Software Reliability Growth Models

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Models

- Which are the models known in literature that may depict system reliability?
- The Software Reliability Growth Models

Reliability Growth Models

- Reliability growth:
  - Successive observed failures times tend to increase
    - This results in models that tend to have horizontal asymptotic (finite) or infinite behaviour
- When the model are finite, the number of failures may be given or unknown

Reliability Growth Models

Uncertainty I:

- Even if we were to know the input of a system completely we cannot know when next we will encounter it

Reliability Growth Models

Uncertainty II:

1. We do not know whether a particular attempt to fix a fault has been successful.
2. And even if the fix is successful, we do not know how much improvement has taken place in the failure rate

Reliability Growth Models

- Good models tends to address both
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Reliability Growth

- Reliability Growth means:
  - The PdF of T_{i+1} is different from the PdF of T_i
  - $E[T_{i+1}] \geqq E[T_i]$
- Expected Failure times tend to increase!

- Reliability Growth is not normally considered in hardware reliability
  - It is a goal of software maintenance!

RG Models

Software systems are updated many times during their life cycle

Each revision introduces some side effects which result in a local increase of failures

Reliability Growth models are good for one revision period rather than the whole life cycle

Some research glues different models over different revisions

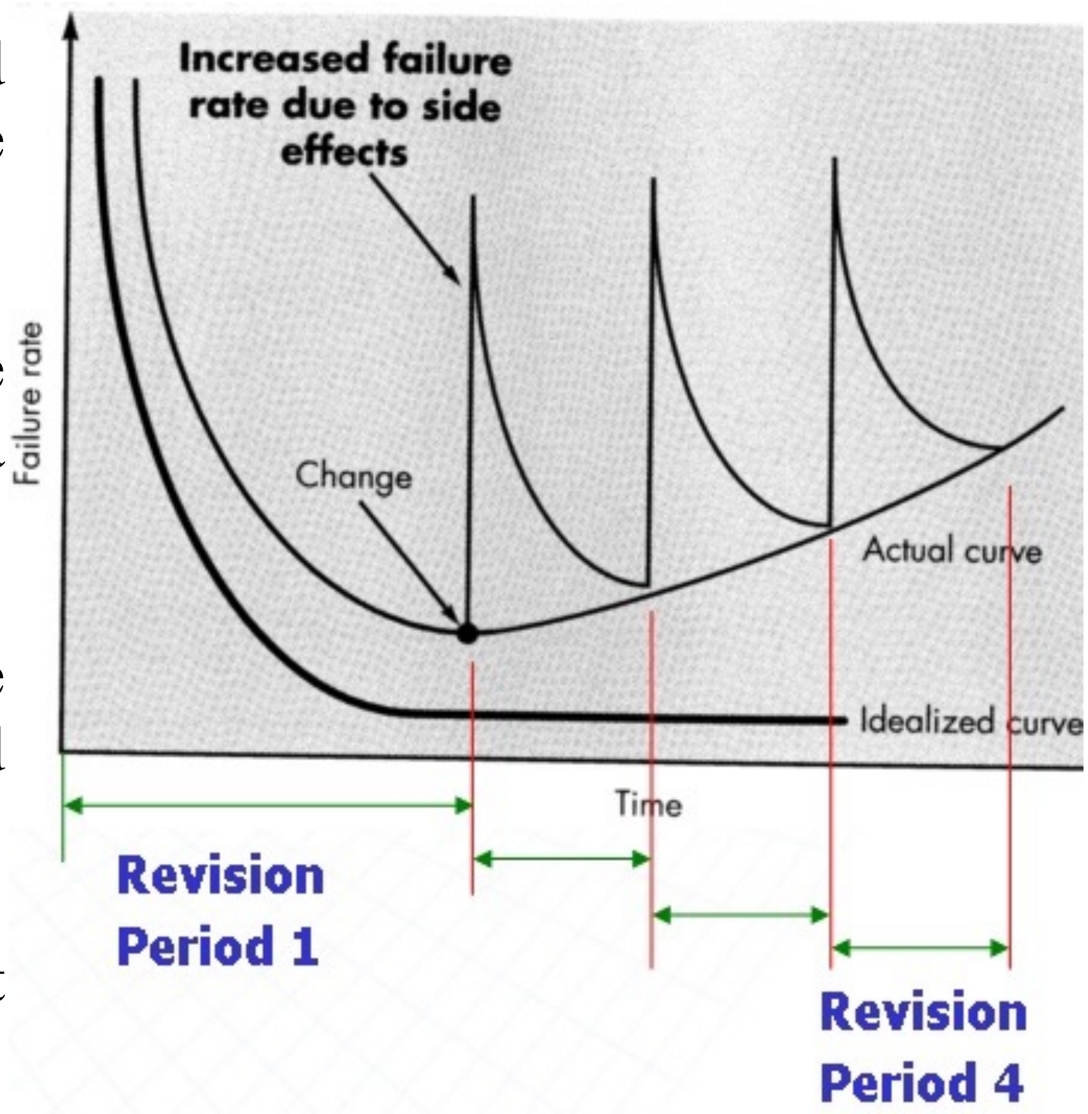


Figure from Pressman's book

Mean function of N(t)

