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Reliability Models Applied to Smartphone Applications

Sonia Meskini
The University of Western Ontario

Supervisor
Luiz Fernando Capretz
The University of Western Ontario

Graduate Program in Electrical and Computer Engineering
A thesis submitted in partial fulfillment of the requirements for the degree in Master of Engineering Science
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Reliability Models Applied to Smartphone Applications

by

Sonia Meskini

Graduate Program: Electrical and Computer Engineering
Department of Engineering Science

A thesis submitted in partial fulfillment
of the requirements for the degree of
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The School of Graduate and Postdoctoral Studies
The University of Western Ontario
London, Ontario, Canada

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Abstract

Smartphones have become the most used electronic devices. They carry out most of the functionalities of desktops, offering various useful applications that suit the user's needs. Therefore, instead of the operator, the user has been the main controller of the device and its applications, therefore its reliability has become an emergent requirement. As a first step, based on collected smartphone applications failure data, we investigated and evaluated the efficacy of Software Reliability Growth Models (SRGMs) when applied to these smartphone data in order to check whether they achieve the same accuracy as in the desktop/laptop area. None of the selected models were able to account for the smartphone data satisfactorily. Their failure is traced back to: (i) the hardware and software differences between desktops and smartphones, (ii) the specific features of mobile applications compared to desktop applications, and (iii) the different operational conditions and usage profiles. Thus, a reliability model suited to smartphone applications is still needed. In the second step, we applied the Weibull and Gamma distributions, and their two particular cases, Rayleigh and S-Shaped, to model the smartphone failure data sorted by application version number and grouped into different time periods. An estimation of the expected number of defects in each application version was obtained. The performances of the distributions were then compared amongst each other. We found that both Weibull and Gamma distributions can fit the failure data of mobile applications, although the Gamma distribution is frequently more suited.

Keywords : Smartphone Applications, Software Reliability, Gamma Distribution, Weibull Distribution, Rayleigh, S-Shaped, NHPP, Musa-Basic, Musa-Logarithmic.

Dedicated to

My dearest father, Noureddine
My lovely mother, Habiba
They have been the biggest motivator and inspiration in my life.

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Table of Contents

List of Tables

List of Figures

Chapter 1

1 Introduction

In the last century, fundamental science and technological progresses have culminated in the design of the computer. It was a huge machine in the beginning and its size was reduced, year after year. Then, its use spread exponentially and it invaded industries, universities, offices, homes and finally, it became a personal portable device in the pocket of the user: the smartphone. Who would ever have thought that over a period of 30 years, nearly everyone would own a hand-held powerful computer at an accessible price?

This hardware progress would not have been possible without another important one; that of software engineering progress [1]. Software is now embedded in every corner of our modern life and without it our machines are simply dead stones. Industrial manufacturing, financial systems, transportation and air traffic control, entertainment, television and film industry, etc. are completely computerized and use complex software systems that contain millions of lines of code.

Nevertheless, besides the benefits of software, there are also dangers. Software can fail, and its failure sometimes leads to great damage and even to human losses. During the last few decades, many instances of catastrophic accidents have happened, where the causes can be traced back to a software failure [2].

Therefore, the quality of software, after its release, became an important issue. By software quality, it is often meant the essential good attributes of software; namely its maintainability, dependability and security, efficiency and acceptability [1]. Addressing quality attributes other than reliability is out of scope of this thesis. Software dependability includes a range of characteristics such as reliability, security, and safety. Software Reliability is the probability that the software system will function without failure under a given environment and during a specified period of time. Reliability emerges as the most important desired feature of software [3] because it is related to its proper functioning without failure; a more precise definition of reliability will be given in Chapter 3. No doubt, a whole new engineering discipline was developed to deal with the reliability problem: Software Reliability Engineering (SRE) [4]. Among the tools of this

discipline, mathematical modeling, heavily based on statistical techniques, has played an important role. Hundreds of reliability models have been elaborated during the last decades. These models define appropriate measures for reliability and their main purpose is the estimation and prediction of the reliability of software, based on the failure data collected during its development, testing, and after release. These measures of reliability include the Mean Time To Failure (MTTF), the Mean Time Between Failures (MTBF), the failure intensity, the more additional testing time required to reach a reliability target, etc.[5] and are, therefore, of great help to the software manager to make decisions.

1.1 Motivation and Research Questions

Nowadays, millions of mobile devices are sold; they even oversold desktops and laptops [6, 7]**.** They became a necessary commodity and their prices are continually decreasing. Hundreds of applications, usually suited to the desktop/laptop area, are adapted and carried out by these smartphones. Owing to their small size, other specific applications are also built in, ranging from simple ones (finding the cheapest gas price in the neighborhood, etc.) to very critical ones (there are nearly 6.000 health-related applications for smartphone devices such as the iPhone, Blackberry and Android) [8].

Many companies in the mobile business, as they expand rapidly and due to market pressure and competition, do not use appropriate software engineering methods in the development of their products and services [9]. As a result, their software is less reliable and even more expensive than it should be. Therefore, the reliability issue, mentioned earlier, is becoming as acute in the mobile area [10] as in the desktop/laptop area. Furthermore, owing to the peculiarities of the Development Life Cycle (DLC) of mobile application software, the reliability issues in the mobile area are likely to differ from those in the desktop/laptop area.

The differences in the reliability issue of applications in desktop/laptop and in smartphones stem from the following main reasons [9, 11, 12]:

1- Differences in hardware between desktop/laptops and smartphone devices.
2- Differences in Operating System (OS) software between desktop/laptops and smartphones.

3- Differences in the nature and size of the applications implemented in the desktop/laptops and smartphones.
4- Differences in the operational environments (where and when the device is used) and usage profiles (how the device is used) in both cases.
5- Differences in the display functionalities.

These differences and peculiarities will be detailed in the next chapter.

As our main concern is the reliability of smartphone applications, we address in this work the following research questions:

1- Is it possible to build a mathematical model that helps software managers assess and predict the reliability of applications implemented in smartphone devices and working under diverse operational environments and usage profiles?
2- Are the basic assumptions needed to build the reliability models suited to desktop/laptop applications still valid in the case of smartphone applications? How do we adapt them to the mobile area?
3- A more focused question is the following: how do the existing successful reliability models, used to assess the desktop/laptops applications, perform when applied to the mobile area? Will these models still be of useful help to smartphone applications managers, as they were in the desktop/laptop case? Will there be a need to change them?
4- On a practical basis, how could a software manager model the daily failure data received from complaining users of a particular smartphone application to get some insight and understanding that can help make decisions? Is there a distribution that can model the failure data?

1.2 Methodology

Before embarking on the elaboration of a new reliability model, our starting point was to first apply the existing famous models, suited to desktop/laptop applications, to some common smartphone applications. To this end, we collected and analyzed the failure data of three known mobile applications, namely Skype, Vtok, and a private Windows phone application. The analysis was carried out using three of the most useful Software

Reliability Growth Models (SRGM): the Musa-basic time execution model, the Musa-Okumoto logarithmic model and the Non-Homogeneous Poisson Process (NHPP) model. In the second step, after realizing the failure of the above-mentioned SRGMs to reproduce adequately the smartphone failure data, we tried several non-linear distributions to better fit the failure data. After numerous experiments, we found that Weibull and Gamma distributions can be used to model new collected failure data of the same applications after sorting them by version number and grouping them into different time periods.

1.3 Thesis Contributions

After searching the literature, we realized that no previous work on the applicability of existing Software Reliability Growth Models (SRGM) to smartphone applications had been published. One of the main challenges for this investigation is the scarcity of the available data; therefore, we relied on our own limited resources: our smartphone data and those collected from other users.

Having collected the failure data, the choice of which of the SRGMs to apply was also a challenge as there are hundreds of them. We finally settled on the above mentioned models. The reasons for our choice of SGRMs are: (i) based on a few simple and reasonable assumptions, (ii) simple to understand on physical grounds, and (iii) implemented in a reliability tool like RGA7 or SMERFS.

The main findings of this work are:

1- The smartphone applications and their failure rates show distinctive features that differ from those of desktop/laptops.

2- The basic assumptions of the usual SRGMs have to be modified to suit the mobile operational conditions and profiles.

3- The selected SRGMs failed to model adequately the failure data.

4- A reliability model suited to assess and predict the reliability of smartphone applications is still needed.

5- The Weibull and Gamma distributions capture the main features of the recorded failure data when they are sorted by application version number and grouped on larger time scales. No one single distribution can account for all the failure data of an application through all of its releases. Nevertheless, the Gamma distribution and its particular case, the S-shaped distribution, are more frequently suited to model the failure data.

The attempt to build a model is a difficult task as it has to consider various factors such as:

- The nature, the size, the operational conditions, and the usage profile of the used application (where, when and how the application is used). This information is not known.
- The type of smartphone device and its hardware limitations (memory, screen size, etc.) and its software configuration (Operating System used).
- The design of suited assumptions (not the stationary ones used in the case of desktop/laptops) on which to base the mathematical structure of the model. The assumptions should include the "mobile feature" of the smartphone applications.
- The dynamic nature of the application's failure data.
- The different releases and the changes made from one release to another.

1.4 Thesis Outline

The thesis outline is as follows:

In Chapter 2, a brief account of the rapid development of the mobile phone and a comparative study of the mentioned differences between desktop/laptops and smartphones are presented. The implications of these differences on the reliability issue are highlighted.

In Chapter 3, theoretical concepts of the reliability theory are introduced and three of the most successful Software Reliability Growth Models (SRGM) are presented, followed by the necessary statistical techniques used to obtain the optimum model parameters values,

on one hand and the Maximum Likelihood Estimation (MLE) tests to validate or reject a chosen model on the other.

In Chapter 4, a description of the data collection process adopted in this work is presented for each of the three chosen mobile applications: Skype, Vtok, and a Windows phone application. The experiment is then pursued by applying the chosen Software Reliability Growth Models to the collected failure data. A discussion of the obtained results is followed by a thorough analysis of why the present models cannot give a satisfactory account of the failure data and the need to reexamine their basic assumptions is stressed.

In Chapter 5, a thorough study of newly collected failure data of the same above applications is carried out and two common distributions, Weibull and Gamma, as well as their particular cases, the Rayleigh and S-Shaped, respectively, are used to model the failure data after sorting them by application version number and grouping them into larger time periods. A comparative study of the performance of these distributions, based on error evaluation criteria, is presented and detailed.

In Chapter 6, conclusions are presented and some ideas for future work are suggested. Finally, appendices A and B are added, where our collected failure data for the three experimented applications are grouped and the JAVA program used for the extraction of the needed information from the crash files is presented.

Chapter 2

2 Reliability Issue in the Mobile Area

This chapter presents a brief account of the astonishing development of the simple cellular phone, followed by a comparative study of the main differences between the desktop/laptop and smartphone devices. These differences are fourfold: (i) hardware, (ii) used software, (iii) operational profile, and (iv) type and size of the implemented applications. Finally, smartphone applications are discussed with the aim of highlighting their relevant features and focusing on the possible factors that affect their reliability in relation to the above-mentioned differences.

2.1 Rapid Development of Mobile Phones

As the design and functionality of cell phones have changed over time, they have become real micro personal computers that contain similar features to desktops/laptops' features and functions. These improved cell phones are called smartphones. They contain video and music players, schedules, cameras, advanced connectivity options, and a large number of other various functions that, just a few years ago, no one could have imagined [6].

IBM was the first to launch a smartphone: The IBM Simon, designed in 1992, and presented the same year as a concept product at the computer industry trade show held in Las Vegas, Nevada (COMDEX) [6]. This first smartphone was released to the public a year later (1993) and sold by BellSouth. As a Micro Personal Computer, it also included the ability to receive/send faxes and e-mails, an address book, games, etc.

Since 2000, the number of smartphones in the market place has significantly increased. During recent years, management applications, touch screen, connectivity, and multimedia have become standard features in smartphones so that vendors have based their product evolution on these multi-function devices which, outside of their phoning capabilities, offer the user very attractive features [6].

2.2 Smartphone Versus Desktop/Laptop: the Hardware Difference

Desktops are bulky machines made of separate components: the central unit, the monitor, the keyboard, the mouse, etc. whereas laptops are integrated steps forward, resulting in only two connected components, the keyboard and the screen. The smartphone is even more integrated, as one single piece with a virtual keyboard that can be popped on a touch screen (i.e. tapping digital keys on a touch screen such as with the iPhone 3G). It can also come as hardware in the form of a small keyboard [6]. As a personal computer, smartphones come with processors, RAM, and other characteristics such as Bluetooth or GPS. Nevertheless, this integration comes with a price: a smaller screen for display and less memory available for software. The small, portable screen can be seen as an advantage, as there is a clear difference between a 4-inch screen that can be used everywhere, and a fixed 24-inch screen. Small batteries to power smartphones offer also another convenience for the user.

2.3 Smartphone Versus Desktop/Laptop: the Software Difference

Smartphones can place and receive calls but are to be distinguished from cell phones as they carry a mobile operating system. The main operating systems for desktops/laptops are Windows, Linux and Mac OSX. Whereas, in the mobile area various operating systems have been developed. The most famous ones are [6, 7]:

1. Windows phone
2. iOS
3. Google's Android
4. Symbian OS
5. RIM's BlackBerry
6. Palm's WebOS
7. etc

The iOS is a descendant of the Unix operating system while Palm's WebOS and Google's Android are built on top of Linux [6, 7].

The mobile world, with its specific hardware and software, has become an independent area having its proper product requirements and its software engineering processes.

2.4 Smartphone Versus Desktop/Laptop: the Operational Profile Difference

In parallel with the huge rise and availability of smartphones there is also a huge proliferation of the various applications they offer to the user. Hundreds of applications that used to run on desktop/laptops are now installed on and carried out by smartphone devices. Other specific applications ranging from very simple to very critical, such as online banking and health monitoring, are now integrated into smartphones.

As smartphones are sold by millions and all over the world, the operational environments and the usage profiles of each application are likely to be as diverse as possible [11] and to differ from those of desktop/laptop applications. A GPS application, used for orientation while driving a car, cannot be operated under the same conditions as an application implemented in a desktop/laptop [10]. Therefore, the reliability issue mentioned many times above is likely to depend on such factors as operating conditions and usage profiles [11].

As reliability is one of the most important attributes of an application, it becomes very important for smartphone future evolution, that predicting and maintaining quality and reliability of its applications will become a matter of permanent focus [10, 13].

Unlike standard software Development Life Cycle (DLC), mobile applications are developed following a meticulous mobile DLC [14]. For each mobile application, the best development strategy is the one chosen for the design. Usually, five phases build up the mobile DLC: the discovery phase, the design phase, the development and testing phase, the deployment phase, and the maintenance and updates phase [15]. The last phase in the most important as far as the reliability of the smartphone application is concerned.

2.5 Reliability of Smartphone Applications

Once the application is in the market, its developers should always track, to check if there are any new bugs or crashes through updating the application and the release of upgraded

versions. On the other hand, during this phase the user plays an important role [11] in the success or failure of the application.

2.5.1 Maintenance and Updates of Released Applications

Up to a certain point, the development of mobile applications follows the same process as the process for desktop/laptop applications. However, there are some additional requirements for mobile applications that are not commonly found with traditional applications such as the complexity of testing, the potential interaction with other applications, the power consumption, and other external issues that could cause a failure [9, 16]. Hence, as hinted to above, the major phases of a mobile application DLC are different from those for a standard application (desktop/laptop) since, for a mobile application, a meticulous DLC has to be chosen specific to each application [14]. In other words, in the mobile world the DLC is application-dependent, whereas for desktop/laptop applications, there are specific models to follow such as the waterfall, V-model, and spiral, etc.

On the other hand, mobile applications are becoming more and more complex, evolving from simple applications to business-based applications [9, 11]. As such, it is imperative that software engineering steps be applied to assure a high-quality, secure mobile application development. Moreover, despite the fact that there are various traditional techniques that can be easily transferred to the mobile application domain [10], there are other areas that need research, such as the Software Reliability, and its models, which are the subject of the following chapters.

2.5.2 Smartphone Applications Reliability

Industry analysis estimation reported in 2012 that more than one million smartphone applications are spread throughout the different existing stores and market places, and most of the applications are developed for different platforms [9]. However, in spite of this large number of mobile applications, there is still not much formal research around their engineering processes. For these smart devices as well as for their applications, not only the hardware properties of the smartphone have to be taken into consideration by the software engineering process [17], but also the key project properties such as usability, robustness, and reliability, which is the topic of our research.

Modern smartphones have really only been around since 2006, and this dramatic improvement in reliability suggests that manufacturers have largely solved the hardware problems [6, 10]. However, the reliability of the basic software of smartphones has an effect on the reliability of its running applications, since its failure may cause the applications' failures (OS failure, Network malfunction, GPS failure, etc.).

Beside these causes, software reliability engineering for the mobile applications themselves is also essential. But are classic software reliability techniques and models applicable for mobile applications as is the case for desktop applications? If so, which is the best model to fit the smartphone failure data? And, what are the modifications needed to make an existing model suitable for the mobile area?

The size of smartphone applications is usually small: a few thousand lines of source code, for example. Consequently, their DLCs are often determined by one or two developers; from the design phase to the testing and release phase [9]. Hence, as an advantage, there are less human errors than in other larger sized applications, which cause them to be developed by a smaller number of programmers and no highly skilled developers are required. However, this does not mean that we do not need software reliability engineering techniques for the smartphone applications simply because developers rarely used formal development processes even if they adhered quite well to recommended sets of "best practices". Thus, reliability is required since the engineering process used is not known; hence the reliability level of the application is also unknown.

An analysis of the smartphone reliability is presented in the following paragraphs in the aim of showing how reliable smartphones are nowadays and of insisting on the most reliable platform.

In 2010, a study conducted by SquareTrade [7] showed the reliability rates of different smartphone models. This group studied the overall failure rates by combining the software and hardware failures such as accidents. Since the focus of this research is on the software reliability, only the results of the malfunction and the overall failure rates will be presented.

To conduct this study, SquareTrade studied different smartphone models, especially, the iPhone from Apple, Android from Google (Motorola and HTC), and the Blackberry from RIM.

Since 2010 was the year that Android became more popular, 8 months of solid data was collected from Android-based phones (HTC and Motorola). In addition, SquareTrade collected 4 months worth of data from the iPhone, and 12 months of data from Blackberry, iPhone 3GS, and other smartphones [7].

For the Android and iPhone smartphones, the group used a failure curve for other smartphone models in order to predict a 12-month failure rate.

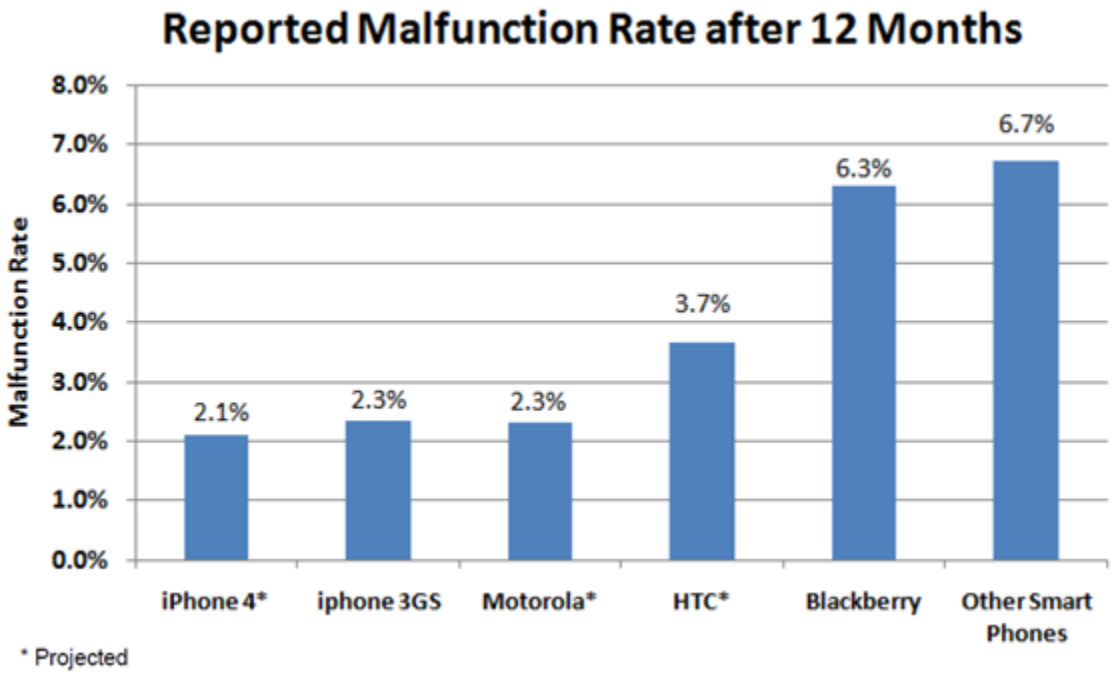


Figure 2-1 : Malfunction rates for various smartphone models [7]

The chart above reported the malfunction rate of the different smartphone models after 12 months. Based on those statistics, iPhone appears to be the most reliable, followed by Android. In the first 12 months, fewer than 2.5% of the users that own an iPhone or Motorola reported a malfunction. Followed by 3.7% of HTC users, and 6.3% of Blackberry users, which is the highest rate recorded among the examined models. The other smartphones examined together reported the worst rate which is 6.7%. Comparing

to the same study in 2008 by SquareTrade, smartphone reliability is improving, even for Blackberry. In 2008, Blackberry had a malfunction rate of 9.1%, compared to 6.7% in 2010, and 3.4% for the iPhone, compared to 2.2%. This is a good example of the improvements of smartphones, from the less reliable (Blackberry) to the most reliable (iPhone) [7].

Those numbers also show that the malfunction rates of smartphones have dropped by 60%. This means that manufacturers, despite the fact that modern smart devices have only really started gaining traction in 2006, have continued to solve their devices' problems and have achieved remarkable improvement in reliability.

The following chart confirms that smartphone devices are the second most reliable portable electronic devices, after digital cameras, with a malfunction rate of 3.9% over a 12-month usage, comparing to other devices.

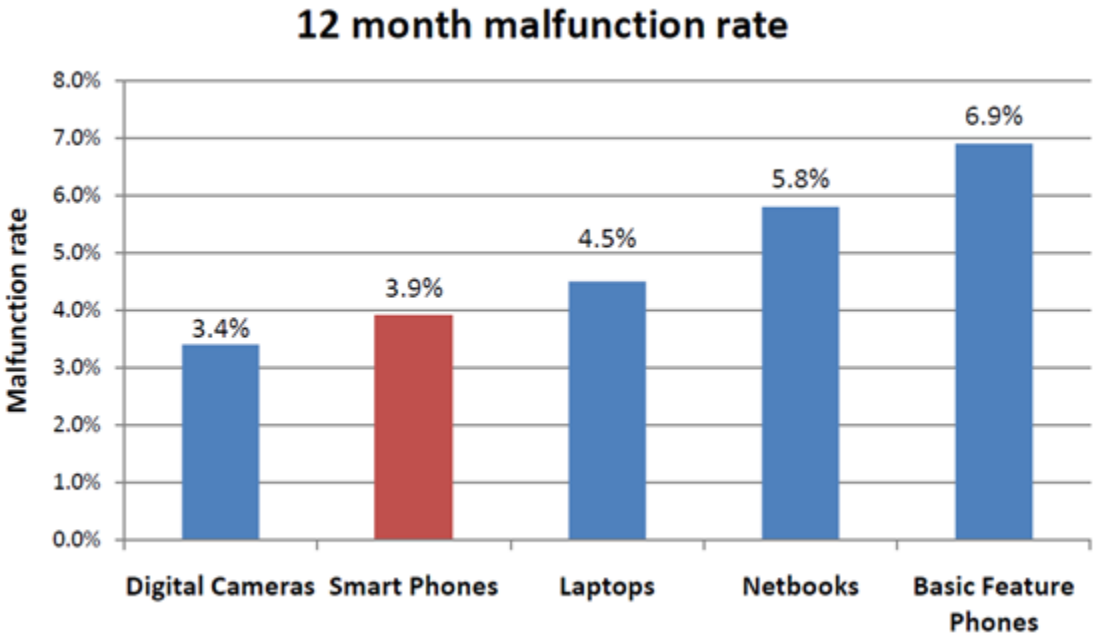


Figure 2-2 : Reliability of portable electronic devices [7]

The DLC of a smartphone application is too short compared to that of a standard application. Thus, developers do not usually track and collect enough metrics from their applications [9]. Hence, increasing reliability is needed since we now have access to

critical applications such as online banking, stock exchange, etc. that might cause a first level severity failure if they are not reliable enough.

In addition to the reliability of its applications, the smartphone reliability depends heavily on the reliability of its operating system that should be studied as well since it could be the reason for an application's failure by rejecting its version, or any other reason.

2.5.3 Smartphone Operating System Reliability

Nielsen Company [18] reported in October 2010 that Android was the most popular OS among smartphone owners. A six-month study conducted by this company showed that Android is quickly gaining traction (from 14% to 32%), while Apple iOS and Blackberry RIM are in a significant decline (from 34% to 26% for the RIM OS and from 32% to 25% for the Apple iOS), as is illustrated in the following chart.

