NONPARAMETRIC ANALYSIS OF SOFTWARE RELIABILITY
Revealing the Nature of Software Failure Dataseries

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Abstract: Software reliability is directly related to the number and time of occurrence of software failures. Thus, if we were able to reveal and characterize the behavior of the evolution of actual software failures over time then we could possibly build more accurate models for estimating and predicting software reliability. This paper focuses on the study of the nature of empirical software failure data via a nonparametric statistical framework. Six different time-series data expressing times between successive software failures were investigated and a random behavior was detected with evidences favoring a pink noise explanation.

1 INTRODUCTION

System reliability is one of the major components identified by the ISO9126 standard for assessing the overall quality of software. More specifically, software reliability can be evaluated on the following factors:

- Maturity: Attributes of software that bear on the frequency of failure by faults in the software (ISO/IEC 9126-1:2001)
- Fault tolerance: Attributes of software that bear on its ability to maintain a specified level of performance in cases of software faults or of infringement of its specified interface (ISO/IEC 9126-1:2001)
- Crash frequency: The number of the system crashes per unit of time
- Recoverability: Attributes of software that bear on the capability to re-establish its level of performance and recover the data directly affected in case of a failure and on the time and effort needed for it (ISO/IEC 9126-1:2001)

The standard definition of reliability for software is the probability of normal execution without failure for a specified interval of time (Musa, 1999; Musa, Iannino and Okumoto, 1987). Going a step further we can state that reliability varies with execution time and grows as faults underlying the occurred failures are uncovered and corrected. Therefore, measuring and studying quantities related to software failure can lead to improved reliability and customer satisfaction. There are four general ways (quantities) to characterize (measure) failure occurrences (Musa, 1999):

- Time of failure
- Time interval between failures
- Cumulative failures experienced up to a given time t_i
- Failures experienced in a time interval t_i

The majority of recent research studies focus on software reliability assessment or prediction using the failure-related metrics mentioned above (e.g. Patra, 2003; Tamura, Yamada and Kimura, 2003), with very few exceptions that experiment with other alternatives, like Fault Injection Theory (e.g. Voas and Schneidewind, 2003), Genericity (Schobel-Theuer, 2003), etc.

As Musa points out (Musa, 1999), the quantities of failure occurrences are random variables in the sense that we do not know their values in a certain time interval with certainty, or that we cannot predict their exact values. This randomness, though, does not imply any specific probability distribution (e.g. uniform) and it is sourced on one hand by the complex and unpredictable process of human errors introduced when designing and programming, and on the other by the unpredictable conditions of program execution. In addition, the behavior of software is affected by so many factors that a deterministic model is impractical to catch.

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The aim of this paper is to study the nature and structure of software failure data using a set of empirical software failure dataseries and a robust nonparametric statistical method. The ReScaled range (R/S) analysis, originated by Hurst (Hurst, 1956), looks deep in a time-series dataset and provides strong evidences of either an underlying deterministic structure, or a random behavior. In the former case it can define the time pattern of the deterministic behavior, while in the latter it reveals the nature of randomness (i.e. the colour of noise).

The rest of the paper is organized as follows: Section 2 outlines the basic concepts of the nonparametric framework used to analyse the available datasets. Section 3 describes briefly the six software failure time-series data used and provides a short statistical profile for the data involved. Section 4 concentrates on the empirical evidence that results from the application of R/S analysis on the different software projects failure data. In addition, this section presents our attempt to investigate through R/S Analysis the nature of software failure data produced by two well-known and widely used Software Reliability Growth Models, namely the Musa Basic model and the logarithmic Poisson Musa-Okumoto execution time model, and compares results with those derived using the empirically collected data. Finally, section 5 sums up the empirical findings, draws the concluding remarks and suggests future research steps.