- The mean function of a counting random variable is the expected value

$$\mu(t)=E(N(t))$$

- Note that t is the global time!
- It is an increasing function

Reliability growth

- In mathematical terms in order to have a good description of a failures detection process, we need:

$$\mu(0) = 0$$

$$\lambda(t)=\mu' \geq 0$$

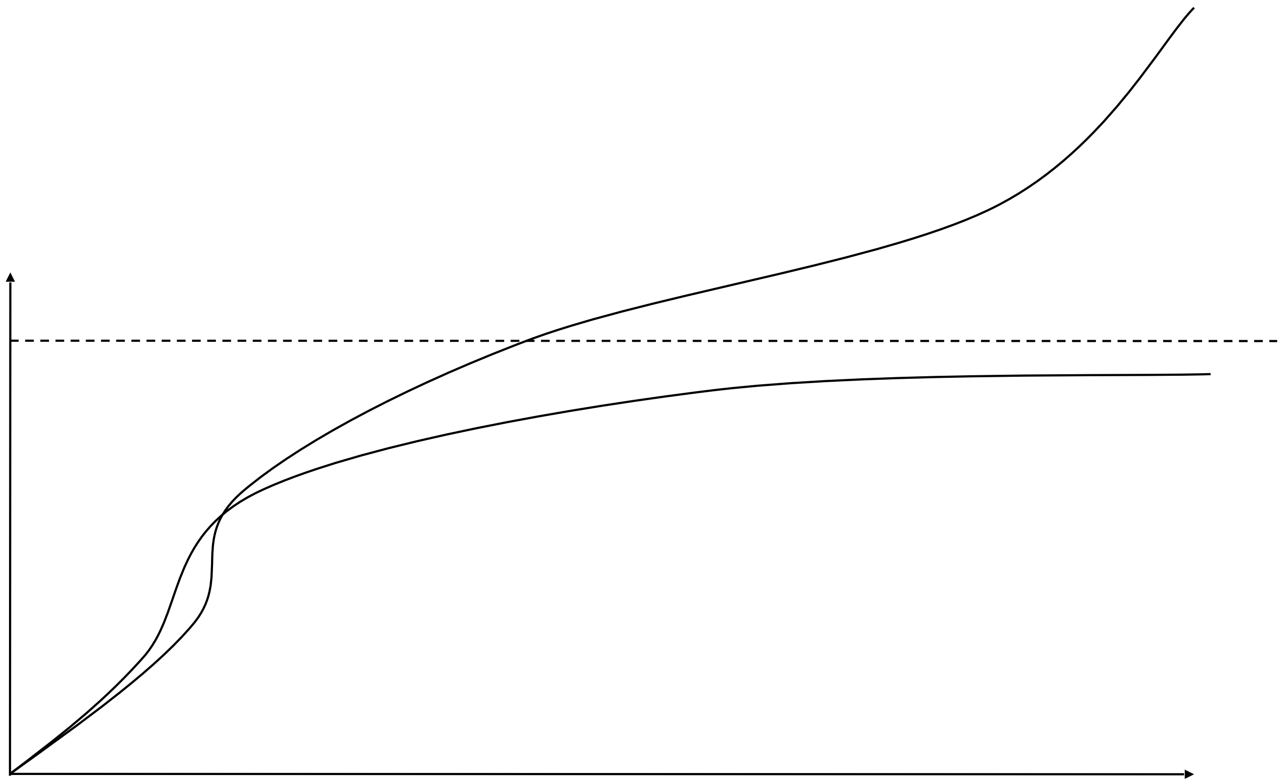
$$\lambda(t)' < 0 \text{ when } t >> o$$

Reliability growth

- If moreover, exists t such that $\lambda' > 0$ the curve is S-shaped, otherwise is concave.
- The flex of $\mu(t)$ identifies the end of the learning period and the starting moment in which it becomes harder to detect new failures

Category

- Category: finite or infinite
  - If lim $_{t \to \infty}$ E[N(t)]<+∞ then the model is finite