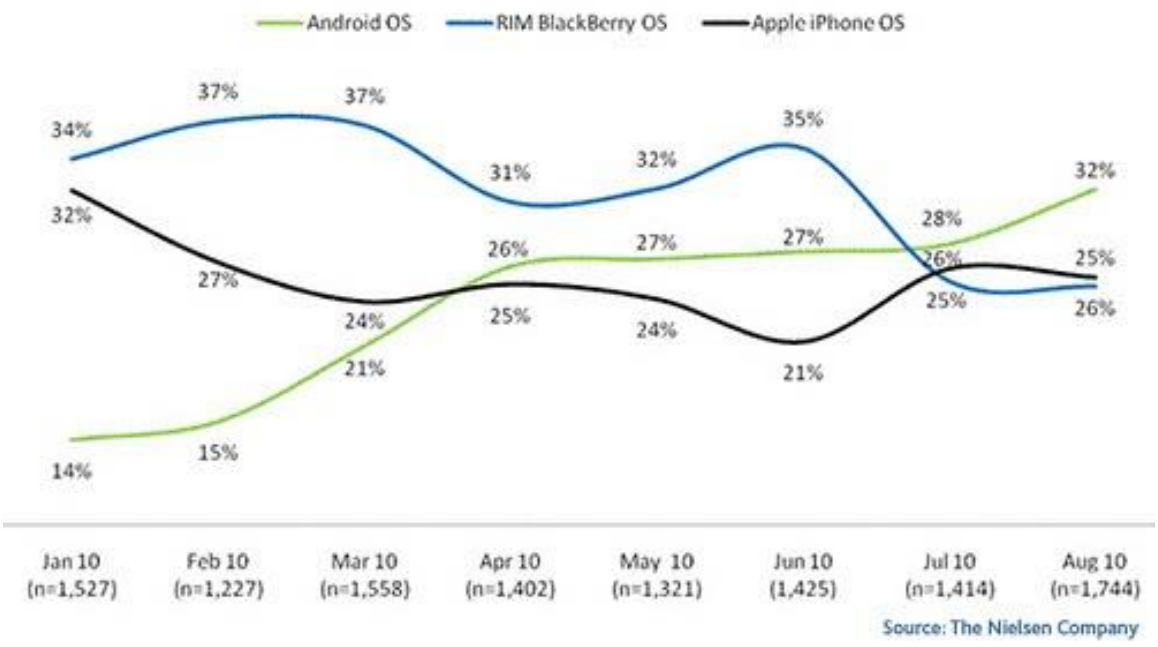


Figure 2-3 : Compared mobile operating systems reliability [19]

For the same period, Nielsen Company reported the top three OS share. The results are presented in Figure 2-4. The chart shows the growth of the Android OS' share and the

decline of the Blackberry RIM OS and Apple iPhone OS' shares. Despite that, Blackberry RIM OS is still the leader with 31% of the market, followed by Apple iPhone OS with 28%, and finally Android with 19%.

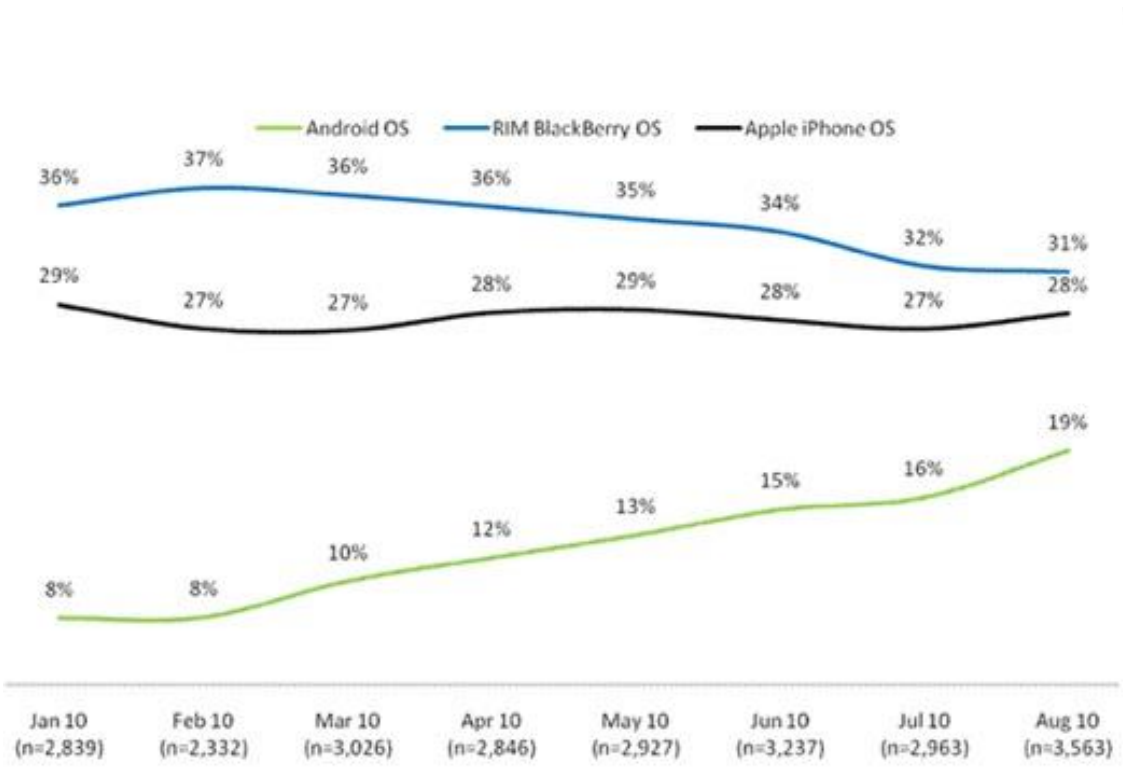


Figure 2-4 : Compared mobile operating systems shares [19]

These numbers were collected during 2010. That said, a year in a smartphone history is considered as an important amount of time to decide a smartphone's future. Hence, to confirm the statistics, the following chart contains predictions until 2014, and clearly shows the decline of the Blackberry's popularity along with the growth of the Android's.

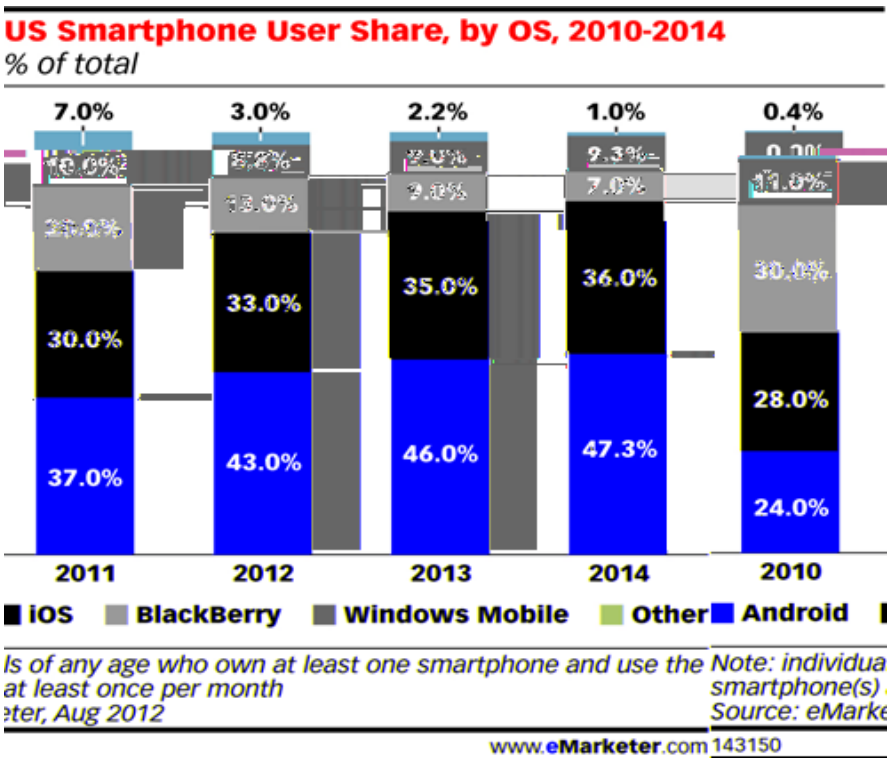


Figure 2-5 : Expected Smartphone user share, by OS [20]

This growth in usage shows the degree of reliability of smartphone OS. Yet this reliability is based more on the hardware and lately, even more, on the OS than on the application itself. Despite this, smartphone owners do not use the OS itself but the application. Thus, the reliability of the application has to be studied independently from the OS' reliability, to assure a high-quality and better performance, especially for the business-based applications. Although there are various traditional software engineering techniques that can be easily transferred to the mobile area, there are still some research issues in the mobile software reliability domain, namely:

- How does one ensure the reliability of a smartphone application?
- Can we apply directly the software reliability models that exist for desktop/laptop applications to smartphone applications to estimate and predict their reliability?
- Are the failure data enough to predict smartphone applications reliability, or do we need to consider the external causes of the application's failure (such as OS versions, network failure, memory, CPU performance, power consumption, etc.)?

- Is there a standard unique reliability model that can be applied to predict the reliability of all smartphone applications? Or, is there a need for a meticulous model for each type of application as is the case for their development models?
- In the case of choosing among many available reliability models, is there a simple criterion on which to base our choice?

2.6 Summary

Despite the large number of current mobile applications this seems to confirm that their development processes are clear and understood, yet there are still an important number of research issues that need to be studied. This chapter highlighted the differences in hardware between desktops/laptops and smartphones as well as the differences in used software, in particular, the reliability and the performances of the existing smartphone operating systems, and stressed the incidence of the DLC of an application on its reliability.

A reliability model, needed for smartphone applications is suggested. In the following chapter, the mathematical reliability modeling and the three software reliability models used later in our experimentation are presented.

Chapter 3

3 Software Reliability Growth Models: A Road Map

After briefly reviewing the major reliability concepts, three Software Reliability Growth Models (SRGMs) used later in our experiments are presented: the Non-Homogenous Poisson Process (NHPP) - Crow-AMSAA model (also termed the NHPP-Power Law model), the Musa-Basic execution time model (or the exponential model), and the Musa-Okumoto model (or the Logarithmic Poisson model). Analytic expressions for the optimum values of the parameters of these models are derived using the Maximum Likelihood Estimate (MLE) method and two common goodness-of-fit tests, namely the Cramer-von Mises and the Chi-Squared are presented.

3.1 Mathematical Software Reliability Modeling

Software is omnipresent in our daily life. It is implemented in home equipment, in telecommunications, in automobiles, in airplanes, etc. It is rapidly increasing in size and complexity, and its proper functioning or its reliability is becoming a major concern. This is reflected in the emerging and rapidly growing field of Software Reliability Engineering (SRE) [21]. One of the techniques of SRE is the mathematical modeling of software reliability. The purpose behind developing reliability models is the measurement, estimation, and prediction of software reliability, the most important quality of software. It is also a quantitative measure of software failures. A software reliability model describes the behavior of the random process underlying software failures with respect to time. A failure is a departure of the software output from its requirements. The basic principle of each model is to accurately fit the observed failure data with a pre-specified formula with some free parameters that have to be estimated by statistical methods such as the least square or the maximum likelihood estimate techniques. The model can then be used to estimate the current reliability or make predictions about future reliability of the software and compare it to an objective reliability required by the costumer [21].

3.2 Reliability Concepts

The most used definition of software reliability is: "*Software Reliability is the probability of failure-free software operation for a specified period of time in a specified environment"* [21]. The mathematical modeling of software reliability, often called reliability theory, is mainly the application of probability theory concepts to the modeling of the failure data of hardware or software system. The concepts for repairable and non-repairable systems are slightly different. Therefore, in the following, the two concepts are examined separately.

3.2.1 Non-Repairable Systems

Non-repairable systems are defined as systems that become useless and discarded after their first failure. The best example of a non-repairable system is a light bulb. It could also be an electronic component inside a computer. Their lifetime is described by a random variable, denoted T , which is their time to failure. Starting from $t = 0$, we begin by defining the probability that the time to failure T, of a non-repairable system, is between t and $t + \Delta t$:$P(t \leq T \leq t + \Delta t) \equiv$ Probability that $t \leq T \leq t + \Delta t$.T is a random variable that can have values from $t = 0$ to infinity. This probability can be written as:

$$P(t \leq T \leq t + \Delta t) \equiv f(t)\Delta t = F(t + \Delta t) - F(t) \tag{3.1}$$

where f(t) and F(t) are the probability density function and the cumulative distribution function, respectively. Taking the limit of an infinitesimal time interval, the second equation leads to:

$$f(t) = \frac{dF}{dt} \tag{3.2}$$

which, following integration gives:

$$F(t) = \int_0^t f(x)dx \tag{3.3}$$

using F(0) = 0. Thus F(t) is nothing but the probability of failure by time t:

$$F(t) = P(0 \leq T \leq t) = \int_0^t f(x)dx \tag{3.4}$$

At this point, a more precise and quantitative definition of the reliability function, denoted $R(t)$, can be given: it is just the probability of survival (or success) or failure-free operation until time t:

$$R(t) = P(T > t) = 1 - F(t) = \int_t^{+\infty} f(x)dx \tag{3.5}$$

where the normalization of the probability density function f(x) is used. Another useful concept in reliability theory is the failure rate. It is defined as the probability that a failure per unit time occurs in the time interval $(t, t + \Delta t)$, provided that the system had survived without failure until time t; it is a conditional probability:

$$Failure\ rate = \frac{P(t \le T \le t + \Delta t | T > t)}{\Delta t}$$

$$= \frac{P(t \le T \le t+\Delta t)}{\Delta t\, P(T>t)} = \frac{F(t+\Delta t)-F(t)}{\Delta t\, R(t)} \tag{3.6}$$

and the closely related concept of hazard rate by taking the limit of infinitesimal time interval:

$$z(t) = \lim_{\Delta t} \frac{F(t + \Delta t) - F(t)}{\Delta t\, R(t)} = \frac{f(t)}{R(t)} \tag{3.7}$$

which is the instantaneous failure rate at time t. The hazard rate $z(t)$, usually undistinguished from the failure rate, is a key variable in reliability theory as it allows access to all the other variables. It has also the following appealing significance:

$z(t)dt$ = Probability that a system of age t will fail in the time interval $(t, t + dt)$.

The average value of the time to failure T is called the Mean Time to Failure (MTTF) and is given by:

$$MTTF = \int_0^{+\infty} t\, f(t)dt = \int_0^{+\infty} R(t)dt \tag{3.8}$$

The last equation follows from integration by parts. From the above definitions, one can show easily the following relationships [21]:

$$R(t) = \exp[-\int_0^t z(x)\,dx] = 1 - F(t) \tag{3.9}$$

$$f(t) = z(t)R(t) \tag{3.10}$$

The general time dependence of the hazard rate, born from experience, is the so-called "bathtub curve" with its three phases in the lifetime of the system [21].

3.2.2 Repairable Systems

A repairable system is a system which, upon failure, is restored to operation by a repair action. These systems can be described by the following random variables [22]:

- The total number of failures $N(t)$ by time t. This cumulative number of failures is always increasing with time. It gives the failure history of the system.
- The time intervals between successive failures X_i .
- The number of failures f_i , $i = 1,2 \ldots . k,$ in each time interval $[T_{i-1}, T_i]$, where T_{i-1} and T_i are the end times of the $(i-1)^{th}$ and the i^{th} time interval.

These data types are not independent and can be transformed from one to the other. If we consider a large number of identical systems (all identical smartphones in London, for example) and record the failure history $N_i(t)$ of each one starting from $t = 0$, we can define the mean cumulative function by averaging over all the histories at each instant of time. This function will give an average behavior. It is the mean value of $N(t)$ that will be denoted by:

$$E(N(t)) = \mu(t) \tag{3.11}$$

The derivative of this mean value function is called the Rate Of oCcurrence Of Failures (ROCOF), or Recurrence Rate (RR), and also called the failure intensity, denoted by $\lambda(t)$:

$$\lambda(t) = \frac{d\mu(t)}{dt} \tag{3.12}$$

The failure intensity can be quite different from the hazard rate which was defined for non-repairable systems [22]. The dimension of the failure intensity is (Number of failures / Unit of time).

Another useful concept for repairable systems is the Mean Time Between Failure (MTBF), defined as the inverse of the failure intensity. An increasing MTBF is indicative of a reliability growth, whereas a decreasing MTBF is indicative of reliability deterioration.

The purpose of all reliability models, designed for repairable systems, such as smartphones, is to arrive at a suitable expression for the mean value cumulative function based on appropriate assumptions. In the following section, the three most used reliability models are presented.

3.3 Three Most Used Software Reliability Growth Models

The first Software Reliability Growth Model (SRGM) was developed in 1972 [21, 23]. SRGMs were initially designed to assess the evolution of software in its successive testing phases. As a result of the corrective actions taken during these phases, the software reliability increases, expressed by the word “growth” (compared to software with a constant failure rate, where no repair actions are planned). These models have also been found to describe adequately the reliability of fielded complex systems, i.e. in the user environment [24]. Relying on simplifying assumptions [21], a SRGM usually results in a set of mathematical equations that accurately fit the collected failure data.

There are some basic assumptions that are shared by all of the models. These common assumptions, referred to as the standard assumptions, are [21]:

- *The software is operated in a similar manner as that in which reliability predictions are to be made, i.e., during the testing phase, the software is executed in a manner similar to the anticipated operational usage.*
- *Every fault has the same chance of being encountered within a severity class as any other fault in that class.*

- *The failures, when the faults are detected, are independent. This assumption allows a simple estimation of the model parameters by using the joint density probability functions.*

There are additional assumptions, specific to each particular model. However, some of these assumptions may not comply with real situations [25]. The assessment and validity of the most used assumptions, and their conformity to real observations, will be examined in the next chapter. In the following sections, the three Software Reliability Growth Models (SRGM) mentioned above are presented.

3.3.1 The NHPP Crow-AMSAA Model

The first Non-Homogenous Poisson Process (NHPP) model was presented by Amrit Goel and Kazu Okumoto in 1979 [21]. In this model, the failure event is modeled by an NHPP distribution where it is assumed that there exists a mean value function giving the expected number of failures up to a given time. It was successfully used as a Hardware Reliability Growth Model. Because of its simplicity and easy implementation, there are several models that have since been developed, based on the NHPP model. In addition to the above Standard Assumptions, there are some others specific to each variant of the NHPP model, that help determine the mean value and other useful equations of the model, in order to predict the software reliability. Those assumptions are detailed in [21].

Including the Standard Assumptions mentioned above, in a NHPP model, the added assumption is that the probability distribution obeyed by the random variable $N(t)$ follows a Poisson Process i.e. is given by:

$$\Pr[N(t) = n] = \frac{(\mu(t))^n}{n!} \exp(-\mu(t)) \tag{3.13}$$

where $\mu(t)$ is the mean value of $N(t)$ or the expected cumulative failure number:

$$E(N(t)) = \mu(t) \tag{3.14}$$

The failure intensity is:

$$\lambda(t) = \frac{d\mu(t)}{dt} \tag{3.15}$$

In a NHPP model, the reliability of a system at time t, defined as the probability of failure free operation until time t is:

$$R(t) = Pr[N(t) = 0] = \exp\big(-\mu(t)\big), \quad 0! = 1 \tag{3.16}$$

Therefore, the cumulative probability distribution which is the probability of failure by time t is:

$$F(t) = 1 - R(t) = 1 - \exp(-\mu(t)) \tag{3.17}$$

and the probability density function is given by:

$$f(t) = \frac{dF}{dt} = -\frac{dR}{dt} = \lambda(t).\exp(-\mu(t)) = \lambda(t).R(t) \tag{3.18}$$

On the other hand, if we denote by f_i , $i = 1,2 \ldots . k$, the number of failures in the time interval $[T_{i-1}, T_i]$, where T_{i-1} and T_i are the end times of the $(i-1)^{th}$ and the i^{th} time interval, then, in a NHPP model:

$$Pr\big[f_i = n\big] = \frac{\big(\mu(T_{i-1}) - \mu(T_i)\big)^n}{n!} \exp(-\big(\mu(T_{i-1}) - \mu(T_i)\big) \tag{3.19}$$

which means that the number of failures in each time interval follows a Poisson distribution with mean value $\big(\mu(T_{i-1}) - \mu(T_i)\big)$. The particular NHPP model used in this work and implemented in the Reliability Growth Analysis (RGA) tool is called the Crow-AMSAA model [24], or the NHPP-Power Law model. This model was first developed by the U.S. Army Material Systems Analysis Activity (AMSAA). It was an extension of an earlier model called the Duane model [21]. The main idea is that the failure intensity is linear when plotted on a log-log scale, as a function of time.

In the NHPP Crow-AMSAA model, the expected value of $N(t)$ is written as:

$$E(N(t)) = \mu(t) = \lambda\, t^{\beta}, \lambda > 0 \;\; ; \;\; \beta > 0 \tag{3.20}$$

It is a two parameter model, λ and β. Therefore, the probability distribution reads:

$$Pr[N(t) = n] = \quad = \frac{(\lambda\, t^{\beta})^n}{n!} \exp(-\lambda\, t^{\beta}) \tag{3.21}$$

and the instantaneous failure intensity is given by:

$$\lambda(t) = \lambda\beta\, t^{\beta-1} \tag{3.22}$$

or on a log-log scale:

$$\log\big(\mu(t)\big) = \beta \log(t) + \log(\lambda) \tag{3.23}$$

$$\log\big(\lambda(t)\big) = (\beta - 1)\log(t) + \log(\lambda\beta) \tag{3.24}$$

These can be represented by straight lines of slope β and $(\beta - 1)$ respectively.

The instantaneous Mean Time Between Failures (MTBF) is defined as:

$$\text{MTBF}(t) = \frac{1}{\lambda(t)} = \frac{t^{1-\beta}}{\lambda\beta} \tag{3.25}$$

Beside the instantaneous failure intensity and the instantaneous Mean Time Between Failures (MTBF), one can define the cumulative failure intensity and the cumulative Mean Time Between Failures by the following relations:

$$\lambda_c = \frac{\mu(t)}{t} = \lambda\, t^{\beta-1} \tag{3.26}$$

and

$$\text{MTBF}_c = \frac{1}{\lambda_c} = \frac{t^{1-\beta}}{\lambda} \tag{3.27}$$

Plotted on a log-log scale, the lines representing the instantaneous and cumulative failure intensity have the same slope and are therefore parallel; the same is true for the instantaneous and cumulative MTBFs.

The reliability of a repairable system following the NHPP Crow-AMSAA model is therefore:

$$R(t) = \exp(-\mu(t)) = \exp(-\lambda\, t^{\beta}) \tag{3.28}$$

and the probability density function (pdf) is given by:

$$f(t) = \lambda(t).\exp(-\mu(t)) = \lambda\beta\, t^{\beta-1}.\exp(-\lambda\, t^{\beta}) \tag{3.29}$$

Three cases are worth noting:

- β=1 is called the Homogeneous Poisson Process (HPP). This case corresponds to a constant failure intensity ($\lambda(t) = \lambda$) and a constant MTBF ($\frac{1}{\lambda(t)} = \frac{1}{\lambda}$). The reliability in this case is given by:

$$R(t) = \exp(-\lambda t) \tag{3.30}$$

- β < 1 in this case the failure intensity is decreasing and the MTBF is increasing. The reliability in this case is given by:

$$R(t) = \exp(-\lambda\, t^{\beta}) > \exp(-\lambda t) \tag{3.31}$$

denoting a reliability growth.

- β > 1 in this case the failure intensity is increasing and the MTBF is decreasing. The reliability in this case is given by:

$$R(t) = \exp(-\lambda\, t^{\beta}) < \exp(-\lambda t) \tag{3.32}$$

indicating a decrease in reliability and a resulting deterioration.

Finally, to implement this model, either the fault counts or the time between failures are required.

3.3.2 Musa's Basic Execution Time Model

The simple and intuitive idea behind this model is that as the cumulative number of failures increases and the corresponding faults are fixed; as such, the failure intensity should decrease. Including the Standard Assumptions, the additional assumptions of this model are:

- The failure intensity decreases is modeled by the simple linear equation [26]:

$$\lambda(\mu) = \lambda_0 \left(1 - \frac{\mu}{\mu_0}\right) \tag{3.33}$$

where:

- μ is the mean (or expected) cumulative number of failures observed at execution time τ.
- λ_0 is the initial failure intensity (at the beginning of the observations) at τ = 0.

- μ_0 is the total number of expected system failure if the observation lasts for an infinite time.