2 THE R/S ANALYSIS

Technically, the origins of R/S analysis are related to the "*T* to the one-half rule", that is, to the formula describing the Brownian motion (B.M.):

$$R = T^{0.5} \tag{1}$$

where R is the distance covered by a random particle suspended in a fluid and T a time index. It is obvious that (1) shows how R is scaling with time T in the case of a random system, and this scaling is given by the slope of the $\log(R)$ vs. $\log(T)$ plot, which is equal to 0.5. Yet, when a system or a time series is not independent (i.e. not a random B.M.), (1) cannot be applied, so Hurst gave the following generalisation of (1) which can be used in this case:

$$(R/S)_n = c\, n^H \tag{2}$$

where $(R/S)_n$ is the ReScaled range statistic measured over a time index n, c is a constant and H the Hurst Exponent, which shows how the R/S statistic is scaling with time.

The objective of the R/S method is to estimate the Hurst exponent, which, as we shall see, can characterise a time series. This can be done by transforming (2) to:

$$\log (R/S)_n = \log(c) + H \log(n) \tag{3}$$

and H can be estimated as the slope of the log/log plot of $(R/S)_n$ vs. n.

Given a time series $\{X_t : t=1,...,N\}$, the R/S statistic can be defined as the range of cumulative deviations from the mean of the series, rescaled by the standard deviation. The analytical procedure to estimate the $(R/S)_n$ values, as well as the Hurst exponent by applying (3), is described in the following steps :

Step 1: The time period spanned by the time series of length N, is divided into m contiguous sub-periods of length n such that $mn = N$. The elements in each sub-period $X_{i,j}$ have two subscripts, the first (i=1,..,n) to denote the number of elements in each sub-period and the second (j=1,...,m) to denote the sub-period index. For each sub-period j the R/S statistic is calculated, as:

$$\left(\frac{R}{S}\right)_j = s_j^{-1}\left[\max_{1\le k\le n}\sum_{i=1}^{k}(X_{ij}-\bar{X}_j) - \min_{1\le k\le n}\sum_{i=1}^{k}(X_{ij}-\bar{X}_j)\right] \tag{4}$$

where s_j is the standard deviation for each sub-period.

In (4), the k deviations from the mean of the sub-period have zero mean; hence the last value of the cumulative deviations for each sub-period will always be zero. Due to this, the maximum value of the cumulative deviations will always be greater or equal to zero, while the minimum value will always be less or equal to zero. Hence, the range value (the bracketed term in (4)), will always be non-negative. Normalizing (rescaling) the range is important since it permits diverse phenomena and time periods to be compared, which means that R/S analysis can describe time series with no characteristic scale.

Step 2: The $(R/S)_n$, which is the R/S statistic for time length n, is given by the average of the $(R/S)_j$ values for all the m contiguous sub-periods with length n, as :

$$\left(\frac{R}{S}\right)_n = \frac{1}{m}\sum_{j=1}^{m}\left(\frac{R}{S}\right)_j \tag{5}$$

Step 3: Equation (5) gives the R/S value, which corresponds to a certain time interval of length n. In order to apply equation (3), steps 1 and 2 are repeated by increasing n to the next integer value, until $n = N/2$, since, at least two sub-periods are needed, to avoid bias.

From the above procedure it becomes obvious that the time dimension is included in the R/S analysis by examining whether the range of the cumulative deviations depends on the length of time used for the measurement. Once (5) is evaluated for different n

periods, the Hurst exponent can be estimated through an ordinary least square regression from (3).

The Hurst exponent takes values from 0 to 1 ($0 \le H \le 1$). Gaussian random walks, or, more generally, independent processes, give $H = 0.5$. If $0.5 \le H \le 1$, positive dependence is indicated, and the series is called persistent or trend reinforcing, and in terms of equation (1), the system covers more distance than a random one. In this case the series is characterised by a long memory process with no characteristic time scale. The lack of characteristic time scale (scale invariance) and the existence of a power law (the log/log plot), are the key characteristics of a fractal series. If $0 \le H \le 0.5$, negative dependence is indicated, yielding anti-persistent or mean-reverting behavior[1]. In terms of equation (1), the system covers less distance than a random series, which means that it reverses itself more frequently than a random process.