Model	E(N[(t)])	Interpretation of Parameters
Goel-Okumoto [1] (**GO**) *Concave*	$a(1-e^{-bt})$ $a>0, b>0$	*a* – expected cumulative total number of MRs *b* – MRs-detection rate per MR NHPP
GO S-shaped [2] (**GO-S**) *S-shaped*	$a(1-(1+bt)e^{-bt})$ $a>0, b>0$	*a* – expected cumulative total number of MR *b* – MR removal: defect detection rate, defect isolation rate NHPP
Gompertz [3] (**G**) *S-shaped for b>e* $^{-1}$	$a \cdot b^{c^t}$ $a>0, 0<b<1, 0<c<1$	*a* – expected cumulative total number of MRs *b, c* – no physical meaning TREND
Hossain-Dahiya/GO [4] (**HD**) *S-shaped for c>1*	$a(1-e^{-bt})/(1+ce^{-bt})$ $a \geq 0, b>0, c>0$	*a* – expected cumulative total number of MRs c – inflection parameter : *c(r)=(1-r)/r ≥1,* 0<r< 1/2 *r* – inflection rate indicating the ratio of detectable MRs to the total number of MRs in the software NHPP
Logistic [3] (**L**) *S-shaped for b>1*	$a/(1+be^{-ct})$ $a>0, b>0, c>0$	*a* – expected cumulative total number of MRs *b* – inflection parameter TREND
Weibull [6] (**W**) *S-shaped*	$a(1-e^{-b\cdot t^c})$ $a>0, b>0, c>0$	*a* – expected cumulative total number of MRs *b* – error-detection rate *c* – parameter that changes error detection rate NHPP
Weibull *more* S-shaped [7] (**W-S**) *S-shaped*	$a(1-(1+b\cdot t^c)\cdot e^{-b\cdot t^c})$ $a>0, b>0, c>0$	*a* – expected cumulative total number of MRs *b* – error-detection rate, error-isolation rate *c* – parameter that changes error detection rate NHPP
Yamada Exponential [8] (**YE**) *Concave*	$a(1-e^{-b(1-e^{-c\cdot t})})$ $a>0, b>0, c>0$	*a* – expected cumulative total number of MRs $b\cdot(1-e^{-c\cdot t})$ – cumulative testing effort based on Exponential model NHPP
Yamada Raleigh [8] (**YR**) *S-shaped*	$a(1-e^{-b(1-e^{-c\frac{t^2}{2}})})$ $a>0, b>0, c>0$	*a* – expected cumulative total number of MRs $b\cdot(1-e^{-c\cdot\frac{t^2}{2}})$ – cumulative testing effort based on Weibull model NHPP

Measures of Accuracy

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Non linear regression

- Let $y=f_{\{a,b,c\}}(x)$ be a model depending on **two or three parameters**, {a,b,c}
- For each model we assess best-fit values of the triple {a,b,c} using the OLS error regression
- This means that we look for the values of a,b,c which minimize the so called cost function of the r
- $$F(a,b,c)=\sum_{(x_i,y_i)}\left(y_i-f_{(a,b,c)}(x_i)\right)^2$$

Non linear regression

- where (x_i,y_i) vary in the experimental data points set
- The model corresponding to the best-fit values of {a,b,c} is called the best-fit regression model
- In computing them one can note that best-fit parameter value depends on the pairs (x_i,y_i)
- Thus, changing sample the best fit values for{a,b,c} can change. We need to test the

How to compare the best fit models:

- Goodness of fit
  - R^2 and AIC
- Coverage of fit
- Relative precision of fit
- Predictive ability
- Accuracy of the final point

R^2 or coefficient of determination

- Then use R^2 to understand how your data are near to your model
- It is also called Coefficient of Determination

$$R^2 = 1 - \frac{\sum (\hat{y}_i - y_i)^2}{\sum (y_i - \bar{y})^2}$$

- the explained values are the values of the model against the mean $\hat{y}_i$ are the function values and y_i are your data values, $\bar{y}$ is the mean of your y_i values

Measure	Formula	Description
Coefficient of Determination (R^2)	$\frac{\sum (\hat{y}_i - \bar{y})^2}{\sum (y_i - \bar{y})^2}$	A measure of Goodness of Fit How the model explains the data
Akaike Information Criterion (AIC)	$2k + n(\ln(\frac{2\pi \sum (y_i - \hat{y}_i)^2}{n} + 1)$	A measure of Goodness of Fit It takes into account the parameters (k) of the model
Relative precision to fit (RPF)	$\left\lvert \frac{AreaCI}{T} \right\rvert$	Size of the bootstrap 95% confidence interval and normalized with the size of the interval of time of failures occurrences
Coverage of fit (COF)	$100 \cdot \frac{\lvert \{y_i \in AreaCI\} \rvert}{A}$	The percentage to which the 95% confidence interval captures the data
Predictive Ability (PA)	$\frac{\inf_i \{y_i : \lvert A - y_i \rvert \le 10\%\}}{T}$	It is a measure of how early the model predicts the total final number of failures
Defect slippage (ACF)	$100 \cdot \left\lvert \frac{A - \alpha}{A} \right\rvert$	It is the percentage of defect slippage. A and α are respectively the true and the predicted final total number of failures