Writing the failure intensity as the derivative of the cumulative number of failures, this leads to the following differential equation satisfied by the function $\mu(\tau)$:

$$\frac{d\mu}{d\tau} = \lambda_0 \left(1 - \frac{\mu}{\mu_0}\right) \tag{3.34}$$

whose solution, for the mean value of failure counts, and for the failure intensity as functions of execution time, are given by:

$$\mu(\tau) = \mu_0[1 - \exp\left(-\frac{\lambda_0}{\mu_0}\tau\right)] \tag{3.35}$$

$$\lambda(\tau) = \lambda_0 \exp\left(-\frac{\lambda_0}{\mu_0}\tau\right) \tag{3.36}$$

and constitute The Musa-Basic model, also termed the exponential model [28]. If the present failure intensity is λ_1 and the target failure intensity λ_2 is required, then the expected number of failures and the additional execution time required to reach that objective are given by:

$$\Delta\mu = \frac{\mu_0}{\lambda_0}(\lambda_1 - \lambda_2) \tag{3.37}$$

$$\Delta\tau = \frac{\mu_0}{\lambda_0}\ln\left(\frac{\lambda_1}{\lambda_2}\right) \tag{3.38}$$

This model is used especially for execution time data but it can also be applied to calendar time data by applying a conversion from calendar to execution time. The required data to build this model are either the time of failure or time between failures.

Based on the software reliability modeling survey from the handbook of SRE [21], this model is considered to be one of the most widely used models [21, 28].

There are several similar models that have been developed. Moreover, Musa mentioned that "*the basic execution model generally appears to be superior in capability and applicability to other published models*" [28, 29].

3.3.3 Musa-Okumoto Logarithmic Poisson Model

According to Farr [21, 28], the Musa-Okumoto model, also termed the Logarithmic Poisson model, is one of the most extensively applied models. Besides that, Musa himself confirmed that this model is more accurate comparing to the exponential model [29].

Including the Standard Assumptions, the additional assumption of this model is that, contrary to the exponential model, the failure intensity decrease is not linear but more rapid and modeled by an exponential equation:

$$\lambda(\mu) = \lambda_0 \, e^{-\theta \mu} \tag{3.39}$$

where:

- θ is a measure of the decrease in failure intensity in the logarithmic model
- λ_0 is the initial failure intensity (at the beginning of the observations) i.e at $\tau = 0$.

As for the previous model, the mean value is the solution of the following differential equation:

$$\frac{d\mu}{d\tau} = \lambda_0 \, e^{-\theta \mu} \tag{3.40}$$

whose solution gives the mean cumulative failure number and the failure intensity as functions of the execution time [28] :

$$\mu(\tau) = \frac{\ln(\lambda_0 \theta \, \tau + 1)}{\theta} \tag{3.41}$$

$$\lambda(\tau) = \frac{\lambda_0}{\lambda_0 \theta \, \tau + 1} \tag{3.42}$$

The required data to build this model are the same as for the exponential model. As one of the best predictive models, the Musa-Okumoto model belongs to the selected models in the AIAA Recommended Practice Standard on Software Reliability [21]. Logarithmic models have been also used in software cost estimation models with high accuracy [27, 30, 31].

Further details on the Musa-Basic and Musa-Okumoto models can be found in [21].

3.4 Parameters Estimation

Once a reliability growth model is chosen, four basic steps have to be followed:

- Estimate (optimize) the parameters of the model using statistical techniques such as the Maximum Likelihood Estimate (MLE), or the Least Square Estimation (LSE) method,
- Substitute the optimum values of the parameters obtained in the previous step, into the selected model.
- Perform a goodness-of-fit test to assess the reasonableness of the model. If the test is conclusive, the data are adequately described by the chosen model, otherwise the model is rejected and another one is chosen.
- Draw conclusions about the reliability of the system based on the fitted model.

Schematic representations of these steps are summarized in the following figure:

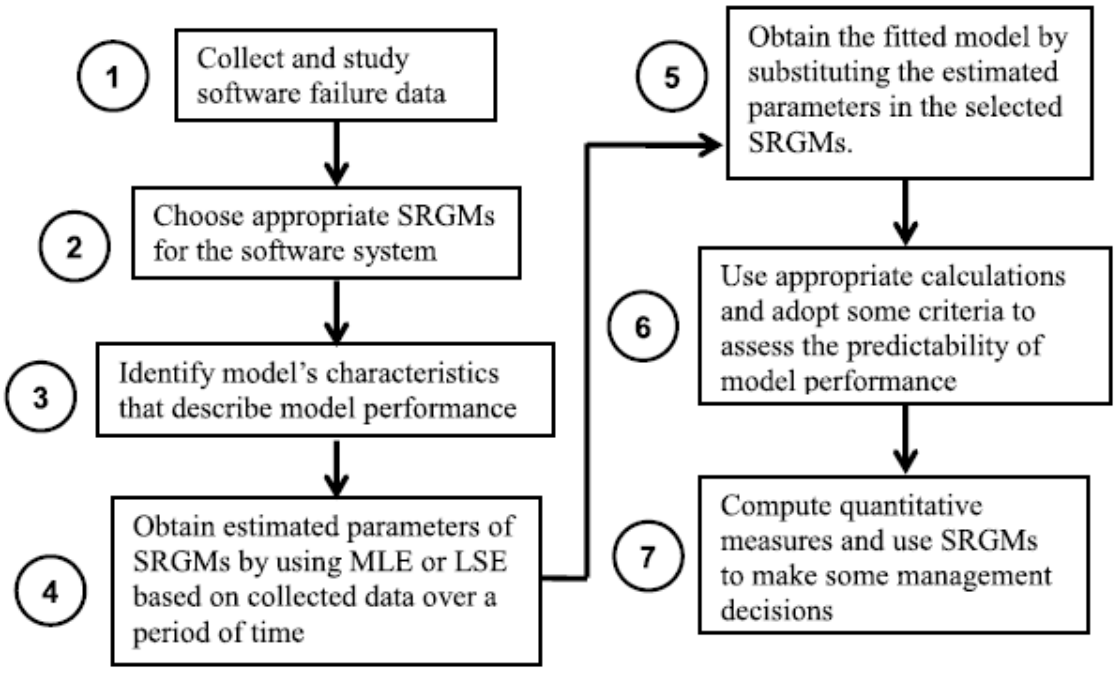


Figure 3-1: Use of a chosen SRGM to study the reliability of an application [32, 33]

The choice of the selected model is based on an examination of the general trend of the observed cumulative failure number curve $N(t)$ as a function of time. For the estimation

of the parameters of a given model, two widely known methods are used: the Maximum Likelihood Estimate (MLE), and the Least Square Estimation (LSE) method. As the LSE is a standard technique in numerical analysis; in the following, only the MLE method is presented.

3.4.1 The Maximum Likelihood Estimate (MLE)

The MLE is the most important and widely used estimation technique. It is based on the idea that the failure data observed (the successive failure events of the studied system) are the most likely to happen i.e. are the most probable ones (have the maximum probability).

3.4.2 The Case of Failure Times Data Type

If we denote by T_i , $i = 1,2 \dots n,$. the observed failure times arranged in an increasing order. For the NHPP model, the probability density function (pdf) of the i^{th} failure occurring at time T_i , given that the $(i-1)^{th}$ failure has occurred at T_{i-1} is given by the conditional probability [21]:

$$f(T_i \,|T_{i-1}) = \frac{f(T_i)}{R(T_{i-1})} = \frac{\lambda(T_i)\exp-(\mu(T_i)).}{\exp-(\mu(T_{i-1}))} = \lambda(T_i).\exp-(\mu(T_i) - \mu(T_{i-1})) \qquad (3.43)$$

Based on the third assumption of the above mentioned Standard Assumptions (independence of occurring failures), the likelihood or the probability of having the observed successive failure times T_i , $i = 1,2 \dots n,$ is:

$$L = \prod_{i=1}^{i=n} f(T_i \,|T_{i-1}) \qquad (3.44)$$

In the case of the Crow-AMSAA model, it is written as [24]:

$$L = L(\lambda, \beta) = \lambda^n \beta^n e^{-\lambda T_n^{\beta}} \prod_{i=1}^{i=n} T_i^{\beta-1} \qquad (3.45)$$

The optimal parameters of the model are those values of λ and β that give the maximum likelihood i.e. the maximum value of L or of its logarithm:

$$\Lambda = \ln(L) = n \ln\lambda + n \ln\beta - \lambda T_n^{\beta} + (\beta - 1)\sum_{i=1}^{n} \ln(T_i) \qquad (3.46)$$

Therefore, to get the optimum values of parameters λ and β, the following system of equations should be solved:

$$\begin{cases} \dfrac{\partial \Lambda}{\partial \lambda} = \dfrac{n}{\lambda} - T_n^{\beta} = 0 \\ \dfrac{\partial \Lambda}{\partial \beta} = \dfrac{n}{\beta} - \lambda T_n^{\beta} \ln T_n + \sum_{i=1}^{n} \ln(T_i) = 0 \end{cases} \tag{3.47}$$

whose solution $\hat{\lambda}$ and $\hat{\beta}$ are:

$$\hat{\beta} = \frac{n}{n \ln T_n - \sum_{i=1}^{n} \ln(T_i)} \tag{3.48}$$

$$\hat{\lambda} = \frac{n}{T_n^{\hat{\beta}}} \tag{3.49}$$

For the case of Musa's basic execution time model and the Logarithmic Poisson model, a similar analysis leads to the optimal model parameters values, given in [21].

3.4.3 The Case of Grouped Data Type

In this case, the data are grouped by time intervals, giving the number of failures in each interval. If we denote by n_i the observed number of failures in the i^{th} time interval, then the likelihood function for the Crow-AMSAA model, is given by:

$$L = \prod_{i=1}^{i=k} \Pr(f_i = n_i) = \prod_{i=1}^{i=k} \frac{(\lambda T_i^{\beta} - \lambda T_{i-1}^{\beta})^n}{n_i!} \exp(\lambda T_i^{\beta} - \lambda T_{i-1}^{\beta}) \tag{3.50}$$

where k is the total number of intervals and T_i is the end of the i^{th} time interval. Using the same procedure as in the previous data type case, the optimum values of the parameters are obtained. The parameter β is a solution of the following equation:

$$\sum_{i=1}^{i=k} n_i \left[\frac{T_i^{\beta} \ln T_i - T_{i-1}^{\beta} \ln T_{i-1}}{T_i^{\beta} - T_{i-1}^{\beta}} - k \ln T_k \right] = 0 \tag{3.51}$$

whereas λ (in equation 3.50) is given by:

$$\hat{\lambda} = \frac{n}{T_n^{\hat{\beta}}} \tag{3.52}$$

where $\hat{\beta}$ is the solution of the previous equation (equation 3.51). $\hat{\lambda}$ and $\hat{\beta}$ are the values of λ and β that maximize the likelihood function L.

3.5 Goodness-of-Fit Tests

Even after having determined the best estimate of the chosen model parameters, there is still the question of its validity and reasonableness. This is a measure of how close the observed data follow the chosen model and that the observed fit is not due to chance. Two common goodness-of-fit tests are: the Cramer-von Mises and the Chi-Squared tests. They are used in this work and implemented in RGA7 [24].

3.5.1 The Cramer- Von Mises Goodness-of- Fit Test

This test is appropriate for the case of the individual failure times data type. The Cramer-von Mises goodness-of-fit statistic is given by the following expression:

$$C^2 = \frac{1}{12N} + \sum_{i=1}^{N}\left[\left[\left(\frac{T_i}{T_N}\right)^{\hat{\beta}} - \frac{2i-1}{2N}\right]\right]^2 \tag{3.53}$$

where T_i i=1,2,3…..N are the observed individual failure times. If this statistic exceeds the critical value corresponding to N for a chosen significance level, then the hypothesis that the failure data follow the NHPP-Crow model is not valid. The critical values for this statistic are tabulated [24].

3.5.2 The Chi-Squared Goodness-of-Fit Test

This test is appropriate for the case of grouped data type. The Chi-Squared goodness-of-fit statistic is given by the following expression:

$$\chi^2 = \sum_{i=1}^{d}\frac{\left(f_i - \hat{\theta}_i\right)^2}{\hat{\theta}_i} \tag{3.54}$$

where f_i is the observed number of failures in interval i (i=1,2,3….d) and $\hat{\theta}_i$ is the expected number of failures in the same interval, given by:

$$\hat{\theta}_i = \hat{\lambda}\left(T_i^{\hat{\beta}} - T_{i-1}^{\hat{\beta}}\right) \tag{3.55}$$

If this statistic exceeds the critical value corresponding to ((d-2), where d is the number of intervals) for a chosen significance level, then the hypothesis that the grouped failure data follow the NHPP-Crow model is not valid. The critical values for this statistic can be found in tables of the Chi-Squared distribution.

3.6 Summary

In this chapter, the main reliability concepts are recalled, and three most used SRGM models are presented, as well as the estimation of their parameters, followed by the two common goodness-of-fit tests. In the next chapter, these models will be applied to the collected failure data of three smartphone applications in order to assess the reliability of their software and consequently, test whether the chosen models perform equally well in the mobile area as in that of desktop/laptop.

Chapter 4

4 Smartphone Failure Data and Application of SRGMs

As previously emphasized, reliability is one of the most important features of an application and great efforts have been devoted to tailor and predict it through the study of recorded failure data. A non-reliable application leads to dissatisfied customers, loss of market share, and significant costs to the supplier. For critical applications, such as banking or health monitoring, non-reliability can lead to great damage. Therefore, it is of great necessity to ensure early detection and resolution of reliability issues in desktop applications as well as, now increasingly, in mobile applications.

This chapter is devoted to a detailed presentation of the main purpose of this work [41, 42], namely the application of three Software Reliability Growth Models, known to be successful in the desktop/laptop area, to three concrete cases of smartphone applications. The Software Reliability Growth Models used later in our experiments are: the NHPP - Crow-AMSAA model (also termed the NHPP-Power Law model), the Musa-Basic execution time model (or the exponential model), and the Musa-Okumoto model (or the Logarithmic Poisson model) and the chosen applications are: Skype, Vtok, and a private Windows phone application.

The detailed procedure devised to collect the failure data for each application is presented first, followed by the results of the application of the chosen SRGM to each application's failure data and, finally, a detailed analysis of the observed results. The collected failure data for each application are reported in appendix A.

4.1 Data Collection

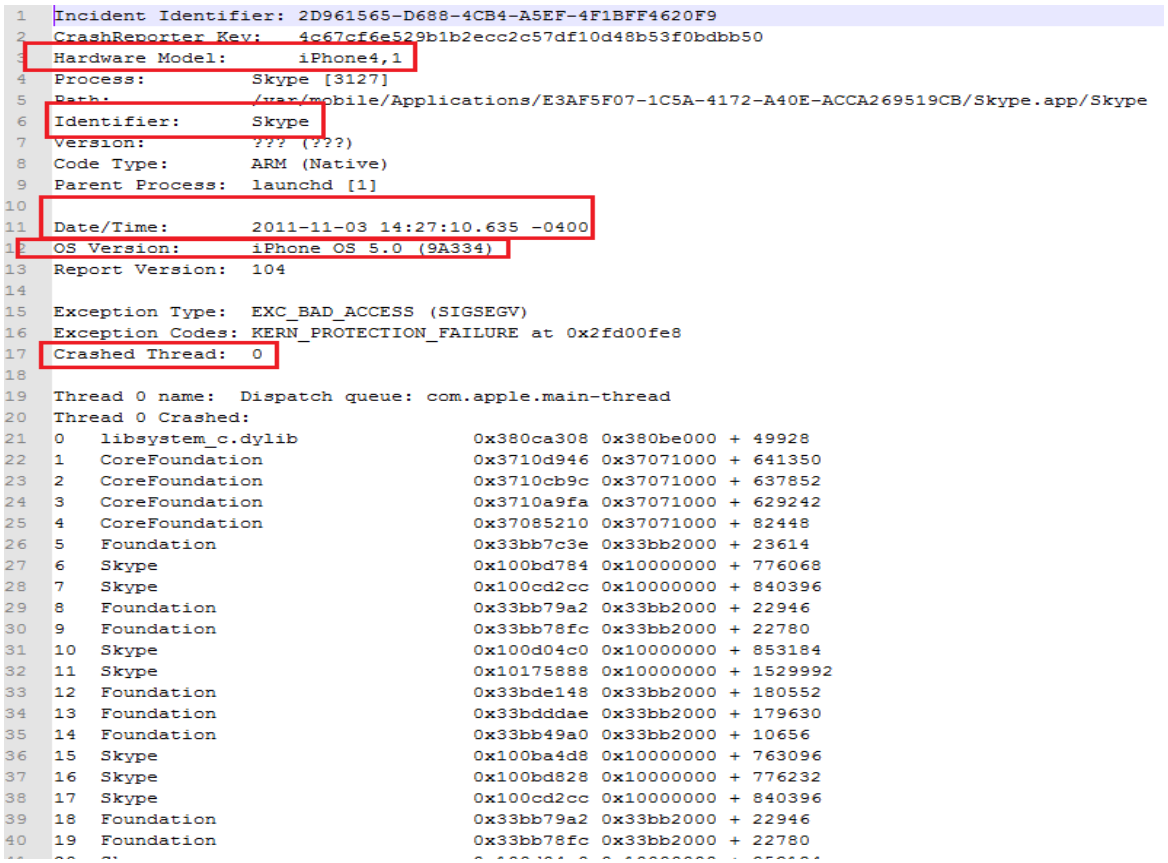
We used Apple devices (iPhone, iPad, iPod Touch) crash files as well as a Windows phone crash file as our "experimental" data. These crash files are not public, therefore are confidential. Hence, we will focus more on the Apple devices crash files since it was easier to collect them from our personal devices as well as through a survey that was sent to different people from different parts of the world. There are those who gratefully accepted to send us their failure data, whereas other did not.

For the Windows phone case, we could only get the crash file report of one application due to confidentiality policies. Collecting the data was, and still is, a challenge especially for Android devices which is left as future work.

Figure 4-1 presents an example of the Apple devices crash log. For each case, we provide the following information:

- Name of the crashed application
- Type
- Hardware type (device as iPhone, iPad or iPod Touch). This information is needed in order to determine whether the crash is of an application of the same device or of the same application from a different device
- Date/Time of the crash (which is the most important information in the crash log for our research work)
- The version of the OS

The crash logs of Apple devices are transferred to a hidden folder located/created in the PC that is used for the synchronization of the device. It contains the crash logs of all of the applications installed on the devices, as well as reports about the battery, memory, and other features. However, we are only interested in the crash files. Thus, we ignored the other files.



```
Incident Identifier: 2D961565-D688-4CB4-A5EF-4F1BFF4620F9
CrashReporter Key:   4c67cf6e529b1b2ecc2c57df10d48b53f0bdbb50
Hardware Model:      iPhone4,1
Process:             Skype [3127]
Path:                /var/mobile/Applications/E3AF5F07-1C5A-4172-A40E-ACCA269519CB/Skype.app/Skype
Identifier:          Skype
Version:             ??? (???)
Code Type:           ARM (Native)
Parent Process:      launchd [1]

Date/Time:           2011-11-03 14:27:10.635 -0400
OS Version:          iPhone OS 5.0 (9A334)
Report Version:      104

Exception Type:  EXC_BAD_ACCESS (SIGSEGV)
Exception Codes: KERN_PROTECTION_FAILURE at 0x2fd00fe8
Crashed Thread:  0

Thread 0 name:  Dispatch queue: com.apple.main-thread
Thread 0 Crashed:
0   libsystem_c.dylib               0x380ca308 0x380be000 + 49928
1   CoreFoundation                  0x3710d946 0x37071000 + 641350
2   CoreFoundation                  0x3710cb9c 0x37071000 + 637852
3   CoreFoundation                  0x3710a9fa 0x37071000 + 629242
4   CoreFoundation                  0x37085210 0x37071000 + 82448
5   Foundation                      0x33bb7c3e 0x33bb2000 + 23614
6   Skype                           0x100bd784 0x10000000 + 776068
7   Skype                           0x100cd2cc 0x10000000 + 840396
8   Foundation                      0x33bb79a2 0x33bb2000 + 22946
9   Foundation                      0x33bb78fc 0x33bb2000 + 22780
10  Skype                           0x100d04c0 0x10000000 + 853184
11  Skype                           0x10175888 0x10000000 + 1529992
12  Foundation                      0x33bde148 0x33bb2000 + 180552
13  Foundation                      0x33bdddae 0x33bb2000 + 179630
14  Foundation                      0x33bb49a0 0x33bb2000 + 10656
15  Skype                           0x100ba4d8 0x10000000 + 763096
16  Skype                           0x100bd828 0x10000000 + 776232
17  Skype                           0x100cd2cc 0x10000000 + 840396
18  Foundation                      0x33bb79a2 0x33bb2000 + 22946
19  Foundation                      0x33bb78fc 0x33bb2000 + 22780
```

Figure 4-1: Apple crash file

The crash log is a long text file full of symbols and information that we do not need, yet it contains useful information that we used to create our failure dataset. To achieve that, we developed a program in JAVA that we run each time we synchronize the devices or receive log folders from other users to update our dataset. The following algorithm allows extracting only the information we need.

1) *Begin*
2) *Open the folder that contains all the crash logs*
3) *Create "Concat.txt" that contains all the crash files*
4) *Create "Crash.txt" that contains only the information needed extracted from "Concat.txt" :*
    a. *Identifier*
    b. *Date/Time*

c. *Crashed Thread*

5) End/Close

The source code of the JAVA file is provided in Appendix B.

Figure 4-2 shows an example of the output file of the JAVA program developed for the extraction purpose, where *Identifier* is the name of the application. *Date/Time* is the date and time of the crash and *Crashed Thread* is the number of the thread that caused the crash.

```
75  Identifier:      Skype
76  Date/Time:       2012-02-25 01:58:19.603 +0300
77  Crashed Thread:  0
78  Identifier:      Skype
79  Date/Time:       2012-02-26 00:15:58.353 +0300
80  Crashed Thread:  0
81  Identifier:      Skype
82  Date/Time:       2012-02-26 00:16:50.428 +0300
83  Crashed Thread:  0
84  Identifier:      Skype
85  Date/Time:       2012-02-26 00:17:00.003 +0300
86  Crashed Thread:  0
87  Identifier:      Skype
88  Date/Time:       2012-02-26 00:17:02.009 +0300
89  Crashed Thread:  0
90  Identifier:      Skype
91  Date/Time:       2012-02-26 00:17:39.870 +0300
92  Crashed Thread:  0
93  Identifier:      Skype
94  Date/Time:       2012-02-26 00:22:15.479 +0300
95  Crashed Thread:  0
96  Identifier:      Skype
97  Date/Time:       2012-02-26 23:54:34.924 +0300
98  Crashed Thread:  1
99  Identifier:      Skype
100 Date/Time:       2012-03-01 20:39:37.216 +0300
```

Figure 4-2: Output of the Java program

4.2 Application of SRGMs to the Failure Data

As it is well established from the experimentations with the SRGM in the desktop/laptop area, there is no universally applicable model that can be trusted to give accurate reliability predictions in all circumstances, and as there are hundreds of software reliability models, we settled on the most used and successful ones.

4.2.1 Choice of the Reliability Models

As already emphasized in Chapter 3, the above mentioned SRGMs are the most commonly used models [21, 28, 29] in the study of the reliability of desktop/laptop applications. They present the following attractive features:

i. Based on a few simple and reasonable assumptions

ii. Simple to understand on physical grounds

iii. Implemented in a reliability tool such as RGA7 or SMERFS

4.2.2 Experiments

The reliability demonstration of smartphone applications is carried out through the traditional testing, failure data collection, and the application of the SRGMs.

For this purpose we used two applications for iOS and one for Windows mobile phone. We could not collect enough data from Android phones, but we are still collecting in the hopes of having enough data to test the models on Android applications.

The first iPhone application studied was Skype, which has been tested and used for one year (from November 1, 2011 to November 11, 2012). Hence, the data has been collected during this year with some missing values due to the occasional non-use of the application. Therefore, we were able to collect 39 data points for the Skype application from our personal device.

The second application studied was Vtok (an application for Google talk). This application was used continuously every day, for two months (from September 19, 2012 to November 25, 2012). Hence, we were able to collect failures everyday (81 data points).

Each of the above mentioned SRGM models was applied to Skype and Vtok failure data, which represent two different situations: the Skype application used during one year but with some missing values, and the Vtok application used every day for two months, with the possibility of collecting more than one failure per day. This is an instance of testing the efficiency and accuracy of the models in different situations with different types of data.

On the other hand, the Windows phone application was used and tested continuously for six months (from March 2012 to August 2012) from different users located in different parts of the world. The crash count of the application is illustrated in Figure 4-3.