A Hurst exponent different from 0.5 may characterise a series as fractal. However a fractal series might be the output of different kinds of systems. A “pure” Hurst process is a fractional Brownian motion (Mandelbrot and Wallis, 1969), also known as biased random walk or fractal noise or coloured noise, that is, a random series the bias of which can change abruptly but randomly in direction or magnitude.

A problem, though, that must be dealt is the sensitivity of R/S analysis to short-term dependence, which can lead to unreliable results (Aydogan and Booth, 1988; Booth and Koveos, 1983; Lo, 1991). Peters (Peters, 1994) shows that Autoregressive (AR), Moving Average (MA) and mixed ARMA processes exhibit Hurst effects, but once short-term memory is filtered out by an AR(1) specification, these effects cease to exist. On the contrary, ARCH and GARCH models do not exhibit long term memory and persistence effects at all. Hence, a series should be pre-filtered for short-term linear dependence before applying the R/S analysis. In our analysis, we use partial autocorrelograms and Schwartz´s information criterion to indicate the best-fit time series linear model to our data.

3 SOFTWARE FAILURE DATA

Before moving to applying R/S Analysis on the available software failure datasets, let us examine some basic features of the data: Six different datasets were used in this paper, which were collected throughout the mid 1970s by John Musa, representing projects from a variety of applications including real time command and control, word processing, commercial, and military applications (DFC, www.dacs.dtic.mil): Project 5 (831 total samples), SS1B (375 total samples), SS3 (278 total samples), SS1C (277 total samples), SS4 (196 total samples) and SS2 (192 total samples).

R/S analysis can be applied only on a transformation of the original data samples which produces the so-called return series eliminating any trend present. This transformation is the following:

$$r_t = \log\left(\frac{S_t}{S_{t-1}}\right) \tag{6}$$

where S_t and S_{t-1} are the failure samples (more specifically, the elapsed times form the previous failure measured in seconds) at times (t) and (t-1) respectively (discrete sample number) and r_t is the estimated return sample.

As mentioned in the previous section, in order to remove the short-term memory all return series were filtered with an AR(1) model. A short statistical profile is depicted in Table 1, where one can easily discern that the series under study present slight differences from the normal distribution: Left skewness is evident for all data series, while, as regards kurtosis, Project 5 samples present leptokurtosis with the rest series being less concentrated around the mean compared to the normal distribution. Figure 1 plots the data samples belonging to Project 5, with the left figure showing the evolution of failures according to the elapsed time and the right figure presenting the de-trended return series. The rest of the datasets present a similar graphical representation, thus their figures were omitted due to space limitations.

The statistical profile of the dataseries given above suggests a general resemblance with the normal (Gaussian random) distribution, but slight differences were also observed. The main questions, though, remain: What is the actual nature of this data? Is there a random component in the behavior of these series? The answers will be provided by closely examining the results derived from the application of R/S Analysis described in the next section.

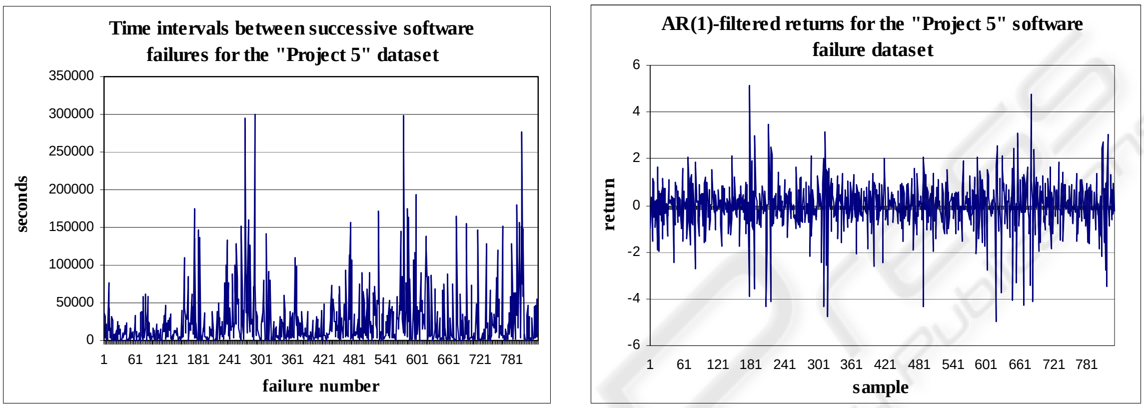
[1] Only if the system under study is assumed to have a stable mean

