and the quantifiable convergence speed of the algorithms are executed 10 times over all kinds of data sets and three kinds of SRMs i.e. GoalKomodomodel, delayed S-shaped model and Goalmodel. The experiment was done by selecting the initial values as 100 pairs of different values. Two norms were used while comparing the algorithms namely rate of convergence and mean relative distance to MLEs. These two norms represent the global/ local convergence property and the convergence speed of algorithms respectively [4=11].
ROC = ((number of estimates following constraints) / (total number of initial values)) * 100

MRD = ∑ | (MLEs) – (estimates) | / (number of estimates following constraints)

Due to the higher convergence ability of the algorithm ROC is more while as MRD is lesser due to the faster convergence speed. Tables 1, 2 and 3 [11] represent the ROC and MRD in Goal and MRD in the above three defined SRGMs for all kinds of data sets. From the tables it is clear that the EM algorithm is superior to the Newton's method and the Fishers scoring method.

Simulated Annealing

Simulated annealing is most likely the best case of advanced met heuristics calculations, what is more, it was created by Kirkpatrick, Gelato and Vichy in 1983 [7], propelled by the tempering procedure of metals and warmth treatment and Metropolis algorithms for Monte Carlo simulations. The essential thought of the simulated annealing calculation is like falling some bouncy balls more than a scene, and as the balls bounce and free vitality, they will settle down at some nearby minima. On the off chance that the balls are permitted to bounce enough times and free vitality gradually enough, some of the balls will in the end fall into the internationally most minimal areas and the subsequently the least will be come to. Obviously, we can utilize numerous balls, or utilize a solitary ball to follow its direction. The advancement handle normally begins from a beginning superposition with higher vitality. It then moves to different areas haphazardly with somewhat decreased vitality. The move is acknowledged if the new state has lower vitality and the arrangement enhances with a superior goal or lower estimation of the target capacity for minimization. Be that as it may, on the off chance that the arrangement does not enhance, it is still acknowledged with a likelihood of

$$p = \exp[-\frac{\delta E}{kT}], \qquad (8)$$

Which is Boltzmann sort likelihood dissemination? Here it is the temperature of the framework, while K is the Boltzmann steady and can be taken to b 1 for effortlessness. The vitality distinction delta E is regularly identified with the target capacity f(x) to be streamlined. The direction in the reenacted strengthening is a piecewise way.\, and this is for all intents and purposes a Marco chain as the new state (new arrangement) just relies on upon the present state/arrangement. Here the diversification by means of randomization delivers new arrangements, whether the new arrangement is acknowledged or not is controlled by likelihood. On the off chance that T is too low then any more terrible arrangement will infrequently be acknowledged, furthermore, the assorted qualities of the arrangements is therefore restricted. Then again if T is too high, the framework is at a high vitality state, most new changes will be acknowledged. So the temperature T is basically controlling the offset of enhancement and escalation. The change of T is known as the cooling schedule. There are two primary classes of cooling schedules: the monotonically diminish also, non-monotonic. **For** monotonic cooling, geometric schedule is the most broadly utilized. The benefit of this schedule is that there is no need to focus at the last temperature. The disservices that on the off chance that you utilize a little benefit of corresponding to the reenacted extinguishing (SQ), then there is a danger for the framework to stop too rapidly and it may be caught in some neighborhood optima. A conceivable arrangement is to utilize non-monotonic cooling calendar so that the framework can be lifted to a higher vitality state when fundamental. Once more, if you raise the temperature too often, the meeting is influenced. This illustrates that there is a fine harmony in between diversification and intensification.

5. Conclusion

It is impossible to determine the software reliability during design phase. In this paper we discussed different types of parameter estimation techniques namely Ant Colony Optimization Technique, Two Parameter Geometric Distribution Technique, Cuckoo Search Technique, Maximum Likelihood Estimation Technique, Least Square Estimation Technique, EM Algorithm for NHPP based SRM's Technique. Estimating the parameters of SRGMs is highly classified as optimization problems.