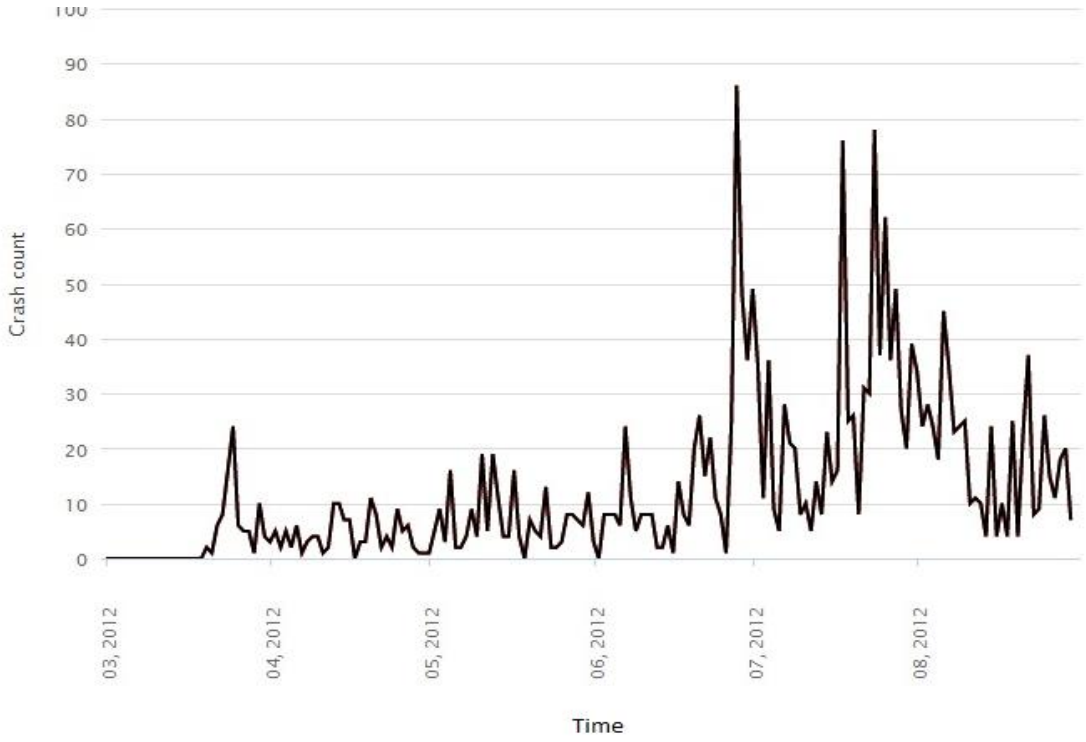


Figure 4-3: Windows phone crash count.

The failure rate is low in the spring period and very pronounced in the summer period, due to intensive usage.

It is important to note that June, July, and August are the months with the highest crash rates. Since this application is developed for the purpose of locating bicycle stations, it is used during the summer period more than in the winter, which explains the high crash rate during the hot season. This reflects the fact that the type of an application and its usage play an important role in its reliability. From the graph we extracted the failure data over the six month period.

We then used two software reliability tools to double check the results. The first tool is the RGA7 from ReliaSoft [24], and the second one is Statistical Modeling and Estimation of Reliability Functions for Software (SMERFS) [34]. We configured our tools as follows: we chose 1 for the severity level of all failures and the time unit selected was hour. As the time scales of the three applications are very different, we choose to normalize our data between 0 and 1 using the following equation:

$$Z_i = \frac{Y_i - \text{lower bound of Y}}{\text{range}} \quad (4.1)$$

where:

range = upper bound of Y – lower bound of Y,

Y_i = value of the raw target variable Y for the training case,

Z_i = standardized value corresponding to Y.

As the RGA7 tool does not accept the zero value as a time to event (because it can also allow a Log-Log display of the failure curves), we entered 0.001 instead of 0 as the first value in order to have results. For the severity level, 1 was selected because the applications used are not going to cause harmful consequences if they fail. But this is not the case with other applications. When working with applications such as online banking, health, and stock exchange, etc., the severity of the failure must be taken into consideration.

4.2.3 Results

Figures 4-4, 4-5 and 4-6, respectively, present the cumulative number of failures per time, the failure intensity per time and the Mean Time Between Failure (MTBF) per time for the Skype application when applying the NHPP model. The RGA7 tool indicates an evident failure of the model to pass the CVM goodness-of-fit test (highlighted in a red box on the bottom right of Figure 4-4), described in Chapter 3.

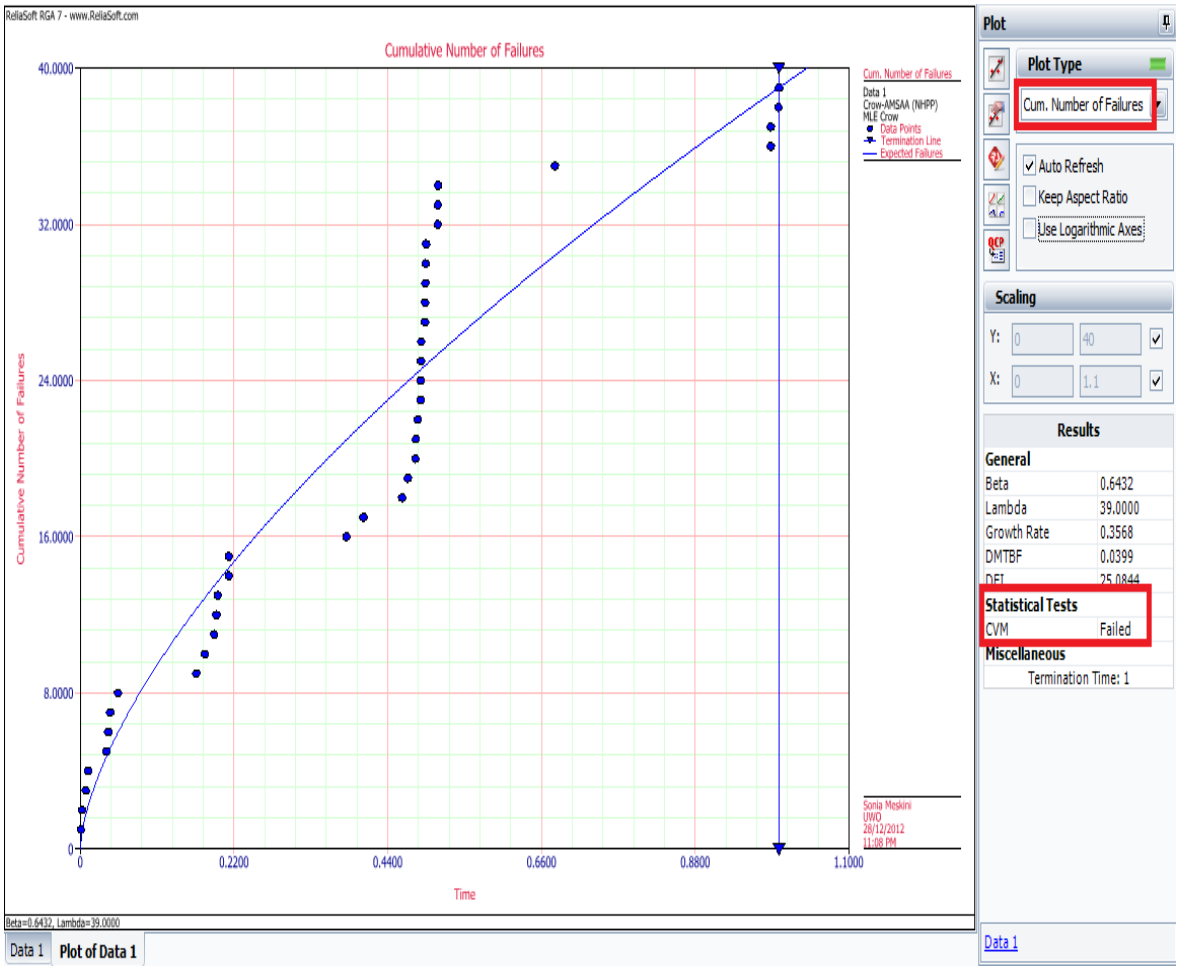


Figure 4-4: Cumulative number of failures and its mean value function per time for the Skype application.

Note the failure occurrences in “bursts” followed by flat plateaus, a feature that cannot be easily accommodated by the theoretical reliability model. The statistical Cramer-Von-Mises test revealed that the chosen NHPP model failed to adequately reproduce the data.

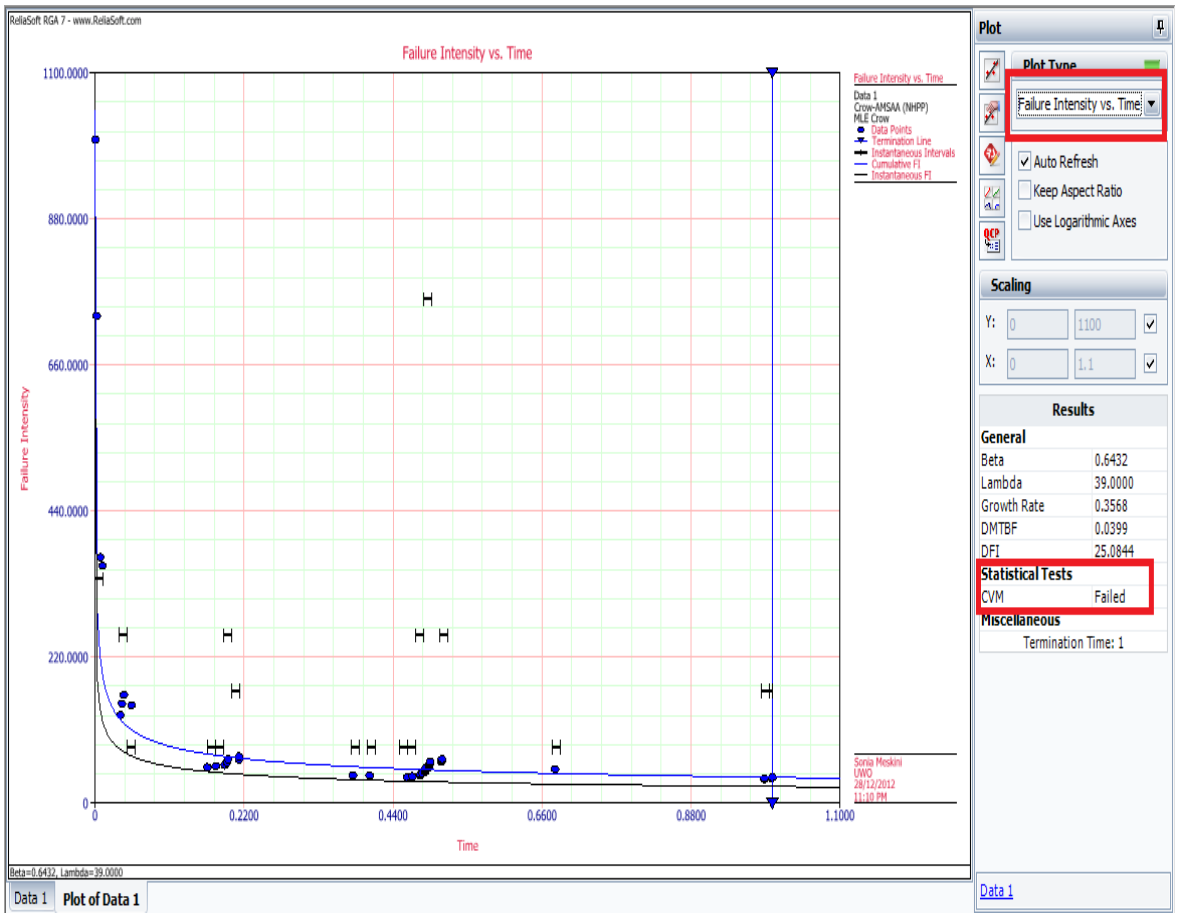


Figure 4-5: Failure intensity per time for the Skype application.

The instantaneous (lower) and the cumulative (upper) failure intensity decrease with time, which is an indication of a reliability growth, whereas the observed failure intensity fluctuates due to the "bursting" feature of the failure data, mentioned above in Figure 4-4.

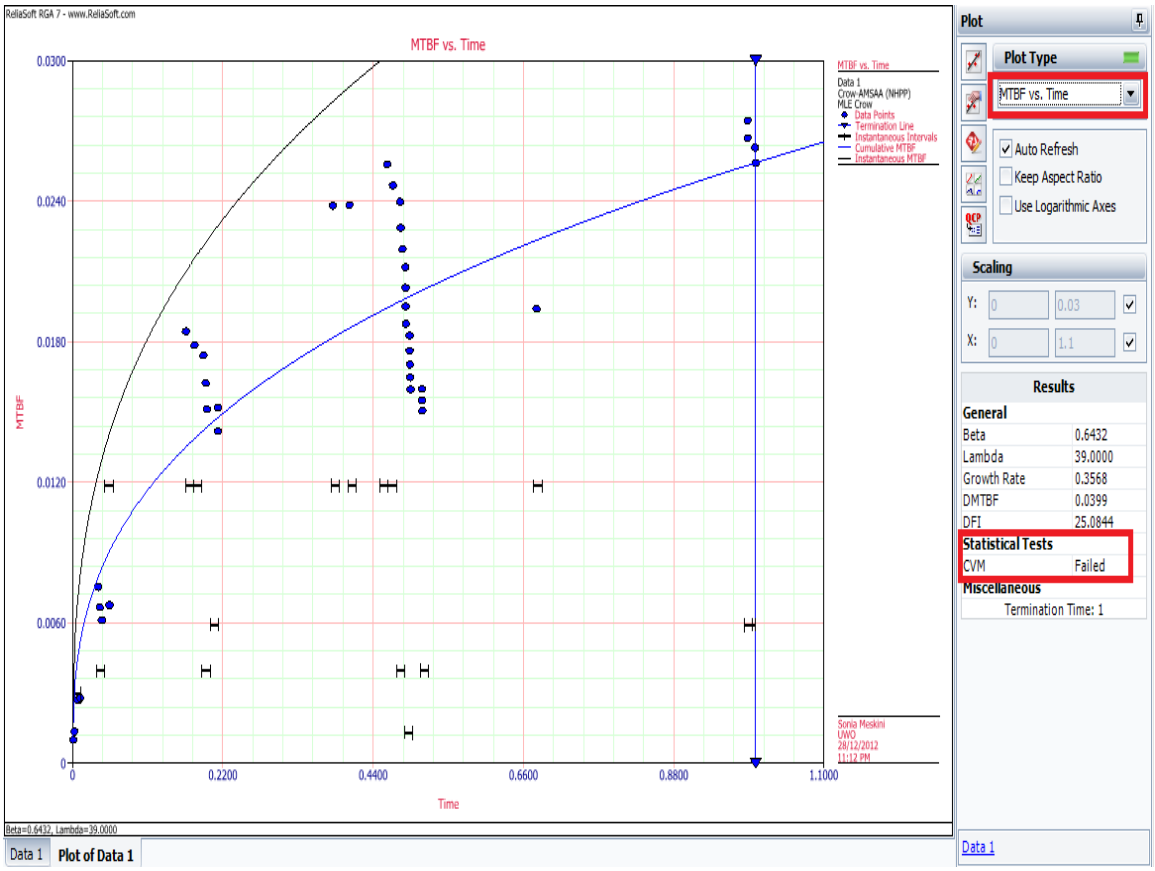


Figure 4-6: Instantaneous (upper) and cumulative (lower) Mean Time Between Failure MTBF of the Skype application.

The same previous comments apply. The MTBF is the reciprocal of the failure intensity and is also a convenient measure of the reliability of an application. An overall increase in the MTBF is indicative of a reliability growth, which is the case in these experiments.

Likewise, Figures 4-7, 4-8, and 4-9, respectively, represent the cumulative number of failures per time, the failure intensity per time, and the MTBF per time of the Vtok application. Again, the NHPP model failed to fit the data as indicated by the CVM goodness-of-fit test (red rectangle at the bottom right of Figure 4-7 indicates the CVM failure).

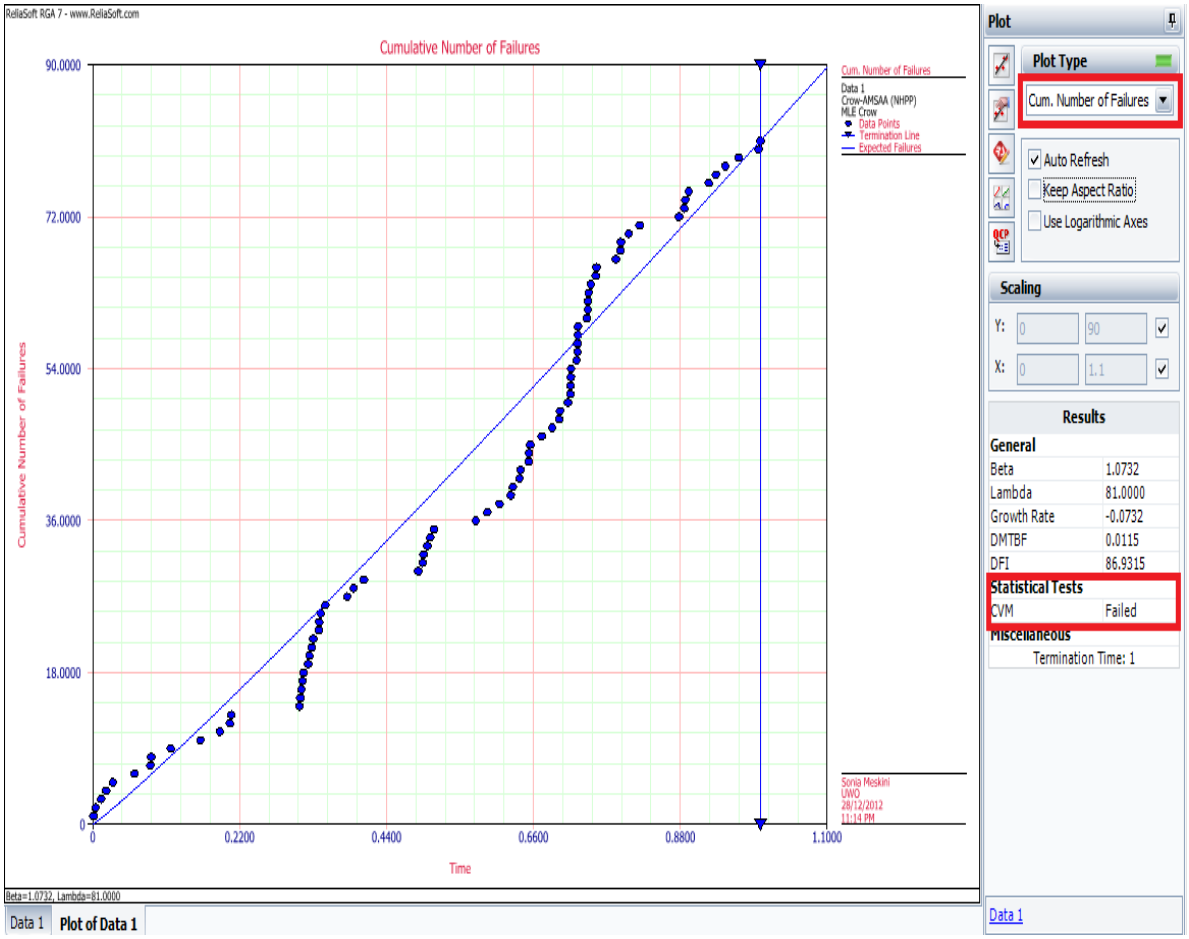


Figure 4-7: Cumulative number of failures and its mean value function per time for the Vtok application.

The "bursting" feature exists but is less pronounced in this case. The model parameter beta is nearly equal to one which results in a nearly straight line for the mean value function. The failure of the CVM test reveals also that the NHPP model is inadequate.

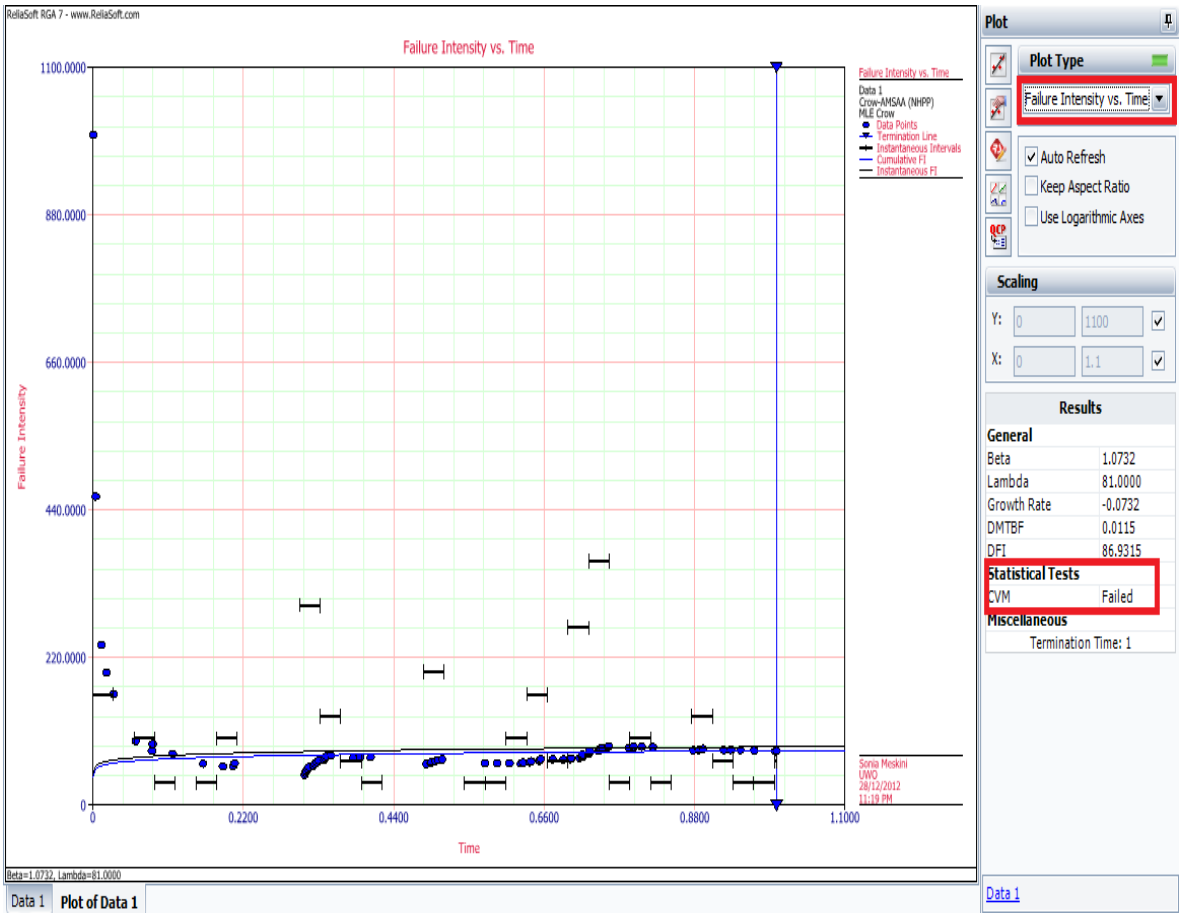


Figure 4-8: Instantaneous (upper) and cumulative (lower) failure intensity per time for the Vtok application.

The failure intensity is nearly constant during the observed period because the above curve for the mean value function of the cumulative number of failures is nearly a straight line (the failure intensity is the derivative of the mean value function).

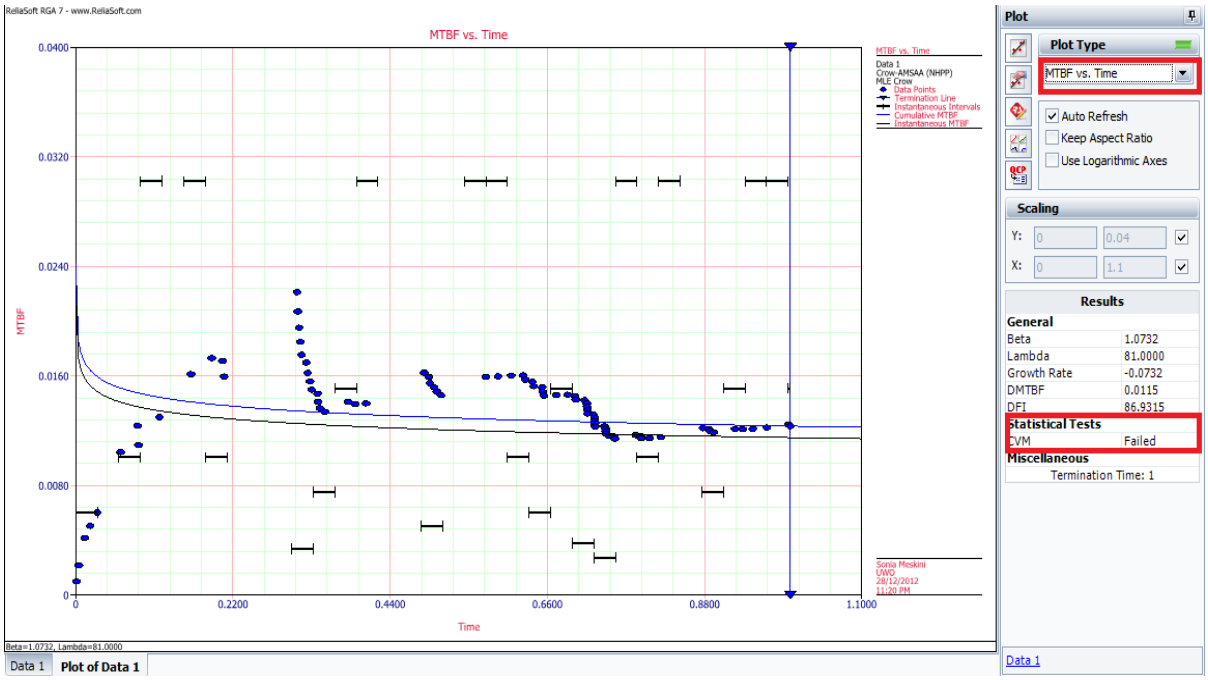


Figure 4-9: Instantaneous (lower) and cumulative (upper) Mean Time Between Failure MTBF for the Vtok application.