4 EMPIRICAL EVIDENCE

4.1 R/S Analysis Results on Software Reliability Data Series

The results of R/S analysis on the six failure return series are listed in Table 2. The Hurst exponent estimated has a low value ranging from 0.27 (Project 5 dataset) to 0.37 (SS1C dataset).

These Hurst exponent values indicate anti-persistency, that is, all return series present negative dependence or antipersistence, yielding a mean-reverting behavior since the data fluctuate around a reasonably stable mean (no trend or consistent pattern of growth). In terms of equation (1), each of the six systems covers less distance than a random series, which means that it reverses itself more frequently than a random process.



(a) (b)

Figure 1: Project 5 sample series: (a) Time intervals between successive failures (b) AR(1)

Table 1: Statistical description of the six software failure returns series data (AR(1)-filtered samples)

	Project 5	SS1B	SS3	SS1C	SS4	SS2
Sample size	829	373	276	275	194	191
Average	5.55E-18	2.97E-18	-1.20E-18	-5.85E-18	1.54E-17	3.95E-17
Median	0.024	0.073	0.075	0.084	0.121	-0.027
Variance	1.150	0.871	1.936	0.988	1.421	1.176
Standard deviation	1.072	0.933	1.391	0.993	1.192	1.084
Minimum	-4.963	-3.120	-5.056	-3.094	-4.127	-2.634
Maximum	5.165	2.879	3.470	4.786	2.832	3.268
Range	10.129	6.000	8.526	7.881	6.960	5.902
Lower quartile	-0.479	-0.536	-0.761	-0.473	-0.699	-0.671
Upper quartile	0.597	0.619	0.942	0.563	0.823	0.712
Skewness	-0.616	-0.263	-0.315	-0.034	-0.432	-0.131
Kurtosis	4.082	0.457	0.180	2.327	0.713	-0.019

Table 2: Hurst estimates and test of significance against two random alternatives for the AR(1)-filtered returns series of the six different Musa's software failure datasets

Dataset	Hurst Exponent	IID-null Hypothesis		Gaussian-null Hypothesis	
		Mean Hurst	Significance	Mean Hurst	Significance
Project5	0.27	0.56	0.1%	0.56	0.1%
SS1B	0.31	0.58	0.1%	0.58	0.1%
SS3	0.28	0.59	0.1%	0.60	0.1%
SS1C	0.37	0.59	0.1%	0.59	0.1%
SS4	0.33	0.60	0.1%	0.60	0.1%
SS2	0.33	0.60	0.1%	0.60	0.1%

A significant problem of R/S analysis is the evaluation of the H exponent from a statistical point of view. Specifically, we should be able to assess whether an H value is statistically significant compared to a random null, i.e. to the H exponent exhibited by an independent random system. Peters (1994) shows that under the Gaussian null, a modification of a formula developed by Anis and Lloyd (1976) allows for hypothesis testing by computing $E(R/S)_n$ and $E(H)$, the expected variance of which will depend only on the total sample size N, as $Var(H)=1/N$. However, if the null is still iid randomness but not Gaussianity, the formal hypothesis testing is not possible. To overcome this problem we used bootstrapping (Efron, 1979) to assess the statistical significance of the H exponents of our series, against both the Gaussian and the iid random null hypotheses.