References

[1] Pay, Ganesh J. "A survey of softwarereliabilitymodels." *arrive preprint arrive: 1304.4539* (2013).
[2] Sharma, Kepi, et al. "Selection of optimal softwarereliability growth models using a distance based approach." *Reliability, IEEE Transactions on* 59.2 (2010): 266-276.
[3] **[7]** R. K. Mohan, V. Ravi, and M. R. Petra, "Hybrid intelligent Systems for predicting Softwarereliability," Elsevier, Applied Soft Computing, vol. 13, No. 1, pp. 189-200, 2013.
[4] R. K. Mohan, V. Ravi, and M. R. Petra, "Application of Machine learning Techniques to Predict softwarereliability," International Journal of Applied Evolutionary Computation, vol. 1, No.3, pp. 70-86, 2010.
[5] T. M. Khoshgoftaar, and P. Retours, "Noise elimination with partitioning filter for software quality estimation," International Journal of Computer Application in Technology, vol. 27, pp. 246-258, 2003.
[6] T. M. Khoshgoftaar, E.B. Allen, W. D. Jones, and J. P. Hudepohl, "Classification –Tree models of software quality over multiple releases," IEEE Transactions on Reliability, vol. 49, No. 1, pp. 4-11, 2000.
[7] L. Tian, and A. Noore, "Evolutionary neural network modeling for software cumulative failure time prediction," Reliability Engineering and System Safety, vol. 87, pp. 45-51, 2005b.
[8] N. RajKiran and V. Ravi. "SoftwareReliability prediction by soft computing technique," The Journal of Systems and Software, vol. 81, No.4, pp. 576-583, 2007.
[9] N. Rajkiran, and V. Ravi, "SoftwareReliability prediction using wavelet Neural Networks," International Conference on Computational Intelligence and Multimedia Application (ICCIMA, 2007), pp. 195-197, 2007
[10] V. Ravi, N. J. Chauhan, and N. RajKiran., "Softwarereliability prediction using intelligent techniques: Application to operational risk prediction in Firms," International Journal of Computational Intelligence and Applications, vol.8, No. 2, pp. 181-194, 2009
[11] E. Bonabeau, M. Dorito, and G. Théraulaz, "Inspiration for optimization from social insect behavior," Nature, pp. 39–42, 2000.
[12] R. Pole, and W.B. Langdon, J.R. Kola, "A field guide to Genetic Programming," ISBN: 978-1-4092-0073-4, publisher- Lulu.com, United Kingdom, 2008.

[13] P. F. Pay, and W. C. Hong, “Software reliability forecasting by support vector machine with simulated annealing algorithms,” Journal of System and Software, vol.79, No.6, pp. 747-755, 2006.
[14] Sudanese S. Maithili, SudhirMurmu, Estimation of reliability in the two parameter geometric distribution, arrive: 1501.05072v1 [satrap] 21 Jan 2015.
[15] R. E. Barlow and F. Proschan, Mathematical Theory of Reliability, John Willy & Sons, Inc., New York, 2000.
[16] M. Yakub and A. H. Khan, Geometric failure law in life testing, Pure and Applied Mathematical Science 14(2001), pp. 69-76.
[17] S. K. Bhattacharya and S. Kumar, Discrete life testing, IAPQR Transactions 13(2004), pp. 71-76.16
[18] H. Krishna and N. Jain, Classical and Bayes Estimation of Reliability Characteristics of some Basic System Configurations with Geometric Lifetimes of Components, IAPQR Transactions 27(2002), pp. 35-49.
[19] J. D. Kalbfleish and R. L. Prentice, the Statistical Analysis of Failure Time Data, Wiley, New York, 2001.
[20] A. G. Laurent, Conditional distribution of order statistics and distribution of the reduced itorders statistics of the exponential model, Ann. Math. Statist. 34(2004), pp. 652-657.
[21] R. F. Tate, Unbiased estimation: Functions of location and scale parameters, Ann. Math. Statist. 30(2005), pp. 341-366.
[22] R. B. Payne, M. D. Sorenson, and K. Klutz, the Cuckoos, Oxford University Press, (2005).
[23] S. Walton; O. Hassan, K. Morgan and M.R. Brown (30 June 2011). "Modified cuckoo search: A new gradient free optimization algorithm". *Chaos, Solitons&Fractals*.Doi: 10.1016/j.chaos.2011.06.004.