The MTBF is nearly constant as the failure intensity is also nearly constant during the observed period.

As was mentioned in the previous section, we used Skype for one year and collected the failure data that contain some missing values, as well as the Vtok application that was used continuously for two months and collected the failure data with more than one failure per day. However, the NHPP model still fails to fit these two different types of data, based on the CVM goodness-of-fit tests. One reason is that the failure data are a dynamic process for mobile applications, which means that the occurring number of failures is unpredictable, sometimes decreasing and sometimes increasing, (for example in Figure 4-7 from t = 0.2076 until t = 0.3097, the application did not experience a failure and from t = 0.3097 until t = 0.3484 an important number of failures occurred). Another way to look at the failure data is that the failure occurrences happen in “bursts” followed by flat plateaus, a feature that is not easy to accommodate by a reliability model.

In order to confirm our results we used a second tool, SMERFS, and we applied the NHPP model on the same data points. The result was the same, which is the failure of the

model each time. An example of the results given by the SMERFS tool is presented in Figures 4-10, 4-11, and 4-12, which show the results of the same data from the Skype application when applying the NHPP, the Musa-Basic and Musa-Okumoto models. Each time, the models fail to fit the data. Likewise, all of the models implemented in SMERFS failed completely to fit the Vtok failure data (Figure 4-13).

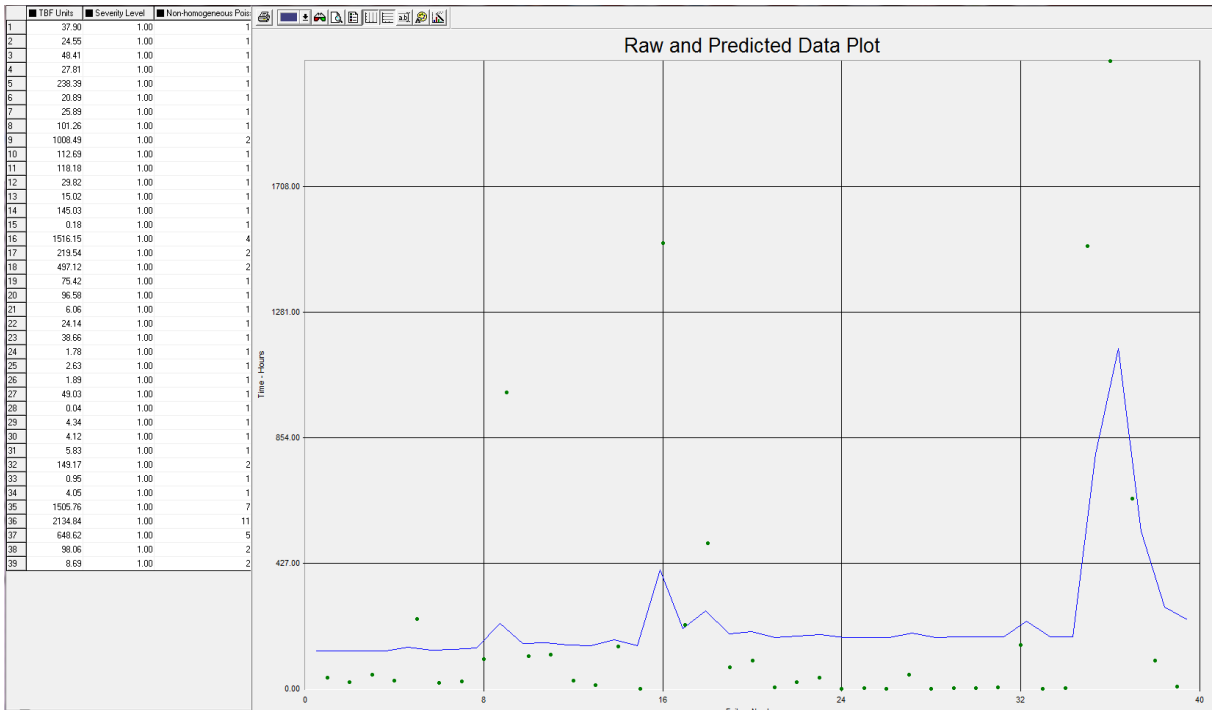


Figure 4-10: NHPP model applied to the Skype application.

The SMERFS tool, contrary to the RGA7 tool used previously, requires as input the Time Between Failure (TBF) data. The model failed to account for the data satisfactorily.

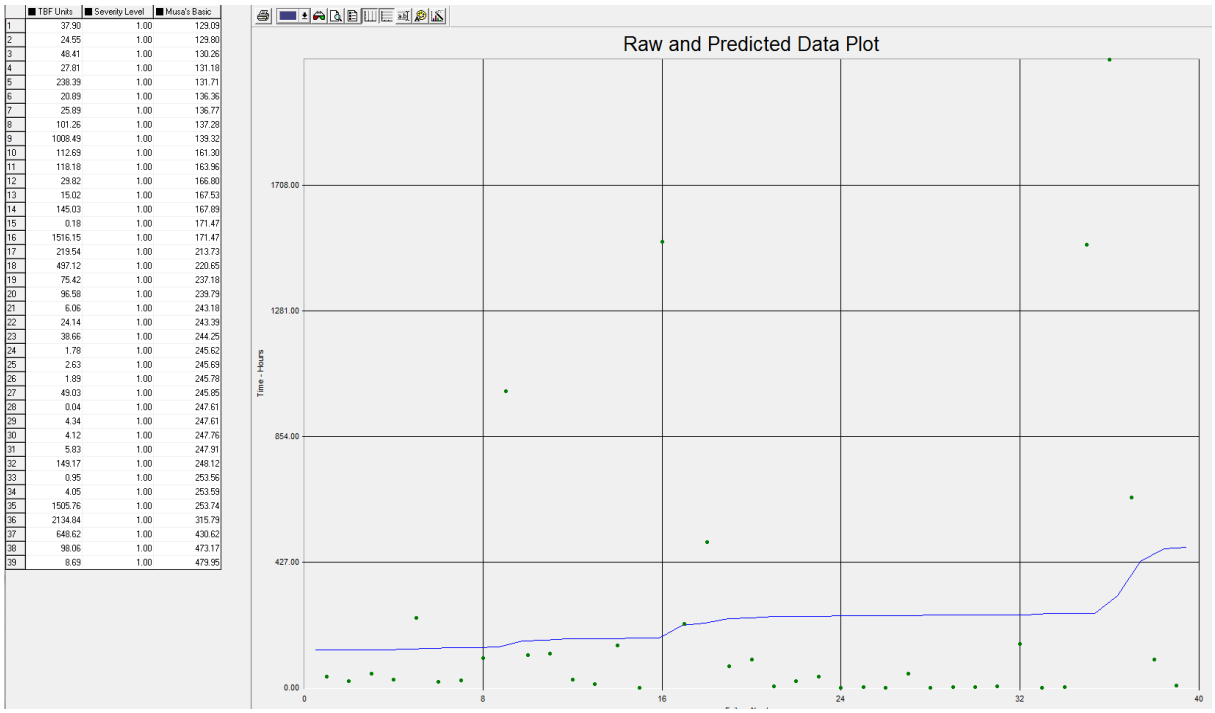


Figure 4-11: Musa-Basic model applied to Skype failure data. Same as above.

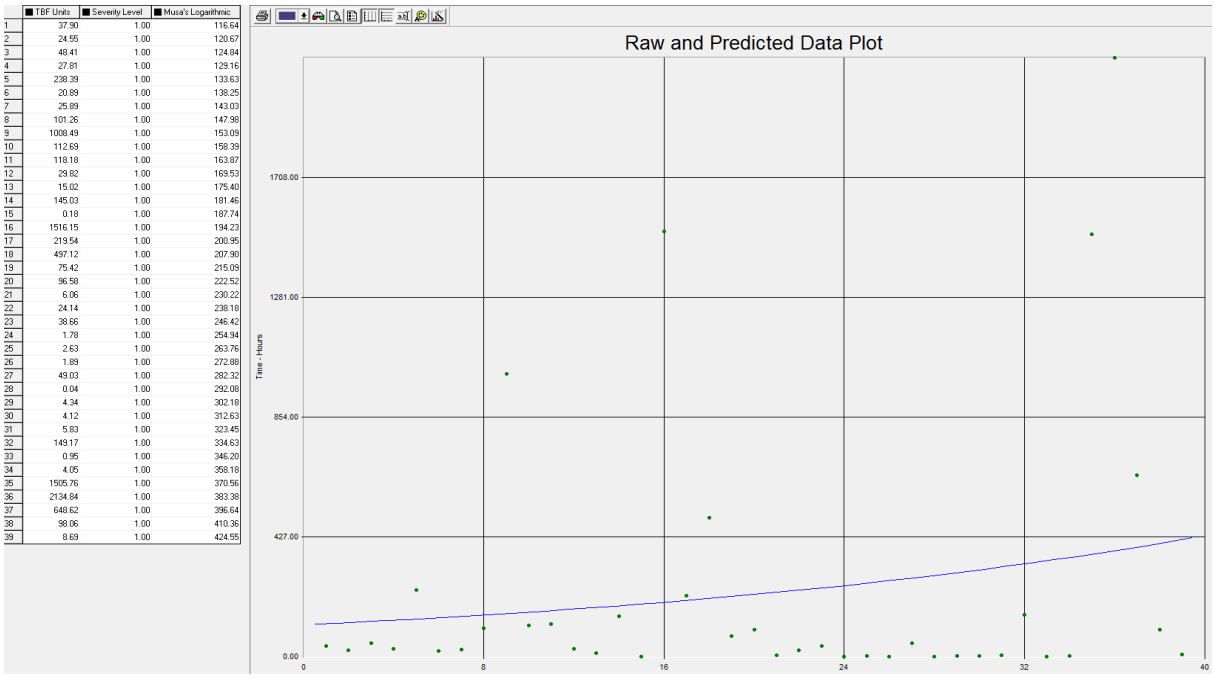


Figure 4-12: Musa-Okumoto model applied to Skype failure data. Same as above.

None of the selected SRGMs fit the data.

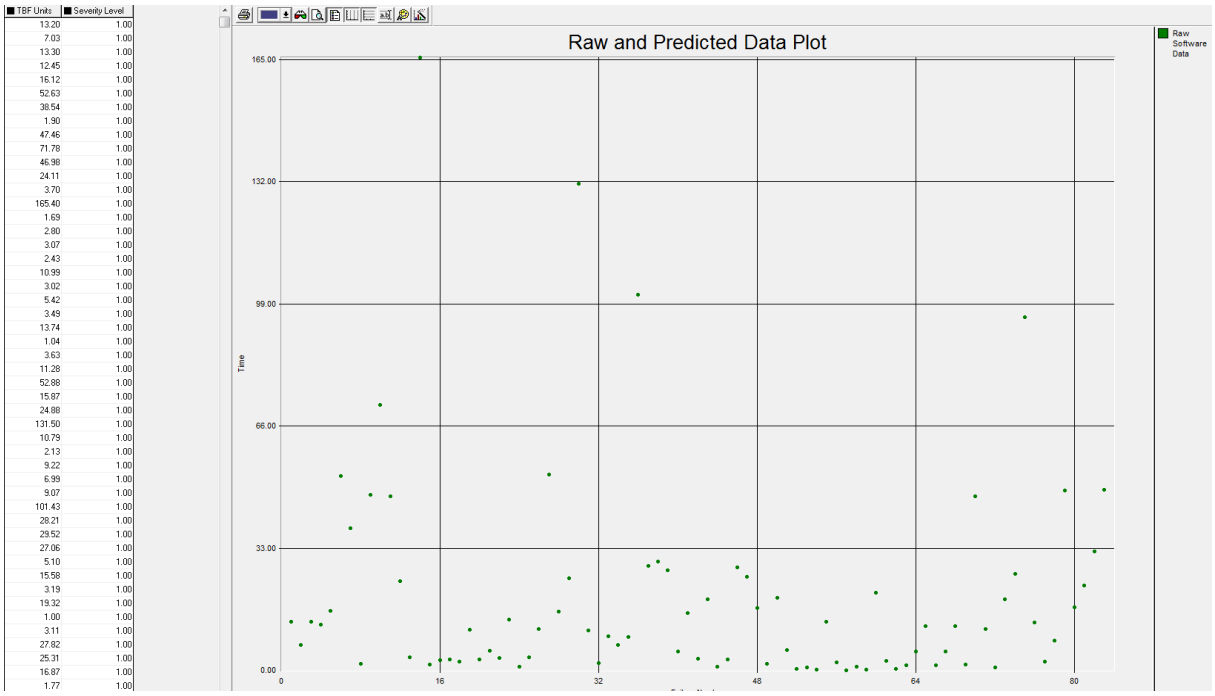


Figure 4-13: Vtok data and failure of the three selected models.

Figures 4-14, 4-15, and 4-16 represent the results of the application of the NHPP model to the Windows phone application failure data. Once again the RGA7 tool indicates the failure of the model by indicating the failure of the Chi-Square test (represented by the red rectangle in the bottom right in Figure 4-14).

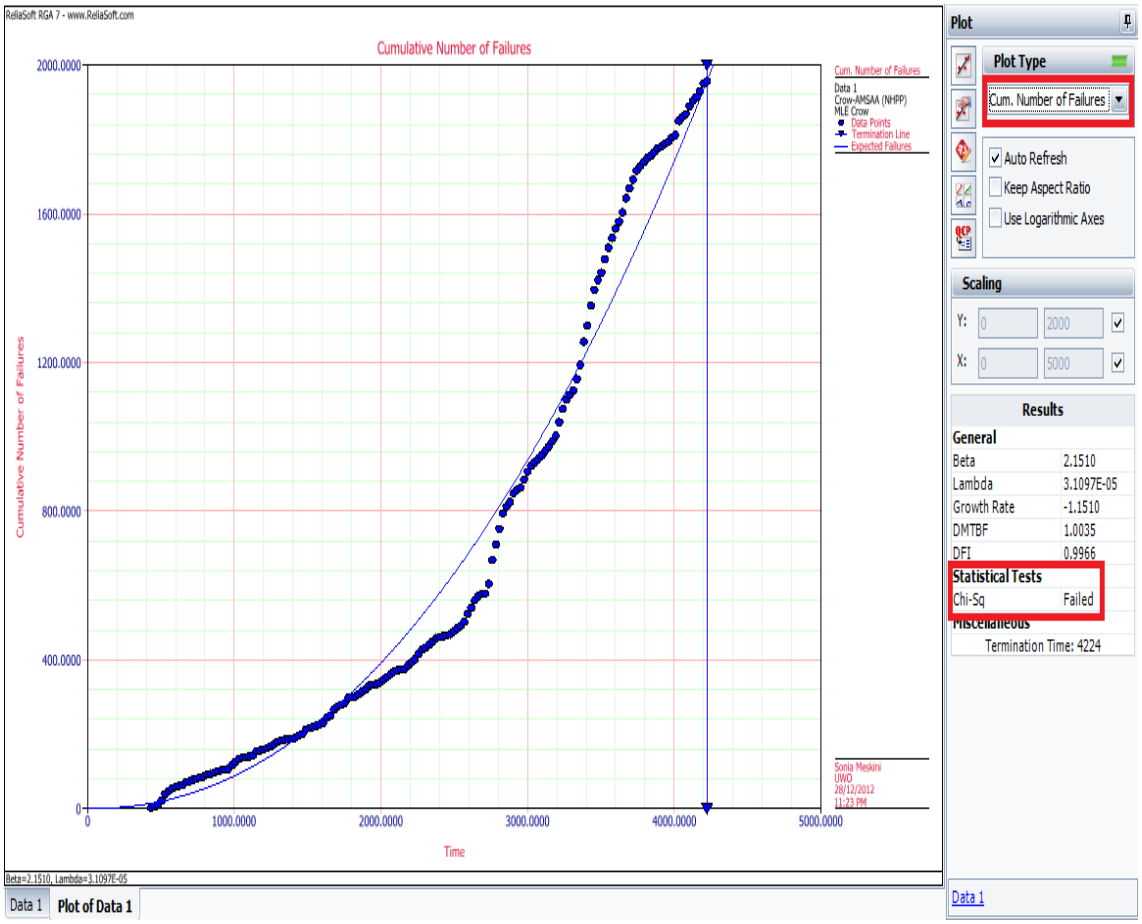


Figure 4-14: Cumulative number of failures and its mean value function per time for the private Windows phone application.

The model parameter beta is greater than one (beta = 2.1510), indicative of a reliability deterioration of this private application during the observed period.

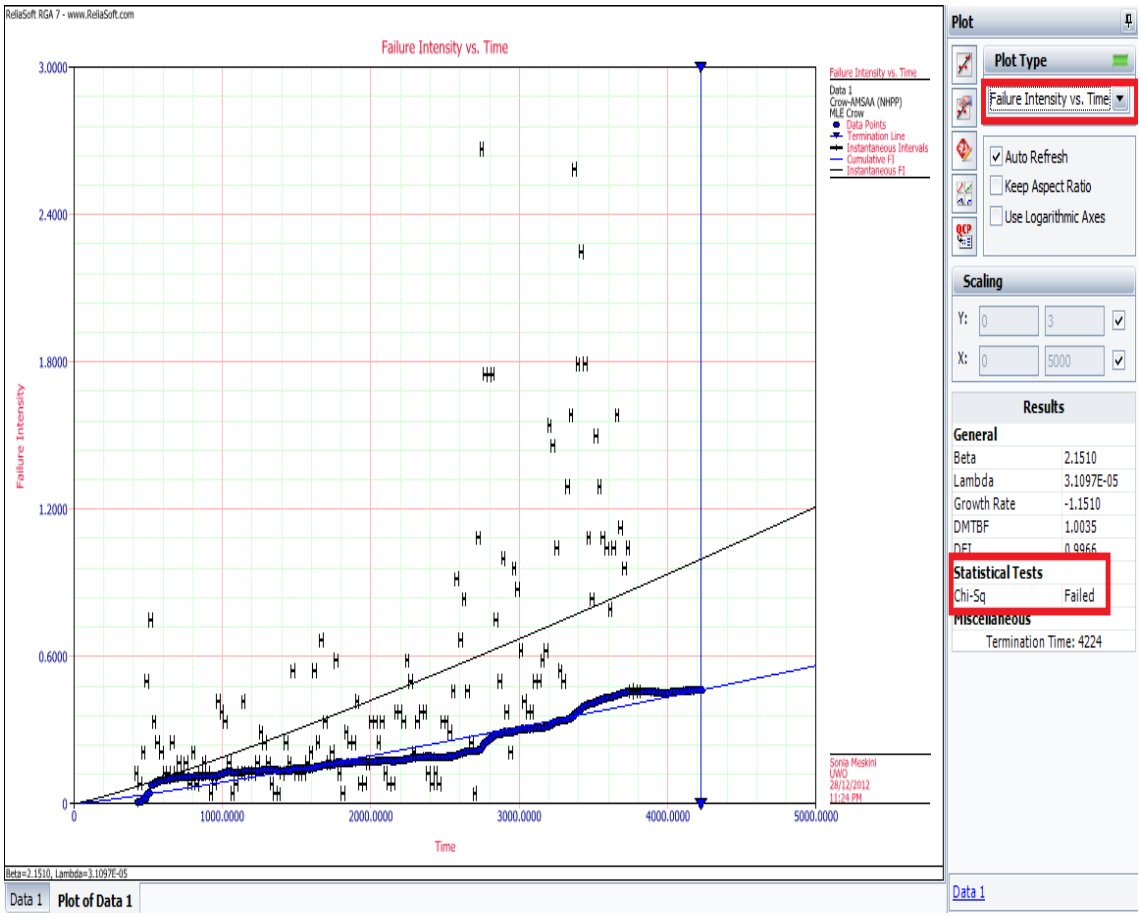


Figure 4-15: Instantaneous (upper) and cumulative (lower) failure intensity per time for the private Windows phone application.

It should be noted that the increase of the failure intensity reveals reliability deterioration. The failure intensity is higher in the summer period in accordance with the intensive use of this application in that period, as mentioned in a previous section.

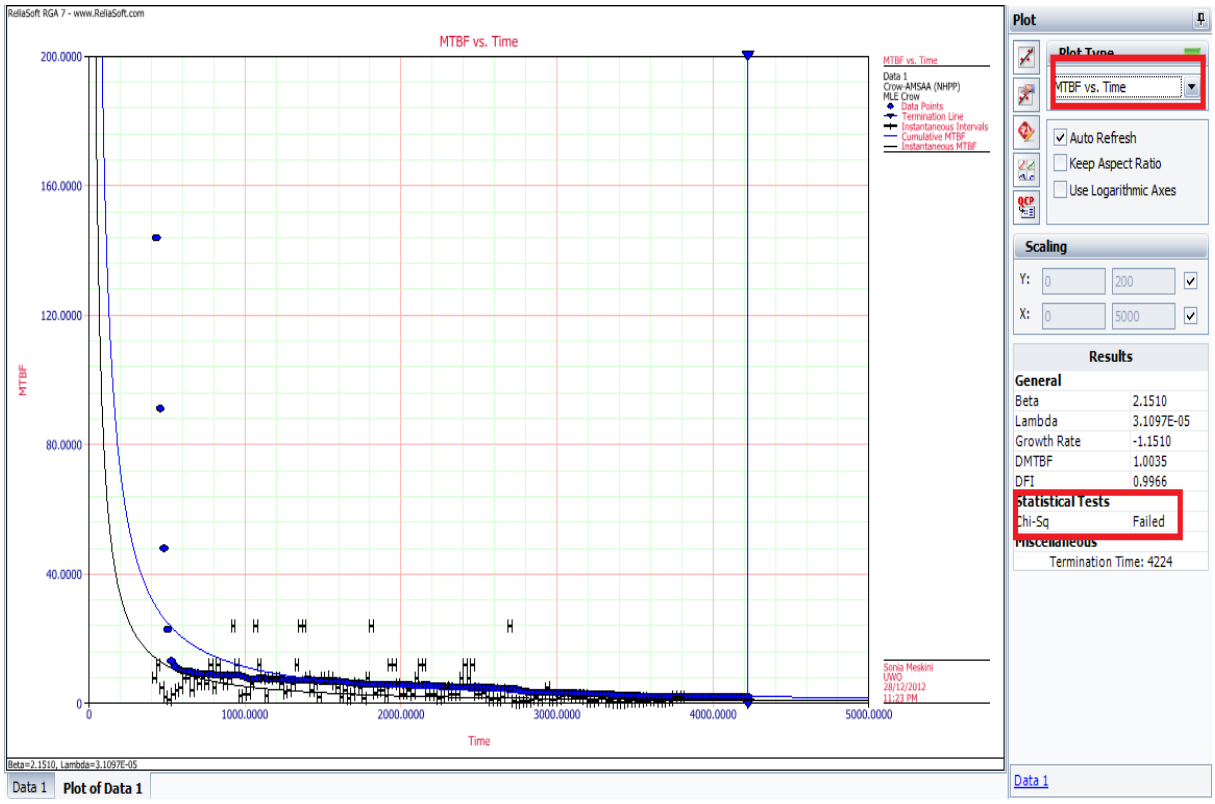


Figure 4-16: Instantaneous (lower) and cumulative (upper) Mean Time Between Failure (MTBF) for the private Windows phone application.

Note the decrease of the MTBF, indicative of reliability deterioration for the observed period.

4.3 Evaluation

Thus, the most successful reliability models [21, 28, 29] failed to fit all of the data and failed to predict the reliability in the mobile area for smartphone applications. This failure can be traced back to the following differences between desktops/laptops and smartphones.

4.3.1 Operational Environments and Usage Profiles of Smartphone Applications

One of the mobile application failure characteristics is that they are application dependent in the sense that they are dynamic and non-homogenously spread over time [16, 35]. Moreover, they are unpredictable, sometimes decreasing and sometimes increasing, i.e.

happening in “bursts”. One possible explanation is that reliability depends on the type of the used application (for example, the Windows phone application mentioned earlier), and on its operational environment and usage profile (where and when and how the application is used). Because the usage may differ from one user to another, from one country to another, from one condition to another [11], this explains the uncertainty of usage of the application in the execution and release time [12], and all of these factors play an important role in the reliability of the applications.