The validity of the results obtained using the R/S analysis may be assessed as follows:

(A) To test against the Gaussian random null, the H exponent from 5000 random shuffles of a Gaussian random surrogate, having the same length, mean and variance with our return series is calculated and compared to the test statistic i.e. the actual H exponent of our series. Since the actual H statistic was found to be lower than 0.5 and anti-persistence is possible, the null can be formed as: $H_0 : H = H_G$ and the alternative is $H_1 : H < H_G$. In this case, the significance level of the test is constructed as the frequency with which the pseudostatistic H_G is smaller than or equal to the actual statistic and the null is rejected if the significance level is smaller than the conventional rejection levels of 1%, 2.5% or 5%.

(B) To test against the iid null, the same procedure is followed but this time we randomise the return series tested to produce 5000 iid random samples having the same length and distributional characteristics as the original series. In this case, rejection of the null means that the actual H exponent calculated from the original series is significantly smaller from the one calculated from an iid random series. Hence, this is also a test for non-iid-ness.

Validation of the R/S analysis results was performed as described above, with both tests being applied to the available dataseries. As Table 2 shows, both hypotheses are rejected since the significance level of the test in both cases was lower than 1%. This means that our Hurst estimates are statistically significant against both the Gaussian and the iid-null hypotheses suggesting an underlying structure that deviates from normal distribution and resembles the one observed for random, non-white noise.

Fractional noise scales according to inverse power laws, which essentially is a function of frequency f, and follows the form f^b. This is a typical characteristic of fractals, which have power spectra that follows the inverse power law as a result of the self-similar nature of the system (Peters, 1994). For white noise (Gaussian, random process) $b = 0$, that is, the power spectra is not related to frequency. There is no scaling law for white noise. When white noise is integrated, then $b = 2$, the power spectra for brown noise. If $0 < b < 2$ we have pink noise, while when $b > 2$ there is black noise. Mandelbrot and Van Ness (Mandelbrot and Van Ness, 1968) postulated, and recently Flandrin (Flandrin, 1989) rigorously defined, the following equation that relates fractional noises with the Hurst exponent:

$$b = 2H + 1 \tag{7}$$

where b is the spectral component and H the Hurst exponent. Therefore, we can relate pink noise to antipersistence: $H < 0.50$, $1 \geq b > 2$.

According to the foregoing notions, and based on the results of the R/S analysis, we can conclude that the six software failure data series are random in nature, thus confirming the findings and supporting the arguments of various researchers (Musa, 1999; Musa and Iannino, 1990). Moving a step forward, we may state that the main conclusion drawn is that software failure empirical behavior resembles that of pink noise.

4.2 R/S Analysis and Software Reliability Growth Models System Variables

Having in mind the results thus far and the evidences suggesting a pink noise explanation for the behavior of the empirical software failure data, we will attempt to study the nature of the data produced by known Software Reliability Growth Models (SRGM) and compare results. Several studies (Dale, 1982; Ramamoorthy and Bastani, 1982; Farr, 1996; Jones 1991) report the superiority of the Musa Basic (MB) and the logarithmic Poisson Musa-Okumoto (MO) execution time models (Musa, 1975; Musa and Okumoto, 1984) over a variety of SRGM widely applied to different actual projects and computer programs. Therefore, we decided to use those two models to produce new software failure time samples and apply R/S analysis to investigate the nature of the produced dataseries, and hence the type of software failure behavior each model is capable to capture. Let $M(t)$ represent the number of failures of the particular software package by time t, $(t\geq 0)$. It is clear that $M(0)=0$. $M(t)$ cannot be easily calculated because it corresponds to a physical quantity and can only be measured as the software is tested. Software Reliability Growth Models are trying to model the behavior of $M(t)$ with the statistical function $\mu(t)$. The mean value function $\mu(t)$ of a SRGM represents the number of failures expected to occur up to time moment t, $(t\geq 0)$:

$$\mu(t) = c(t)N \tag{8}$$

where $c(t)$ is the time variant test coverage function and N is the number of faults expected to have been exposed at full coverage. This is distinguished from the expected number of faults to be detected after infinite testing time, perfect testing and fault detection coverage, which can be denoted as $\hat{N}$. Equations (9) and (10) describe the test coverage function for the MB and MO models respectively:

$$\text{MB}: \; c(t) = 1 - e^{-fKBt} \tag{9}$$

$$\text{MO}: \; c(t) = \ln(1 + \phi t) \tag{10}$$

where φ is the failure rate per fault, K is the so-called fault exposure ratio, B is a fault reduction factor and f can be calculated as the average object instruction execution rate of the computer r, divided by the number of source code instructions of the application under testing I_S, times the average number of object instructions per source code instruction, Q_x (Musa, 1999):

$$f = \frac{r}{I_S Q_x} \tag{11}$$

Both $M(t)$ and $\mu(t)$ are sequences of the form $0,1,2, \ldots$ with $M(0)=0$ and $\mu(0)=0$. Assuming that as t approaches infinity $\mu(t)$ becomes a good approximation of $M(t)$ (the number of failures that has been realized up to time t) we will have $\mu(t)$ taking by definition integer positive values (since $\mu(t)$ corresponds to the expected number of failures experienced by time t; hence $\mu(t) \in [0,1,2,\ldots]$). Both SRGMs (MB and MO) converge to the number of failures being realized up to time t as t approaches infinity is generally acceptable. Therefore, our assumption that $M(t)$ will be approached by $\mu(t)$ as t approaches infinity. But $\mu(t)$, which characterizes a SRGM, is given as a model property, thus we should try to reverse engineer the process of failure occurrence and artificially reproduce the " failure occurrences". The failure reproduction process is as follows:

First we replace $\mu(t)$ in equation (8) with an integer positive variable i, (i=0,1,2...). Thus, we have:

$$i = c(t_i)N \tag{12}$$

Substituting $c(t_i)$ in (9) and (10) and solving for t_i we have:

$$\text{MB:}\; i = (1 - e^{-fKBt_i})N \Leftrightarrow t_i = -\frac{1}{fKB}\ln\left(1 - \frac{i}{N}\right) \tag{13}$$

$$\text{MO:}\; i = \ln(1 + \phi t_i)N \Leftrightarrow t_i = \frac{1}{\varphi}\left(e^{i/N} - 1\right) \tag{14}$$

Time variable t_i represents discrete failure time moments, i.e. the time elapsed from the start of this process (t_0 for i=0) until the occurrence of the i_{th} failure (t_1 for i=1, t_2 for i=2 etc.).

Consequently we can calculate times between successive failures as:

$$\Delta t_i = t_i - t_{i-1}. \tag{15}$$

Following the analysis described above, we reproduced artificial failure times data via equations 13 to 15, for which we used the following parameter values suggested by Musa (1975, 1999) and the Defense Software Collaboration (DFC, www.dacs.dtic.mil):

φ = 7.8 E-8, f = 7.4 E-8, K = 4.2 E-7, B= 0.955

Two new software failure dataseries were thus generated, with their size being equal to that of Project 5 (829 samples). R/S analysis was then applied on the AR(1)-filtered returns of the artificially reproduced series. The Hurst exponent estimations indicate that the MB-based reproduced series exhibit long-memory or persistent effects (H=0.9), while the corresponding MO-based sample data is characterized as antipersistent (H=0.2). These findings are very interesting considering the fact that they suggest a strong diversification between two models that are both used as software reliability growth estimators, and hence as software failure predictors. The similar antipersistent characterization of the six software failure dataseries under study and the MO-based generated data is also consistent with the findings of other researchers who report the superiority of the MO model in actual software projects. It is therefore natural that this model proved to be more successful compared to the rest of the SRGMs simply because its underlying modeling nature is similar to the behavior observed with actual empirical data.