Another reason is that the DLC of a mobile application is short (up to 90 days) and the programmer aims to develop the application as fast as possible to satisfy the time-to-market constraint, which leads to skip phases from the DLC. The most skipped phase is the design phase, which is the most important phase in the DLC of the application [9]. Thus, it would be difficult to identify the causes of errors, during the execution time, and to find a convenient solution to fix them. In addition, the failure or unreliability of the application may be caused by the technology used during the development process. Also, the skills of the developer and the tester play a huge role in the reliability of the application.

4.3.2 Hardware and Software Limitations

Moreover, the device itself and its hardware characteristics such as the size of the screen, the performance, the keyboard, etc. can have a direct effect on the reliability of the application. For example, to adjust the map size to a certain zoom level, a zoom in/out function is needed. However, to assure a perfect usage of this function, the performance of the device has to be taken into consideration [12].

Other reasons that may explain this dynamic aspect of the smartphone applications are summarized in Table 4-1, which gives an idea of the different causes, external and internal, of the unreliability of the application.

Table 4-1 : Possible causes of applications crash [36]

Cause of Failure	Description
Code	Failures arise when not taking into consideration the limited resources of the device such as power and memory.
Interfaces	WAP Gateway fails when converting WTP request to HTTP request.
Hardware	Various models of devices: developers should take into consideration the specific platform and performance of each device.
Non-executable files	Failure to open the help, demonstration, or samples files of an application.
Interaction	Thanks to the Service Oriented Architecture (SOA), many application interfaces are located on a server. Thus, mobile applications have to connect to the server to accomplish data transfer and carry out tasks. Failure in the server may cause the crash of the application.
Data input	The application has to be developed in a manner that the data input has to be optimized to ensure maximum efficiency for the user.
Third-party software failures	Smartphone application architecture uses third-party software applications (for example, Facebook and Adobe Photoshop Express, to be able to modify and upload pictures). A crash/problem in the third-party application may cause the failure of the other application.
Wireless network	The sudden loss of connection or failure in configuration may cause the failure of the application.
Mobile database	Failure to connect to the database due to an error occurring in the database server.
OS version	Some smartphone applications may not be compatible with upgraded OS version (for example, the Gas Prices Canada application is no longer available for iOS 6).
Software upgrades	Upgrading from one version to another may fix problems but cause others, as was the case with Skype 4.2.2601 and Skype 4.2.2604 where the updated version crashes more often than the previous version when making calls.

Due to space limitations, a complete list of causes and their descriptions along with examples can be found in [36].

4.3.3 The Need to Reexamine the Standard Assumptions

Software managers usually base their assessment of the reliability of software and its future evolution (after release) on a simple extrapolation in time of a reliability model, based on the failure data collected in the testing phase. They implicitly assume that the

field operational usage of the application will not differ greatly from that of the Lab testing phase [23, 37]. This is the first standard assumption on which most reliability models are based. As mentioned previously, this assumption is no more valid in the mobile area as there is a large variation and uncertainty in the operational profile of smartphone applications (there are so many possible operational profiles, as there are millions of users). If an application is used in different environments, its reliability may be different for each environment [11]. Therefore, the "mobile feature" has to be included in the initial assumptions of any reliability model suited to the mobile area in order for its assessments and predictions to be taken seriously, and to be of any help to manager decisions.

4.4 Summary

Based on different surveys and studies, reliability was identified as one of the most important quality attribute of the application software. Thus, the reliability of smartphone applications needs to be assured since everyone is using their own smartphones for daily life activities and tasks, now more than PCs. Our study confirms that a reliability growth model adapted to smartphone applications is needed since the traditional reliability models turned out to be inefficient. This conclusion is based on the experimentation we carried out with three SRGMs applied to three smartphone application failure data.

Therefore this chapter is a clear-cut answer to the research questions 2 and 3, raised in the introduction.

- To the research question 3: "… *how do the existing successful reliability models, used to assess the desktop/laptops applications, perform when applied to the mobile area? Will these models still be of useful help to smartphone applications managers, as they were in the desktop/laptop case? Will there be a need to change them?"* As evidenced in all of the experiments carried out in this chapter, the answer is that the existing successful reliability models, suited to assess the desktop/laptops applications, do not equally perform when applied to the mobile area; they fail to reproduce the observed failure data adequately. Therefore, they need to be changed and adapted to the mobile area.

- To the research question 2: "*Are the basic assumptions needed to build the reliability models suited to desktop/laptop applications still valid in the case of smartphone applications? How do we adapt them to the mobile area?* " as detailed in Sections 2.4 and 4.3, the answer is that there is a need to change the assumptions on which these models are based, particularly, to adapt them to the mobile area, these assumptions should be complemented by including the "mobile feature" reflected in the inherent uncertainties and dynamic operational profiles of mobile applications, in contrast to the stationary operational profiles of desktop/laptop applications. This "mobile feature" is application-dependent and cannot be the same for all smartphone applications.

After realizing the failure of the above mentioned SRGMs to adequately reproduce the smartphone failure data, in the next chapter we use and compare two common distributions, Weibull and Gamma, to model new collected failure data of the same applications, after sorting it by version number and grouping it into different time periods.

Chapter 5

5 Failure Data Analysis of Smartphone Applications Using the Weibull and Gamma Distributions

The preceding chapter was devoted to the application of three most used SRGMs to two common smartphone applications, Skype and Vtok, and one private Windows phone application. The inputs to these models were the instantaneous failure data (the failure number and its exact occurrence time). Those models failed to adequately describe the failure data. One possible reason is that on a real time scale, the failure data of smartphone applications are highly fluctuating. Having tried several non-linear regression models to better fit the failure data and after numerous experiments, we found that Weibull and Gamma distributions [38, 39] can be used to model new collected failure data of the same applications, after sorting them by version number and grouping them into different time periods. Therefore, we used the two mentioned distributions and their particular cases, the Rayleigh (the particular case of Weibull) and the S-Shaped (the particular case of Gamma) models and compared their performances for each application. This study is carried out after two steps: (i) the failure data for each application are sorted by version number (ii) the data are grouped on larger time scales (days, weeks and months). A by-product of this approach is an estimation of the total number of defects in each smartphone application version.

The chapter is organized as follows: Section 5.1 describes the experiments, Section 5.2 is a brief presentation of the Weibull distribution and its particular case, the Rayleigh distribution, and Section 5.3 presents the Gamma distribution and its particular case, called the S-Shaped distribution. Section 5.4 recalls the used evaluation criteria and Section 5.5 presents the results of the proposed approach and their discussion. Section 5.6 is reserved for the threats to validity issues and a summary is given in Section 5.7.

5.1 Experiments

As several users from many regions had responded to our call for failure data collection of smartphone applications, we obtained new enriched data for Skype and Vtok applications. The data are collected synchronously and come from different versions of

the applications. When we plot the raw data on the real timescale, the obtained curves are highly fluctuating and no regularity can be detected. But, after sorting the data by version number and grouping the data using a larger time scale (days, weeks, months), the relationship between failure counts and time (days, weeks, months) was represented by a non-linear graph. After testing several non-linear models, we concluded that the failure counts present shapes reminiscent of the Weibull or the Gamma distributions: each application version shows an early "burst of failures" followed by a decrease, where the failures become less and less frequent. For the Windows phone application, we saw in the preceding chapter that the failure count curve was highly fluctuating (Figure 4-3), but when plotted with larger time periods, it also represents the Weibull shape.

Based on this observation, we conducted a thorough study of the collected data. Each version of each application is studied separately, if there was sufficient data. The versions with very few failure data are not considered, and they are evidently the most stable. For the Skype application we collected enough data for three versions, whereas for Vtok we collected enough data for two versions. For the Windows phone application, we simply grouped the failure data in larger time scales and modeled the failure count curves.

We present in the following sections, a brief presentation of the Weibull and the Gamma distributions, and their applications to the modeling of the observed failure data grouped, as previously indicated. A comparison between the models was carried out in each case, based on the error criteria. As the Rayleigh and S-shaped models are particular cases of the Weibull and Gamma distributions respectively, and as they are often used in many reliability investigations, we also included them in the comparison.

5.2 The Weibull Distribution

The Weibull distribution [38] is a two parameter function whose expression is given by:

$$f(t) = \text{wblpdf}(t,a,b) = \frac{b}{a} * \left(\frac{t}{a}\right)^{b-1} \exp\left(-\left(\frac{t}{a}\right)^{b}\right) \qquad (5.1)$$

The parameters a and b take positive values as well as the variable t. If we define $A = \frac{1}{a^b}$ and $B = b$, this expression simplifies to:

$$f(t) = B\,A\,t^{B-1}\exp\left(-A\,t^{B}\right) \tag{5.2}$$

For b = 1, this function reduces to the exponential function, whereas for b = 2, it reduces to the Rayleigh function.

A maximum for this function occurs at time $t = T_{max}$, such that

$$T_{max}^{b} = \frac{B-1}{A\,B} \tag{5.3}$$

or using the a, b notation is such that:

$$T_{max}^{b} = a^{b}\,\frac{b-1}{b} \tag{5.4}$$

The cumulative distribution function associated with the Weibull distribution is given by:

$$F(t) = 1-\exp\left(-A\,t^{b}\right) \tag{5.5}$$

The failure count <u>at time</u> t is written as:

$$y(t) = C\,f(t) = C\,B\,A\,t^{B-1}\exp\left(-A\,t^{B}\right) \tag{5.6}$$

and the cumulative failure number <u>by time</u> t is given by:

$$Y(t) = C\,F(t) = C\left(1-\exp\left(-A\,t^{b}\right)\right) \tag{5.7}$$

where the parameter C is the total number of expected failures: $C = Y(t = \infty)$.

Therefore the cumulative number of observed failures by time $t = T_{max}$ is:

$$Y\left(t = T_{max}\right) = C\,F\left(t = T_{max}\right) = C\left(1-\exp\left(-\frac{B-1}{B}\right)\right) \tag{5.8}$$

The famous 40% rule for the Rayleigh distribution is obtained from the preceding equation when B = 2: the fraction (or the proportion) of failures, observed by time $t = T_{max}$ is given by:

$$\frac{Y(t = T_{max})}{C} = \left(1 - \exp\left(-\frac{2-1}{2}\right)\right) = 0.3934 \sim 40\% \tag{5.9}$$

5.3 The Gamma Distribution

The Gamma distribution [39] is a two parameter function whose expression is given by:

$$f(t) = \text{gampdf}(t, a, b) = \frac{1}{b^a \Gamma(a)} (t)^{a-1} \exp\left(-\frac{t}{b}\right) \tag{5.10}$$

$$f(t) = \text{gampdf}(t, a, b) = \frac{1}{b\ \Gamma(a)} \left(\frac{t}{b}\right)^{a-1} \exp\left(-\frac{t}{b}\right) \tag{5.11}$$

for a, b, and t taking positive values. For a = 1, this function reduces to the exponential distribution. The maximum of this function occurs at $t = T_{max}$ such that:

$$T_{max} = b(a-1) \tag{5.12}$$

The cumulative distribution function associated with the Gamma distribution is given by:

$$F(t) = \int_0^t f(t)\,dt = \frac{\gamma\left(a, \frac{t}{b}\right)}{\Gamma(a)} \tag{5.13}$$

where $\gamma(a, \frac{t}{b})$ is the incomplete Gamma function, $\Gamma(a)$ being the complete Gamma function. When $t \to +\infty$, $\gamma\left(a, \frac{t}{b}\right) \to \Gamma(a)$ and $F(t) \to 1$, as expected.

The failure count at time t is written as:

$$y(t) = C\, f(t) = \frac{C}{b\,\Gamma(a)}\left(\frac{t}{b}\right)^{a-1} \exp\left(-\frac{t}{b}\right) \tag{5.14}$$

and the cumulative failure number by time t is given by:

$$Y(t) = C\, F(t) = C\,\frac{\gamma\left(a, \frac{t}{b}\right)}{\Gamma(a)} \tag{5.15}$$

where the parameter C is the total number of expected failures.

Therefore the cumulative number of observed failures by time $t = T_{max}$ is:

$$Y(t = T_{max}) = C\, F(t = T_{max}) = C\,\frac{\gamma\left(a, \frac{T_{max}}{b}\right)}{\Gamma(a)} \tag{5.16}$$

The relative proportion of failures encountered by time $t = T_{max}$ is, in Matlab notation:

$$\frac{Y(t = T_{max})}{C} = \frac{\gamma\left(a, \frac{T_{max}}{b}\right)}{\Gamma(a)} = \text{Gammainc}\left(\frac{T_{max}}{b}, a\right) \tag{5.17}$$

and for the case of the S-shaped model distribution, it reduces to:

$$\frac{Y(t = T_{max})}{C} = \text{Gammainc}(1, 2) = 26.4\% \tag{5.18}$$

because a = 2 and therefore $T_{max} = b(a-1) = b$. This is in fact an attractive result because it is valid for all applications and for all of their versions.

5.4 Evaluation Criteria

For each application, the four used distributions are compared on the basis of their Root-Mean-Squared-Error (RMSE) and their Adjusted R-Square. The results of the estimated total number of defects will be evaluated using the Magnitude of Relative Error (MRE).

1. Root Mean Squared Error: the RMSE is the square root of the mean of the square of the differences between the actual and the predicted values and is expressed as:

$$\mathrm{RMSE} = \sqrt{\sum_{i=1}^{N} \frac{\left(y_i - y_i \right)^2}{N}} \tag{5.19}$$

where y_i and $\hat{y}_i$ are the actual and predicted number of failures respectively, N is the number of observations.

2. The Magnitude of Relative Error (MRE) for each observation i can be obtained as follows :

$$\mathrm{MRE} = \frac{\left| C - \hat{C} \right|}{C} \tag{5.20}$$

where C and $\hat{C}$ are the actual and predicted cumulative number of failures respectively.

3. The adjusted R-square: measures the proportion of the variation in the dependent variable accounted for by the explanatory variables. Unlike R square, adjusted R square allows for the degrees of freedom associated with the sums of the squares. Therefore, even though the residual sum of squares decreases or remains the same as new explanatory variables are added, the residual variance does not. For this reason, adjusted R square is generally considered to be a more accurate goodness-of-fit measure than R square. The adjusted R-square can be negative [40].

5.5 Results

This section presents a comparison and evaluation of the use of the above mentioned distributions to model the failure data of three versions of Skype, two versions of Vtok, and the Windows phone application, based on the evaluation criteria explained above.

5.5.1 Skype Application

The accumulated failure data from the Skype application were sorted by version number, and sufficient failure data for three different versions were collected. They will be called in the following: Skype Version 1, 2, and 3. Skype Version 2 follows Skype Version 1 chronologically.

5.5.1.1 Skype Version 1

Table 5-1 summarizes the results of the model parameters, RMSE, Ad-R-Square, the estimated cumulative number of failures C and the MRE, given by each model. The model parameters a, b and the unknown total number of failures C, $(C = Y(t = \infty))$, result from the least square fitting scheme.

Table 5-1: Skype Version 1 - Error evaluation and model comparison

Skype V1	Model parameters	RMSE	Ad R Square	C : Estimated cumulative number of failures or defects	MRE (%)
Weibull	a = 6.17 (5.26, 7.09) b = 2.82 (1.81, 3.84)	2.1966	0.6374	50.54 (34.51, 66.58)	6.4
Rayleigh	a = 6.61 (5.01, 8.21) b = 2	2.3746	0.5763	58.33 (39.9, 76.77)	8
Gamma	a = 6.14 (1.84, 10.44) b = 0.97 (0.21, 1.73)	2.2305	0.6262	51.81 (34.32, 69.31)	4
S-Shaped	a = 2 b = 3.76 (1.90, 5.62)	2.8630	0.3840	67.43 (36.18, 98.67)	24.8

Note that the value of each parameter is given in a 95% confidence interval; particularly the estimated total number of failures C, which has a lower and an upper bound. Only the optimum value is used to calculate the MRE. For Skype Version 1, 54 failures were collected. It can be concluded from Table 5-1 that Weibull (with parameters: a = 6.179 and b = 2.826) is the best distribution that models the failure data, compared to the other distributions. It has the lowest RMSE: 2.1966 associated with the highest Ad-R-Square: 0.6374. The lowest MRE belongs to the Gamma distribution (with parameters a = 6.141 and b = 0.975) with a value of 4%, but based on the other evaluation criteria it is the second best distribution that fit the data.

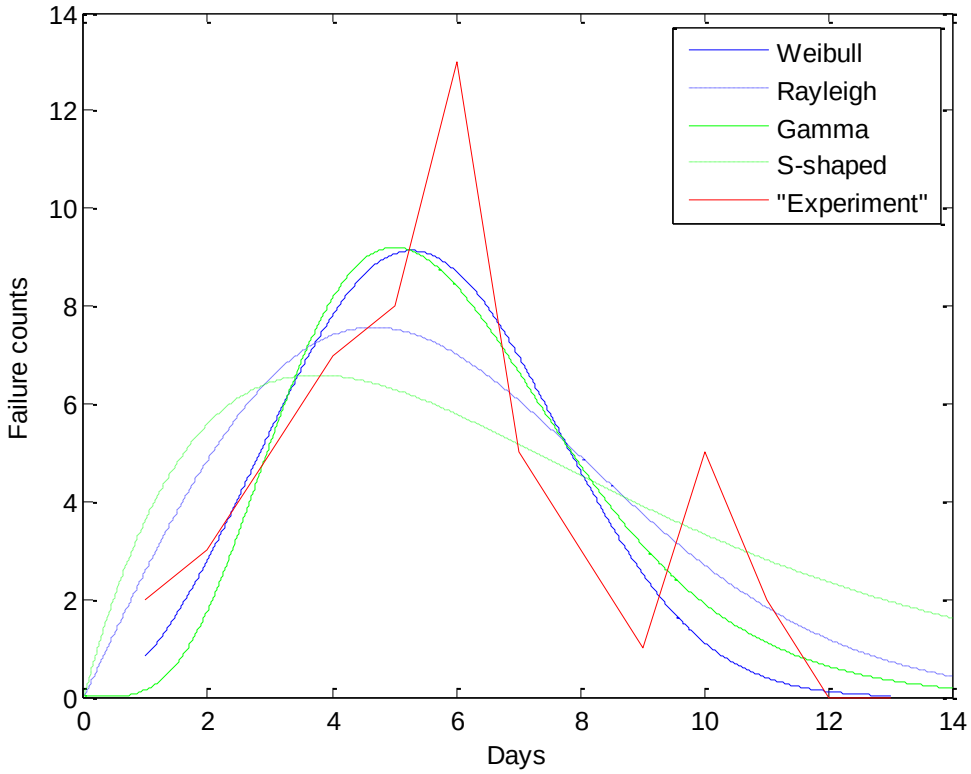


Figure 5-1: Skype Version 1 - Model comparison

Figure 5-1 illustrates the results reported in Table 5-1. It can be noted from this figure that the Weibull distribution is the closest to the actual behavior curve of the application, followed by the Gamma distribution. The difference between the actual curve and the modeling curves is explained by: (i) the random nature of the failure event which gives the spiky feature of the observed data and, (ii) the size effect: have we collected more data, the real failure curves would be smoother; but we still expect the general shapes to be explained by the chosen distributions because they capture the main behavior of the failure data of each smartphone application version. Only a big "Claim Center", collecting failure data from millions of users of each application version would provide a definite answer for the right model. In addition, the eventual modifications made to the application, its usage that differs from one environment to another and one user to another [11], may play an important role in the behavior of the collected failure data.

5.5.1.2 Skype Version 2

Table 5-2 summarizes the results of the model parameters, RMSE, Ad-R-Square, the estimated cumulative number of failures C, and the MRE, given by each model.

Table 5-2: Skype Version 2 - Error evaluation and model comparison

Skype V2	Model parameters	RMSE	Ad R Square	C : Estimated cumulative number of failures or defects	MRE (%)
Weibull	a = 6.30 (4.56, 8.04) b = 1.45 (1.04, 2.86)	2.7891	0.6952	116.4 (85.27, 147.5)	8.7
Rayleigh	a = 5.96 (4.73, 7.19) b = 2	3.685	0.4676	99.38 (72.31, 126.4)	7.1
Gamma	a = 1.81 (0.97, 2.65) b = 3.36 (0.98, 5.75)	2.7835	0.6965	118.2 (85.42, 151.1)	10.4
S-Shaped	a = 2 b = 2.93 (2.30, 3.57)	2.6889	0.7168	114.4 (90.36, 138.5)	6.9

For Skype Version 2, 107 failures were collected over 11 days. It can be concluded from Table 5-2 that S-shaped (with parameters: a = 2 and b = 2.937) is the distribution that best models the failure data and predicts the total number of failures, compared to the other distributions with the lowest RMSE: 2.6889, the highest Ad-R-Square: 0.7168, and the lowest MRE: 6.9%. It is to be noted that although the S-shaped distribution is a particular case of the Gamma distribution, it fits the data slightly better. The reason is that parameter a of the Gamma distribution is given by a = 1.812 (0.972, 2.652), which includes the fixed value a = 2 in its 95% confidence interval, a = 2 being the value of a in the S-shaped model distribution. According to the S-shaped model distribution, the estimated total number of defects in the worst scenario is 138.5 i.e.139. A defect is to be understood in this context as the cause of the observed failure, not only a bug in the application code.

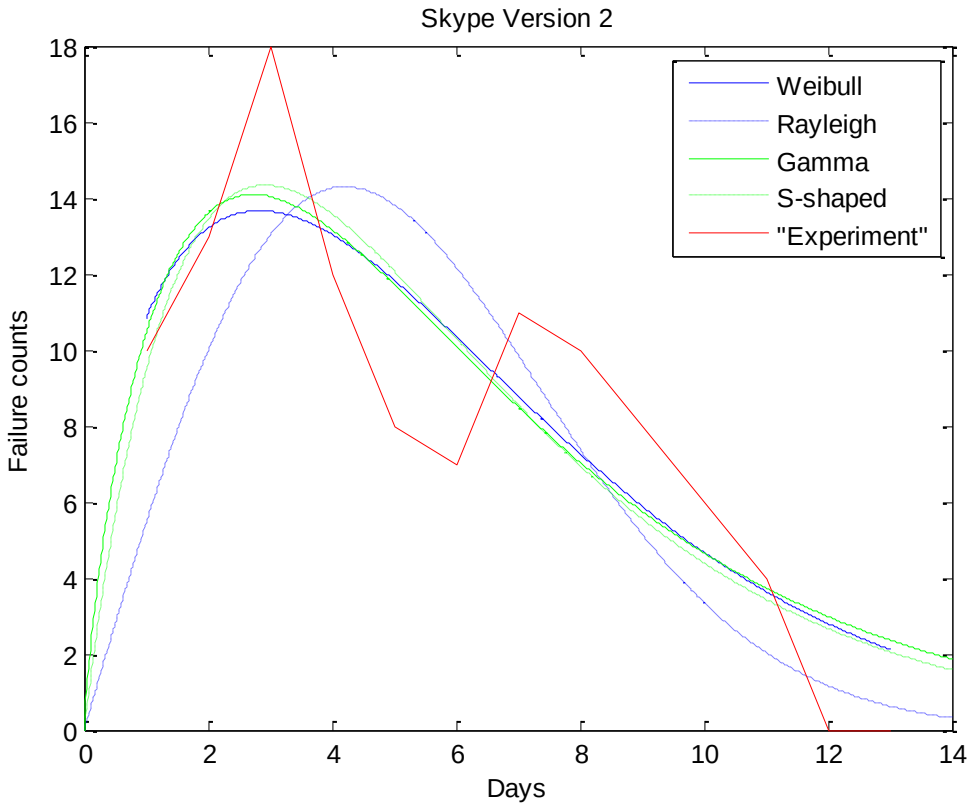


Figure 5-2: Skype Version 2 - Model comparison

Figure 5-2 illustrates the results summarized in Table 5-2. It can be concluded that the S-shaped distribution is the closest to the actual behavior curve of the application, followed by the Gamma distribution. The Rayleigh curve is the worst; it drops quickly to almost zero, and does not correctly reproduce the maximum. As noted previously, the second version of Skype chronologically follows the first version and its failure data come from the same users. Therefore, the evident conclusion is that modifying one version of an application can lead to the inclusion of more bugs in the second version than in the first.

5.5.1.3 Skype Version 3

Table 5-3 summarizes the results of the model parameters, RMSE, Ad-R-Square, the estimated cumulative number of failures C, and the MRE, given by each model.

Table 5-3: Skype Version 3 - Error evaluation and model comparison

Skype V3	Model parameters	RMSE	Ad R Square	C : Estimated cumulative number of failures or defects	MRE (%)
Weibull	a = 8.73 (7.20, 10.2) b = 1.94 (1.44, 2.43)	2.5482	0.6302	107.7 (81.98, 133.3)	4.5
Rayleigh	a = 8.69 (7.35, 10.03) b = 2	2.4694	0.6527	106.3 (84.97, 127.6)	3.2
Gamma	a = 2.96 (1.66, 4.26) b = 2.76 (1.18, 4.34)	2.4427	0.6602	109.8 (83.25, 136.4)	6.6
S-Shaped	a = 2 b = 4.73 (3.45, 6.02)	2.7151	0.5802	124.1 (92.33, 155.8)	20.4

For Skype Version 3, 103 failures were collected over 15 days. Based on Table 5-3, it can be concluded that Gamma (with parameters: a = 2.965 and b = 2.763) is the distribution that best models the failure data of this application version. It has the lowest RMSE: 2.4427, and the highest Ad-R-Square: 0.6602. The lowest MRE belongs to the Rayleigh distribution (with parameters: a = 8.69 and b = 2) with a value of 0.032, but based on the other evaluation criteria it is the second best distribution that fit the data with an Ad-R-Square value of 0.6527 and an RMSE of 2.4694. According to the Gamma model distribution, the estimated total number of defects in the worst scenario is 137.

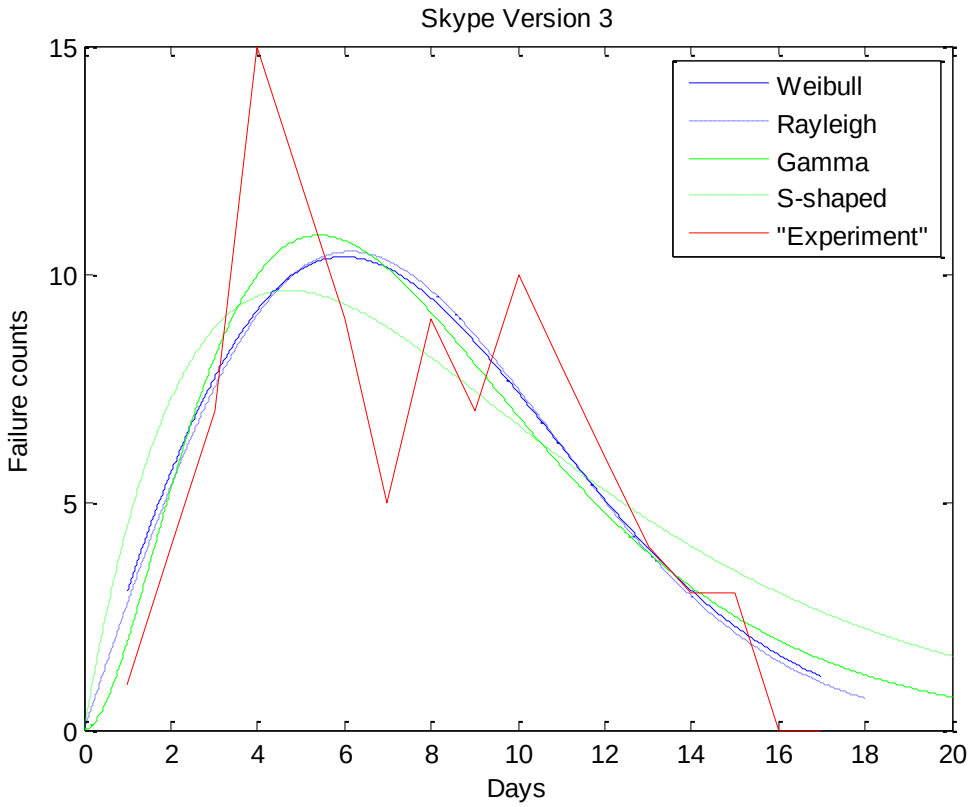


Figure 5-3 : Skype Version 3 - Model comparison

Figure 5-3 illustrates the results summarized in Table 5-3. From this figure it can be concluded that the Gamma distribution is the closest to the actual behavior curve of the application failure data, followed by the Rayleigh distribution. There is a noticeable change in the curve of the actual behavior between the 6th and 12th days, that drops and jumps to a higher value to finally drop to meet the Gamma distribution curve. These changes are explained by the fact that some modifications may have taken place in the third version, and some process decisions such as modifying features that cause issues, changing the developers, etc. have happened. In addition, the usage and environment where the application operated played an important role, as mentioned above, in the behavior of the application because the failure data were collected from different users from all over the world.

5.5.2 Vtok Application

The accumulated Vtok failure data were sorted by version number, and sufficient failure data for two different versions were collected. They will be referred to as Vtok Version 1 and 2 in the following sections.

5.5.2.1 Vtok Version 1

Table 5-4 summarizes the results of the model parameters, RMSE, Ad-R-Square, the estimated cumulative number of failures C, and the MRE, given by each model.

Table 5-4: Vtok Version 1 - Error evaluation and model comparison

Vtok V1	Model parameters	RMSE	Ad R Square	C : Estimated cumulative number of failures or defects	MRE (%)
Weibull	a = 11.26 (9.99, 12.53) b = 2.706 (2.003, 3.41)	2.1151	0.6429	93.69 (70.36, 117)	8.9
Rayleigh	a = 12.05 (9.49, 14.61) b = 2	2.4165	0.5338	105 (78.55, 131.4)	22
Gamma	a = 5.61 (1.71, 8.52) b = 1.89 (0.76, 3.03)	2.0970	0.6490	91.91 (71.06, 112.7)	6.8
S-Shaped	a = 2 b = 7.84 (4.01, 11.66)	2.8689	0.3429	138.7 (74.53, 202.9)	61.2

For Vtok Version 1, 86 failures were collected over 16 weeks. Based on Table 5-4, it can be concluded that Gamma is the distribution that best models the failure data (with parameters: a = 5.618 and b = 1.899), compared to the other distributions. It has the lowest RMSE: 2.0970, the highest Ad-R-Square: 0.6490, and the lowest MRE. The Weibull distribution (with parameters: a = 11.26 and b = 2.706) with a value of RMSE of 2.1151 and Ad-R-Square of 0.6429 is the second best distribution.

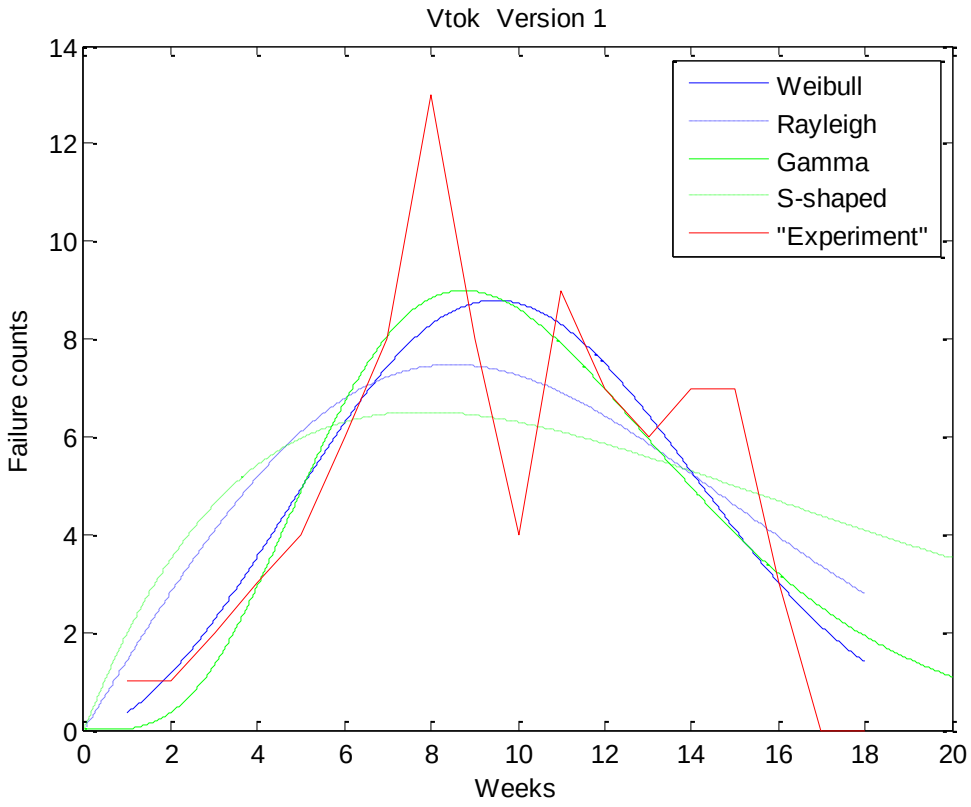


Figure 5-4: Vtok Version 1 - Model comparison

Figure 5-4 illustrates the results summarized in Table 5-4. From this figure, it is noted that the best fit to the actual failure data is the Gamma distribution. A major fall in failure detection, starting from the seventh week until the tenth week, is also worth noting.

5.5.2.2 Vtok Version 2

Table 5-5 summarizes the results of the model parameters, RMSE, Ad-R-Square, the estimated cumulative number of failures C, and the MRE, given by each model.

Table 5-5: Vtok Version 2 - Error evaluation and model comparison

Vtok V2	Model parameters	RMSE	Ad R Square	C : Estimated cumulative number of failures or defects	MRE (%)
Weibull	a = 5.75 (4.63, 6.86) b = 1.79 (1.32, 2.26)	2.3401	0.7386	80.28 (60.58, 99.99)	0.3
Rayleigh	a = 5.59 (4.68, 6.49) b = 2	2.3372	0.7393	76.1 (59.81, 92.39)	4.8
Gamma	a = 2.69 (1.55, 3.83) b = 1.99 (0.89, 3.09)	2.2120	0.7665	80.93 (61.63, 100.2)	1.1
S-Shaped	a = 2 b = 2.95 (2.26, 3.64)	2.3387	0.7390	87.66 (67.39, 107.9)	9.5

For Vtok Version 2, 80 failures were collected over 13 weeks. Based on Table 5-5, it can be concluded that Gamma (with parameters: a = 2.696 and b = 1.996) is the distribution that best models the failure data of this application version. It has the lowest RMSE: 2.2120 and the highest Ad-R-Square: 0.7665. The lowest MRE belongs to the Weibull distribution (with parameters: a = 5.75 and b = 1.793) with a value of 0.3%, but based on the other evaluation criteria it is the second best distribution that models the data with an Ad-R-Square value of 0.7386 and an RMSE of 2.3401. According to the Gamma model distribution, the estimated total number of defects in the worst scenario is 100.

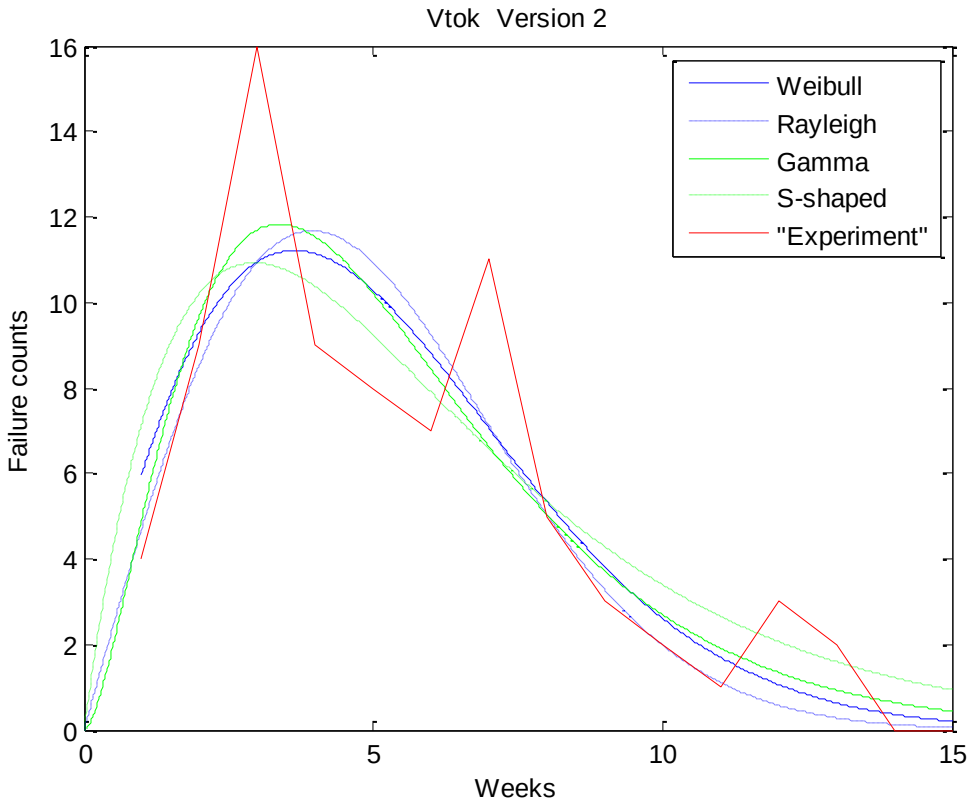


Figure 5-5 : Vtok Version 2 - Model comparison

Figure 5-5 illustrates the results summarized in Table 5-5. It can be concluded that the Gamma distribution adequately models the failure data. It is to be noted that a small "burst" of failures occurred in the seventh week, followed by a steady decrease.

5.5.3 Windows Phone Application

As mentioned earlier, when plotted on the real time scale, the failure data of this application is highly fluctuating, and the time to event models could not adequately describe the data. Two time scales are adopted in the following: the failure data were first grouped by weekly periods, and then grouped by monthly periods. In each case, the same modeling previously carried out is performed again. Only the results of the Weibull and Gamma distributions are presented because, for the case of the S-shaped and Rayleigh distributions, the numerical schemes become instable and give unreasonable values for

the optimum parameters, indicating that they are not suited to adequately model the failure data. They were, therefore, discarded.

5.5.3.1 Windows Phone Application in Weeks

For the Windows phone application, 1957 failures were collected over 6 months and one week, namely 26 weeks and a fraction of the 27th week. Table 5-6 summarizes the model parameters, results of RMSE, Ad-R-Square, the estimated cumulative number of failures C, and the MRE, given by each model. It can be concluded that the Weibull distribution (with parameters: a = 22.11 and b = 6.248) performs better than Gamma (with parameters: a = 29.64 and b = 0.724) but they do not differ markedly in modeling the failure data.

Table 5-6: Windows phone application (per weeks) - Error evaluation and model comparison

Windows phone application	Model parameters	RMSE	Ad R Square	C : Estimated cumulative number of failures or defects	MRE (%)
Weibull	a = 22.11 (21.09, 23.14) b = 6.24 (4.47, 8.02)	44.298	0.611	1722 (1315, 2130)	12
Gamma	a = 29.64 (10.49, 48.7) b = 0.72 (0.24, 1.20)	47.542	0.552	1721 (1245, 2198)	12.05

Figure 5-6 confirms the results summarized in Table 5-6. It is to be noted that, even portioned in weeks, the Windows phone application failure data are still not smooth, but the general trend is reproduced by the two models.

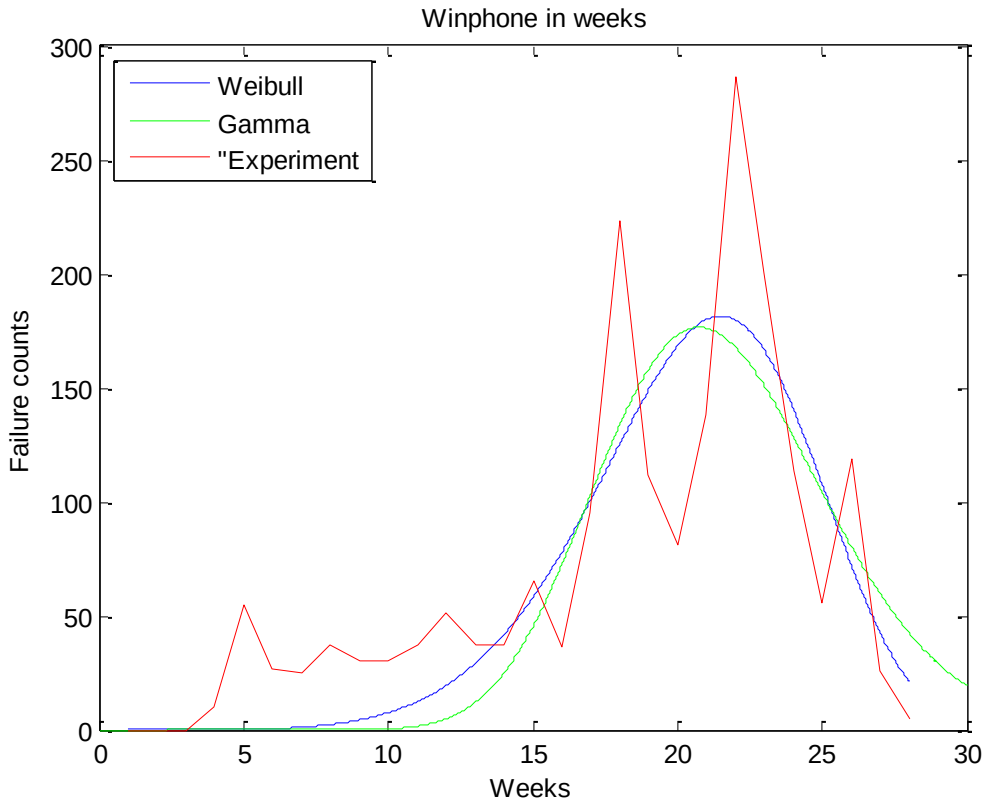


Figure 5-6: Windows phone application failure data per week - Model comparison

5.5.3.2 Windows Phone Application in Months

A further grouping of the Windows phone application failure data in monthly periods and the above analysis was then performed. Table 5-7 summarizes the results of the model parameters, RMSE, Ad-R-Square, the estimated cumulative number of failures C, and the MRE, given by each model. Based on this table, it can be concluded that again, the Weibull model distribution (with parameters: a = 5.20 and b = 5.42) performs better than Gamma (with parameters: a = 25.48 and b = 0.196).

Table 5-7: Windows phone application (per months) - Error evaluation and model comparison

Windows phone application	Model parameters	RMSE	Ad R Square	C : Estimated cumulative number of failures or defects	MRE (%)
Weibull	a = 5.20 (4.94, 5.46) b = 5.42 (3.95, 6.88)	64.7462	0.9363	1831 (1420, 2243)	6.43
Gamma	a = 25.48 (2.74,48.21) b = 0.19 (0.01, 0.37)	106.89	0.8264	1767 (1081, 2454)	9.7

Figure 5-7 illustrates the results summarized in Table 5-7. It can be concluded that the Weibull distribution adequately models the failure data.

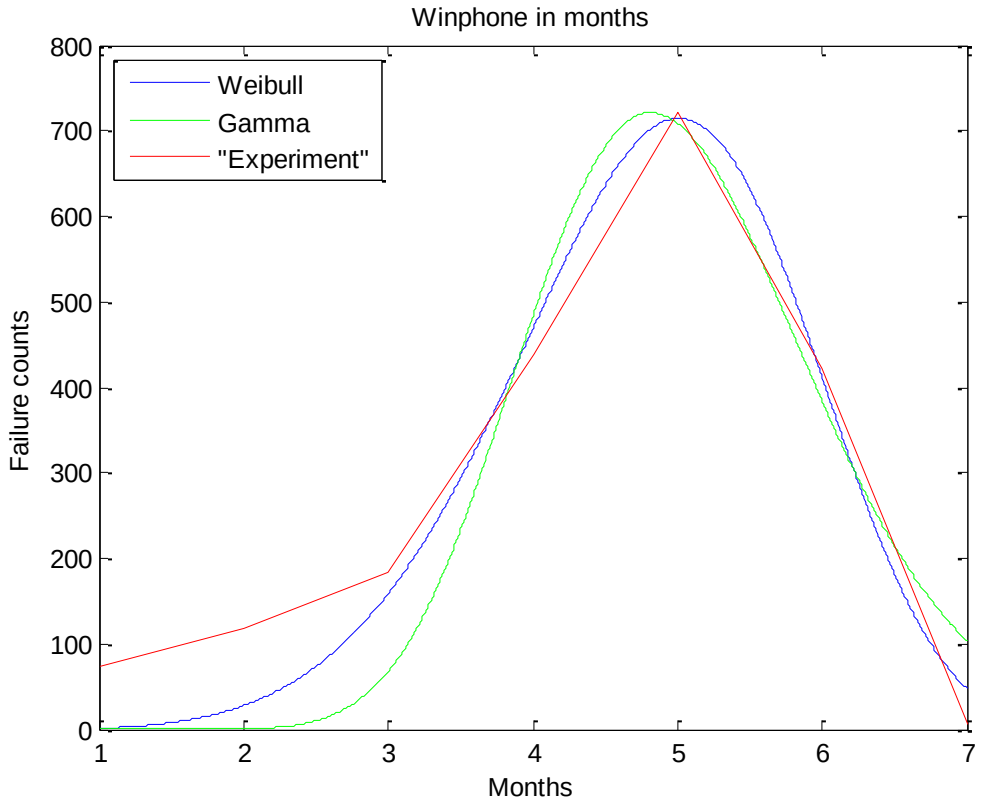


Figure 5-7: Windows phone application failure data per month - Model comparison

5.6 Discussion

The first contribution of this study is that, in applying the most used traditional SRGMs to smartphone applications failure data, we could conclude that those models failed to fit

the data on the basis of goodness-of-fit tests, and a meticulous failure time model (i.e. the input data are the exact failure occurrence times) is still needed. For these experiments, we first used the data collected from our personal device, without paying attention to the different versions of the applications. The other factors such as the region, the OS version, or the way the application was used are irrelevant since the data are collected from only one device.

As a second step, we collected data from all over the world and divided them into different versions, and grouped them into different time periods (days, weeks, and months). Each application version failure data, when plotted in time periods, shows the same pattern: an early "burst of failures", likely due to the most evident defects, followed by a steep decrease in failure rate. We first tried several non-linear distributions to better fit the failure data, and after numerous experiments, we found that the observed behaviour is better modeled by the Weibull or Gamma distributions, and therefore the answer to the research question 4 raised in the introductory chapter is provided. Based on this observation, we therefore selected these two distributions to study the reliability of smartphone applications and we chose two other famous particular cases of the two distributions, which are the Rayleigh and the S-Shaped distributions.

We found that the results are different from one version to another of the same application, which can be explained by the fact that the application is used differently from one region to another and from one user to another. In addition, the version of the OS plays a role in the behavior or reliability of the application. Moreover, the modifications made to the application from one version to another have an impact on the performance, reliability, and usability, etc.

Tables 5-8 and 5-9 are compilations of all model parameters for each application, along with the predicted or estimated T_{max}, and the expected proportion $\left(\frac{Y(t=T_{max})}{C}\right)$ of encountered failures by T_{max} . The last quantities are calculated using equations (5.4) and (5.12) for T_{max} and equations (5.8) and (5.17) for $\left(\frac{Y(t=T_{max})}{C}\right)$. The expected proportion $\left(\frac{Y(t=T_{max})}{C}\right)$ of encountered failures by T_{max} can only be estimated, due to the unknown total number of failures C, as its value depends on each adopted model. The

comparison of estimated and observed T_{max} is satisfactory. The following comments can be drawn from these tables:

1- As the parameters are given, along with their 95% confidence intervals, it is to be noted that parameter b of the Weibull distribution, which is fixed to the value b = 2 for the particular case of Rayleigh distribution, has confidence intervals that include the value b = 2. The same can be noted for the parameter a of the Gamma distribution, which is fixed to the value a = 2 in the case of the S-shaped model distribution. But most of the time, the general distribution models fit better the failure data, than the particular cases. For example, the Skype application, for the 3 versions, we can conclude that the Weibull parameter b is always close to 2, which is the Rayleigh distribution. Besides that, for the Vtok applications, the Gamma distribution was the best for both versions, with a parameter a close to 2 for the second version, but greater than 2 for the first version. Thus, in this case, for the particular choice a = 2, the S-Shaped distribution is not a good model for this application.

2- In each application version, the model distributions are in fact distinguished by tiny differences in the RMSE and Ad-R square. Nevertheless, we can conclude that one distribution does not fit all the data of a given application.

3- Similar to the famous 40% rule of the Rayleigh distribution, independent of any application, the S-shaped distribution has an attractive 26.4% rule. This means that by T_{max} , only 26.4% of the defects in a smartphone application will be uncovered. This can be tested on larger datasets and across many applications. However, the highest percent is 47% with the Weibull distribution applied to Skype version 1.

4- For the Windows phone application, the estimated and observed T_{max} are in good agreement and only the Weibull and Gamma distributions can model the data because the value of parameter b for Weibull and that of parameter a for Gamma, are greater than 2.

5- It can be noted that the Gamma distribution, along with its particular S-Shaped case, model more frequently the failure data.