5 CONCLUSIONS – DISCUSSION

The nature of empirical software reliability time series data was investigated in this paper using a robust nonparametric statistical framework called ReScaled range (R/S) analysis. This type of analysis is able to detect the presence (or absence) of long-term dependence, thus characterizing the system under study as persistent / deterministic (or mean-reverting / antipersistent).

The results of the R/S analysis on six different software failure dataseries suggested a random explanation, revealing strong antipersistent behavior. The validity of these results was tested against the Gaussian and iid-null hypotheses and both alternatives were rejected with highly significant statistical values. Our findings are consistent with other reports in the international literature that comment on the random nature of software failures in terms of number and time of occurrence. Going a step further and relating the values of the Hurst exponent estimated via the R/S analysis with colored noise, we concluded that the six series examined are better described by a pink noise structure.

Two well known and successful software reliability growth models, namely the Musa Basic (MB) and the Musa-Okumoto (MO) logarithmic model, were used to reproduce sample series of times between failures. The new series were also tested with R/S analysis and found to be long-term dependent in the case of the MB data and antipersistent in the case of the MO series. The latter finding justifies the superiority of the MO model over a variety of other SRGM tested on a number of actual projects: The MO model is ruled by the same structure as the empirical software failure data (i.e. mean reverting), thus it can capture the actual behavior of software failures better.

The framework for statistical characterization of empirical software failure data proposed by the present work can assist towards the identification of possible weaknesses in the assumptions of SRGMs and suggest the most suitable and accurate model to be used for controlling the reliability level of the software product under development.

One thing that remains to investigate, and this will be the focus of our future work, is the high value of the Hurst exponent for the MB series. Chaotic systems have also Hurst exponents $H > 0.5$, and in chaotic terms long memory effects correspond to sensitive dependence on initial conditions. Actually, the latter property combined with fractality characterises chaotic systems. Pure chaotic processes have Hurst exponents close to 1. Our future research will concentrate on employing R/S analysis to detect the existence of cycles (i.e. repeating patterns) in the MB series and will attempt to characterise it in terms of periodicity: Cycles detected can be periodic or non-periodic in the sense that the system has no absolute frequency. Non-periodic cycles can be further divided to statistical cycles and chaotic cycles. Fractal noises exhibit statistical cycles, i.e. cycles with no average cycle length.

Software Reliability is cited by the majority of users as the most important feature of software products. Hence, the software reliability engineering process should play a central role in the planning and control of software development activities (Musa, 1999) to ensure that product reliability meets user needs, to reduce product costs and to improve customer satisfaction. In this context, it is quite important to record and study the time of fault occurrences, their nature and the time spent on correction, throughout the design and implementation phases, as well as during testing activities. This data can prove very useful when trying to model the reliability behavior of the software product being developed and it can also play a central role to the empirical verification of Software Reliability Growth Models (SRGMs). With such data available it is easier to select suitable reliability models for estimating the time at which the software product will have reached a desirable level of reliability, and/or to devise methods to decrease that time. As we mentioned before, the datasets used in this study were gathered by John Musa around mid seventies. Although the datasets are quite old, we believe that their analysis is a good starting point for studying the behavior of software failure occurrences.

Currently we are making efforts towards gathering synchronous failure data, that is, data from systems that have been developed and are in operation during the last five years. We are trying to build a database with failure data from various modern application domains and operating systems. In our days, where most computer applications and operating systems are multitasking and/or distributed, it is very interesting to elaborate on how to gather accurate failure data. This problem, the definition of the right metrics to assess software reliability, has a particular interest due to the fact that software products nowadays include some new and unique characteristics, such as distribute computing, mobility and web accessibility / immediacy. Once this reliability data gathering is accomplished, we will be able to compare the characteristics of modern reliability data with those of the datasets developed by Musa in the 70ies, and investigate whether the random nature of software failure occurrences revealed by the R/S analysis holds true for modern software systems as well. Furthermore, we will attempt to investigate whether there is a relationship between the datasets used and the results obtained, i.e. whether certain application domains are more error prone than others.

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