Table 5-8: Skype - The parameter values of the model distributions

	Skype Version 1	Skype Version 2	Skype Version 3
Weibull	a = 6.179 (5.262, 7.096) b = 2.826 (1.811, 3.84) c = 50.54 (34.51, 66.58) observed T_{max}= 6 Estimated T_{max}= 5.98 Estimated $\left(\frac{Y(t=T_{max})}{\quad}\right) = 47\%$	a = 6.305 (4.564, 8.046) b = 1.457 (1.047, 2.866) c = 116.4 (85.27, 147.5) observed T_{max}= 3	a = 8.734 (7.201, 10.27) b = 1.941 (1.447, 2.436) c = 107.7 (81.98, 133.3) observed T_{max}= 4
Rayleigh	a = 6.618 (5.017, 8.218) b = 2 c = 58.33 (39.9, 76.77) observed T_{max}= 6 Estimated T_{max}= 4.68 Estimated $\left(\frac{Y(t=T_{max})}{\quad}\right) =$	a = 5.965 (4.733, 7.196) b = 2 c = 99.38 (72.31, 126.4) observed T_{max}= 3 Estimated T_{max}= 4.21	a = 8.69 (7.354, 10.03) b = 2 c = 106.3 (84.97, 127.6) observed T_{max}= 4 Estimated T_{max}= 6.14 Estimated
Gamma	a = 6.141 (1.842, 10.44) b = 0.975 (0.2143, 1.736) c = 51.81 (34.32, 69.31) observed T_{max}= 6 Estimated T_{max}= 5.01	a = 1.812 (0.972, 2.652) b = 3.366 (0.982, 5.75) c = 118.2 (85.42, 151.1) observed T_{max}= 3 Estimated T_{max}= 2.73	a = 2.965 (1.662, 4.268) b = 2.763 (1.184, 4.342) c = 109.8 (83.25, 136.4) observed T_{max}= 4
S-shaped	a = 2 b = 3.767 (1.909, 5.624) c = 67.43 (36.18, 98.67) observed T_{max}= 6 Estimated T_{max}= 3.76 Estimated $\left(\frac{Y(t=T_{max})}{\quad}\right) = 26.4\%$	a = 2 b = 2.937 (2.302, 3.572) c = 114.4 (90.36, 138.5) observed T_{max}= 3 Estimated T_{max}= 2.93	a = 2 b = 4.738 (3.454, 6.022) c = 124.1 (92.33, 155.8) observed T_{max}= 4 Estimated T_{max}= 4.73

Table 5-9 : Vtok - The parameter values of the model distributions

	Vtok Version 1	Vtok Version 2
Weibull	a = 11.26 (9.993, 12.53) b = 2.706 (2.003, 3.41) c = 93.69 (70.36, 117) observed T_{max}= 8 Estimated T_{max}= 9.40 Estimated $\left(\frac{Y(t=T_{max})}{c}\right) = 46\%$	a = 5.75 (4.636, 6.865) b = 1.793 (1.327, 2.26) c = 80.28 (60.58, 99.99) observed T_{max}= 3 Estimated T_{max}= 3.64 Estimated $\left(\frac{Y(t=T_{max})}{c}\right) = 39\%$
Rayleigh	a = 12.05 (9.493, 14.6) b = 2 c = 105 (78.55, 131.4) observed T_{max}= 8 Estimated T_{max}= 8.52 Estimated $\left(\frac{Y(t=T_{max})}{c}\right) = 40\%$	a = 5.592 (4.687, 6.497) b = 2 c = 76.1 (59.81, 92.39) observed T_{max}= 3 Estimated T_{max}= 3.95 Estimated $\left(\frac{Y(t=T_{max})}{c}\right) = 40\%$
Gamma	a = 5.618 (1.712, 8.523) b = 1.899 (0.7642, 3.034) c = 91.91 (71.06, 112.7) observed T_{max}= 8 Estimated T_{max}= 8.76 Estimated $\left(\frac{Y(t=T_{max})}{c}\right) = 37.8\%$	a = 2.696 (1.556, 3.836) b = 1.996 (0.8937, 3.098) c = 80.93 (61.63, 100.2) observed T_{max}= 3 Estimated T_{max}= 3.38 Estimated $\left(\frac{Y(t=T_{max})}{c}\right) = 31\%$
S-shaped	a = 2 b = 7.841 (4.018, 11.66) c = 138.7 (74.53, 202.9) observed T_{max}= 8 Estimated T_{max}= 7.84 Estimated $\left(\frac{Y(t=T_{max})}{c}\right) = 26.4\%$	a = 2 b = 2.953 (2.26, 3.646) c = 87.66 (67.39, 107.9) observed T_{max}= 3 Estimated T_{max}= 2.95 Estimated $\left(\frac{Y(t=T_{max})}{c}\right) = 26.4\%$

Table 5-10: Windows phone application - Parameter values of the model distributions

	Windows phone application in weeks	Windows phone application in months
Weibull	a = 22.11 (21.09, 23.14) b = 6.248 (4.474, 8.021) c = 1722 (1315, 2130) observed T_{max}= 22 Estimated T_{max}= 21.5 Estimated $\left(\frac{Y(t=T_{max})}{c}\right) = 56.83\%$	a = 5.204 (4.94, 5.469) b = 5.42 (3.953, 6.887) c = 1831 (1420, 2243) observed T_{max}= 5 Estimated T_{max}= 5.01 Estimated $\left(\frac{Y(t=T_{max})}{c}\right) = 55.76\%$
Gamma	a = 29.64 (10.49, 48.7 b = 0.7247 (0.2417, 1.208) c = 1721 (1245, 2198) observed T_{max}= 22 Estimated T_{max}= 20.75 Estimated $\left(\frac{Y(t=T_{max})}{c}\right) = 45\%$	a = 25.48 (2.743, 48.21) b = 0.1969 (0.01633, 0.3775) c = 1767 (1081, 2454) observed T_{max}= 5 Estimated T_{max}= 4.82 Estimated $\left(\frac{Y(t=T_{max})}{c}\right) = 44.65\%$

5.7 Threats to Validity:

As studying the reliability of smartphone applications is a new approach and no previous work or techniques were suggested, some limitations can become a threat to our approach's validation, such as:

- The data collection was a challenge and not enough data were collected due to privacy policies from smartphone application developers and friends who believed that from the crash report of their applications one can control their phone. Therefore, the limited datasets of our investigation make the generalization of the results difficult. Moreover, predicting the reliability should be in the development phase but because of lack of data during this stage, we used the data collected after release.
- Experimentation with more elaborate data and other model distributions can be investigated.
- Data from different platforms, such as Android and its users, will be useful to obtain more accurate results.

- The data were collected during the operational phases. Also we do not have an idea about the early development stages of the application and its architecture as to whether it is complex or simple. In addition, we do not know how the application was used and under which conditions. All of these factors may create more defects than anticipated.
- Only a few versions were used in this study, more versions of the applications would help to provide a better idea as to whether the versions' failure data are independent of each other, or correlated in a particular way.
- It is not guaranteed that the modifications made to the application from one version to another would not introduce more bugs or complexity. Moreover, it cannot be assured that the correction of old bugs would not result in other, newer bugs.

5.8 Summary

The collected failure data of several smartphone application versions were analyzed using the two model distributions, Weibull and Gamma, and their particular cases: the Rayleigh and the S-shaped distributions, respectively. Each model distribution provided an estimation of the expected cumulative number of failures (or equivalently, the number of defects) in each smartphone application version. The results show that not only one distribution is useful for the different versions of the same application, but, based on the evaluation criteria, one distribution can give a better prediction for one version than when applied to another. Nevertheless, among the cases studied the Gamma distribution and its particular case, the S-shaped distribution, are more frequently suited, and seem to perform better than the Weibull and its particular case, the Rayleigh distribution. Further investigation with more elaborated failure data basis must be pursued in order to rank the performances of these two model distributions accurately.

Although the distributions did not perfectly fit the data, they were useful in predicting the cumulative number of failures at the end of each version, with a calculated error. The 40% rule, issued from the Rayleigh distribution, often used by software managers to estimate the residual defects in a desktop application, has been extended to the Weibull

and Gamma distributions in the case of smartphone applications. The proposed approach in this chapter, namely the use of distributions to model the collected failure data of a smartphone application versions, suffers greatly from the above mentioned size effect. However, we believe that the main behavior of the failure event in smartphone applications is captured by the chosen distributions.

Concerning research question 4, raised in the introductory chapter: "*On a practical basis, how could a software manager model the daily failure data received from complaining users of a particular smartphone application to get some insight and understanding that can help in decisions? Is there a distribution that can model the failure data?"*, as evidenced by all of the experiments carried out in this chapter, the answer is that both the Weibull and the Gamma distributions can be used adequately to model the failure data of an application by sorting this data by application version number and grouping it into appropriate time periods.

Finally, there still exists the goal, raised in research question 1 in Chapter 1, to come up with a new time-to-failure model, i.e. taking as input the exact failure occurrence times, which will assess and predict the reliability of applications implemented in smartphone devices, or operating under diverse environmental conditions and usage profiles and that will be of valued help for software managers in the mobile area. This is still an unanswered question. We believe that this goal cannot be achieved by a simple model equation, as there are many interacting variables affecting the reliability of a mobile application such as: the size of the application, its modular structure or complexity, the hardware limitations of the devices, the severity of the encountered failures, the network condition, the operating system used, the uncertainty in operational profile, the other unknown simultaneously running applications, etc. The right approach would have to take into account of all these interacting factors. Neural networks and fuzzy-logic simulations would be appropriate for this investigation.

Chapter 6

6 Conclusions

This chapter summarizes the conclusions drawn from our research and suggests possible directions for future work.

The investigation of smartphone application reliability through the use of well-known available reliability growth models, suited primarily to desktop applications, was twofold: (i) highlight the versatile nature of mobile applications, their dynamic configuration, unknown operational profile, and varying execution conditions in contrast to the static and stable desktop applications, (ii) stress the need for the design of new reliability models suited for mobile applications, that take into account the inherent versatility of such applications.

6.1 Conclusions and Perspectives

In order to answer the first research question raised in the introductory chapter, namely, *"…is it possible to build a mathematical model that helps software managers assess and predict the reliability of applications implemented in smartphone devices and working under diverse operational environments and usage profiles?"* we began by examining the related question of the applicability of the available desktop/laptop software reliability models to the case of mobile applications. Therefore, to answer the focused research question 3, raised in the introduction, namely "… *how do the existing successful reliability models, used to assess the desktop/laptops applications, perform when applied to the mobile area? Will these models still be of useful help to smartphone applications managers, as they were in the desktop/laptop case? Will there be a need to change them?"* we selected, as a first step, three of the most used models that are known for their efficiency in the desktop area: the NHPP, Musa-Basic, and Musa-Okumoto models. These models, as well as reliability concepts, are presented in Chapter 3. They use as their input the failure occurrence times. We used two iPhone applications, Skype and Vtok, used and tested differently in order to evaluate the models under different conditions, and one Windows phone application that we kept confidential due to the company's confidentiality policies. It turned out that none of the selected SRGMs were

able to account for the observed failure data satisfactorily. This investigation was carried out in Chapter 4 and answered this research question.

As each reliability model relies on its assumptions, the failure of a model is an indication of the inadequacy of its assumptions. This is formulated by research question 2, namely: "*Are the basic assumptions needed to build the reliability models suited to desktop/laptop applications still valid in the case of smartphone applications? How do we adapt them to the mobile area?* " and answered in detail in Sections 2.4 and 4.3.

After noting the failure of the above models, the research question 4, namely: "*On a practical basis, how could a software manager model the daily failure data received from complaining users of a particular smartphone application to get some insight and understanding that can help in decisions? Is there a distribution that can model the failure data?"* was logically asked. To this end, we tested many non-linear models based on the nature of the failure data and found that the Weibull and Gamma distributions were best suited to model the collected failure data of each application, after sorting its data by application version number and grouping it into different time periods. Chapter 5 was entirely devoted to answering this research question.

Another related question to the above mentioned primary question is whether the differences in hardware and software between desktops/laptops and smartphone devices, as well as their highly varying operational conditions, could affect their reliability. This was detailed in Chapter 2, which has also presented an overview of the mobile world.

Our study also highlighted the causes of the failure of the above models and the need for a meticulous Software Reliability Growth Model for smartphone applications; this is because the existing software reliability approaches were developed for traditional stationary desktop software applications that are static and stable during their execution, which is not the case for smartphone applications that have unknown operational profiles, highly dynamic configurations, and changing execution conditions. On a continuous background, the smartphone failures occur in relatively short bursts, from time to time, which explain the abrupt changes in the observed cumulative failure data curves. This particular feature cannot be accommodated by the selected SRGMs. Thus, in order to evaluate the reliability of smartphone applications, new models, principles, and tools are

needed, in order to incorporate the underlying uncertainties of such applications. In an attempt to make further progress, and assuming the above mentioned uncertainties and many other unknown factors concerning the hardware and software used by each application, two common distributions, Weibull and Gamma, were used to model the collected failure data after sorting it by application version number and grouping into varying time periods. The main features of the observed failure behavior of these applications are captured by the two distributions. Nevertheless, due to the lack of published smartphone failure data for secrecy reasons, we relied on our own limited resources and, therefore, our approach suffers from the small sizes of the collected failure data, preventing us from devising a generalization of the obtained results.

6.2 Future Work

An immediate future work will be to focus on analyzing more in depth those selected (and other) SRGMs, and to attempt to modify the closest one to the data, to then adapt it to smartphone applications by altering its basic assumptions, taking into account the "mobile" feature of the applications. Moreover, we will determine if we need to have a specific model for each type of application, or if one model is applicable to all of the categories of smartphone applications, taking into consideration the severity of the failure, the size and the modular complexity of the application, etc. using machine learning and more advanced algorithms. Successful examples of the application of machine learning techniques can be found in [43], [44] and [45].

The availability of hundreds of software reliability models makes it difficult for the software manager to select among them the most adequate to deal with the reliability of a specific smartphone application. Nevertheless, the selection should be based on simple criteria such as the "predictive ability" of a model. It is, therefore, our aim to carry out a comparative study of many existing reliability models applied to numerous smartphone applications (recent collected data) and to choose the model that gives the least error across these applications.

Another immediate future work will be to apply the two model distributions, Weibull and Gamma, to further collected failure data of other applications, and to assess their respective performances.

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Appendix A: Collected Failure Data for Skype, Vtok, and Windows Phone Applications

We report in this appendix our collected failure data for the three chosen smartphone applications: Skype, Vtok, and the Windows phone application.

Failure Data of the Skype Application

Date and Time	Failure Date and Time	Time Between Failure (TBF)	Time to event (Cumulative time)	Time to Failure in hours (TTF)	Normalised values (TTF)	TBF in Hours
01/11/2011 00:00	02/11/2011 13:54	37:54:17	37:54:17	37,9	0	37,9
02/11/2011 13:54	03/11/2011 14:27	24:32:54	62:27:11	62,45	0,00272472	24,55
03/11/2011 14:27	05/11/2011 14:51	48:24:23	110:51:34	110,86	0,008097579	48,41
05/11/2011 14:51	06/11/2011 18:39	27:48:18	138:39:52	138,66	0,011183006	27,81
06/11/2011 18:39	16/11/2011 17:03	238:23:22	377:03:14	377,05	0,037641092	238,39
16/11/2011 17:03	17/11/2011 13:56	20:53:36	397:56:50	397,95	0,039960711	20,89
17/11/2011 13:56	18/11/2011 15:50	25:53:19	423:50:09	423,84	0,042834153	25,89
18/11/2011 15:50	22/11/2011 21:05	101:15:35	525:05:44	525,1	0,054072652	101,26
22/11/2011 21:05	03/01/2012 21:35	1008:29:30	1533:35:14	1533,59	0,166001487	1008,49
03/01/2012 21:35	08/01/2012 14:16	112:41:18	1646:16:32	1646,28	0,178508563	112,69
08/01/2012 14:16	13/01/2012 12:27	118:10:38	1764:27:10	1764,45	0,191623844	118,18
13/01/2012 12:27	14/01/2012 18:16	29:49:02	1794:16:12	1794,27	0,194933464	29,82
14/01/2012 18:16	15/01/2012 09:17	15:01:26	1809:17:38	1809,29	0,196600482	15,02
15/01/2012 09:17	21/01/2012 10:19	145:01:59	1954:19:37	1954,33	0,212697972	145,03
21/01/2012 10:19	21/01/2012 10:30	0:10:45	1954:30:22	1954,51	0,21271795	0,18
21/01/2012 10:30	24/03/2012 14:39	1516:08:53	3470:39:15	3470,65	0,380989112	1516,15
24/03/2012 14:39	02/04/2012 18:11	219:32:41	3690:11:56	3690,2	0,405356211	219,54
02/04/2012 18:11	23/04/2012 11:19	497:07:15	4187:19:11	4187,32	0,46052985	497,12
23/04/2012 11:19	26/04/2012 14:44	75:25:20	4262:44:31	4262,74	0,468900456	75,42
26/04/2012 14:44	30/04/2012 15:19	96:35:00	4359:19:31	4359,33	0,479620648	96,58
30/04/2012 15:19	30/04/2012 21:23	6:03:44	4365:23:15	4365,39	0,480293226	6,06
30/04/2012 21:23	01/05/2012 21:31	24:08:38	4389:31:53	4389,53	0,482972442	24,14
01/05/2012 21:31	03/05/2012 12:11	38:39:47	4428:11:40	4428,19	0,487263182	38,66
03/05/2012 12:11	03/05/2012 13:58	1:46:52	4429:58:32	4429,98	0,487461848	1,78
03/05/2012 13:58	03/05/2012 16:36	2:37:38	4432:36:10	4432,6	0,487752633	2,63
03/05/2012 16:36	03/05/2012 18:29	1:53:30	4434:29:40	4434,49	0,487962398	1,89
03/05/2012 18:29	05/05/2012 19:31	49:02:03	4483:31:43	4483,53	0,493405179	49,03
05/05/2012 19:31	05/05/2012 19:34	0:02:31	4483:34:14	4483,57	0,493409618	0,04
05/05/2012 19:34	05/05/2012 23:54	4:20:31	4487:54:45	4487,91	0,4938913	4,34
05/05/2012 23:54	06/05/2012	4:07:16	4492:02:01	4492,03	0,494348564	4,12

06/05/2012	06/05/2012 09:51	5:49:52	4497:51:53	4497,86	0,494995616	5,83
06/05/2012 09:51	12/05/2012 15:01	149:10:00	4647:01:53	4647,03	0,511551481	149,17
12/05/2012 15:01	12/05/2012 15:58	0:56:53	4647:58:46	4647,98	0,511656918	0,95
12/05/2012 15:58	12/05/2012 20:01	4:03:06	4652:01:52	4652,03	0,512106414	4,05
12/05/2012 20:01	14/07/2012 13:47	1505:45:52	6157:47:44	6157,8	0,679226646	1505,76
14/07/2012 13:47	11/10/2012 12:37	2134:50:10	8292:37:54	8941,25	0,988152185	2134,84
11/10/2012 12:37	07/11/2012 13:15	648:37:08	8941:15:02	8941,25	0,988152185	648,62
07/11/2012 13:15	11/11/2012 15:18	98:03:42	9039:18:44	9039,31	0,999035527	98,06
11/11/2012 15:18	11/11/2012 23:59	8:41:15	9047:59:59	9048	1	8,69

Failure Data of the Vtok Application

Date and Time	Failure Date and Time	Time Between Failure (TBF)	Time to event (Cumulative time)	Time to Failure in hours (TTF)	Normalised values (TTF)	TBF in Hours
19/09/2012 00:00	19/09/2012 13:11	13:11:46	13:11:46	13,2	0	13,2
19/09/2012 13:11	19/09/2012 20:13	7:01:47	20:13:33	20,23	0,004342723	7,03
19/09/2012 20:13	20/09/2012 09:31	13:18:10	33:31:43	33,53	0,012558685	13,3
20/09/2012 09:31	20/09/2012 21:58	12:26:48	45:58:31	45,98	0,020249568	12,45
20/09/2012 21:58	21/09/2012 14:05	16:07:27	62:05:58	62,1	0,030207561	16,12
21/09/2012 14:05	23/09/2012 18:43	52:37:30	114:43:28	114,72	0,062713121	52,63
23/09/2012 18:43	25/09/2012 09:15	38:32:27	153:15:55	153,27	0,086527057	38,54
25/09/2012 09:15	25/09/2012 11:10	1:54:17	155:10:12	155,17	0,087700766	1,9
25/09/2012 11:10	27/09/2012 10:37	47:27:20	202:37:32	202,63	0,117018779	47,46
27/09/2012 10:37	30/09/2012 10:24	71:46:48	274:24:20	274,41	0,161360267	71,78
30/09/2012 10:24	02/10/2012 09:23	46:58:50	321:23:10	321,39	0,190381764	46,98
02/10/2012 09:23	03/10/2012 09:29	24:06:37	345:29:47	345,5	0,205275513	24,11
03/10/2012 09:29	03/10/2012 13:12	3:42:16	349:12:03	349,2	0,207561156	3,7
03/10/2012 13:12	10/10/2012 10:36	165:24:17	514:36:20	514,61	0,309741784	165,4
10/10/2012 10:36	10/10/2012 12:17	1:41:13	516:17:33	516,29	0,31077959	1,69
10/10/2012 12:17	10/10/2012 15:05	2:47:45	519:05:18	519,09	0,312509266	2,8
10/10/2012 15:05	10/10/2012 18:09	3:04:11	522:09:29	522,16	0,314405733	3,07
10/10/2012 18:09	10/10/2012 20:35	2:25:43	524:35:12	524,59	0,315906845	2,43
10/10/2012 20:35	11/10/2012 07:34	10:59:30	535:34:42	535,58	0,322695824	10,99
11/10/2012 07:34	11/10/2012 10:35	3:01:07	538:35:49	538,6	0,324561404	3,02
11/10/2012 10:35	11/10/2012 16:01	5:25:12	544:01:01	544,02	0,327909563	5,42
11/10/2012 16:01	11/10/2012 19:30	3:29:12	547:30:13	547,5	0,330059303	3,49
11/10/2012 19:30	12/10/2012 09:14	13:44:41	561:14:54	561,25	0,338553249	13,74
12/10/2012 09:14	12/10/2012 10:17	1:02:09	562:17:03	562,28	0,339189523	1,04
12/10/2012 10:17	12/10/2012 13:54	3:37:39	565:54:42	565,91	0,341431925	3,63

12/10/2012 13:54	13/10/2012 01:11	11:16:45	577:11:27	577,19	0,348400049	11,28
13/10/2012 01:11	15/10/2012 06:04	52:52:36	630:04:03	630,07	0,381066222	52,88
15/10/2012 06:04	15/10/2012 21:55	15:51:54	645:55:57	645,93	0,390863603	15,87
15/10/2012 21:55	16/10/2012 22:48	24:52:47	670:48:44	670,81	0,406233012	24,88
16/10/2012 22:48	22/10/2012	131:29:43	802:18:27	802,31	0,487466024	131,5
22/10/2012	22/10/2012 21:06	10:47:38	813:06:05	813,1	0,494131455	10,79
22/10/2012 21:06	22/10/2012 23:13	2:07:38	815:13:43	815,23	0,495447245	2,13
22/10/2012 23:13	23/10/2012 08:27	9:13:23	824:27:06	824,45	0,501142822	9,22
23/10/2012 08:27	23/10/2012 15:26	6:59:32	831:26:38	831,44	0,505460835	6,99
23/10/2012 15:26	24/10/2012 00:31	9:04:22	840:31:00	840,52	0,511069928	9,07
24/10/2012 00:31	28/10/2012 05:56	101:25:30	941:56:30	941,94	0,573721275	101,43
28/10/2012 05:56	29/10/2012 10:09	28:12:46	970:09:16	970,15	0,591147764	28,21
29/10/2012 10:09	30/10/2012 15:40	29:31:02	999:40:18	999,67	0,609383494	29,52
30/10/2012 15:40	31/10/2012 18:43	27:03:34	1026:43:52	1026,73	0,62609958	27,06
31/10/2012 18:43	31/10/2012 23:49	5:06:01	1031:49:53	1031,83	0,629250062	5,1
31/10/2012 23:49	01/11/2012 15:24	15:34:34	1047:24:27	1047,41	0,638874475	15,58
01/11/2012 15:24	01/11/2012 18:35	3:11:21	1050:35:48	1050,6	0,64084507	3,19
01/11/2012 18:35	02/11/2012 13:54	19:19:06	1069:54:54	1069,92	0,652779837	19,32
02/11/2012 13:54	02/11/2012 14:54	0:59:54	1070:54:48	1070,91	0,653391401	1
02/11/2012 14:54	02/11/2012 18:01	3:06:46	1074:01:34	1074,03	0,655318755	3,11
02/11/2012 18:01	03/11/2012 21:50	27:49:16	1101:50:50	1101,85	0,672504324	27,82
03/11/2012 21:50	04/11/2012 23:09	25:18:47	1127:09:37	1127,16	0,688139362	25,31
04/11/2012 23:09	05/11/2012 16:02	16:52:28	1144:02:05	1144,03	0,698560662	16,87
05/11/2012 16:02	05/11/2012 17:48	1:46:01	1145:48:06	1145,8	0,699654065	1,77
05/11/2012 17:48	06/11/2012 13:23	19:35:51	1165:23:57	1165,4	0,711761799	19,6
06/11/2012 13:23	06/11/2012 19:02	5:38:03	1171:02:00	1171,03	0,715239684	5,63
06/11/2012 19:02	06/11/2012 19:29	0:27:42	1171:29:42	1171,49	0,715523845	0,46
06/11/2012 19:29	06/11/2012 20:26	0:57:01	1172:26:43	1172,45	0,716116877	0,95
06/11/2012 20:26	06/11/2012 20:45	0:18:19	1172:45:02	1172,75	0,716302199	0,31
06/11/2012 20:45	07/11/2012 10:01	13:16:26	1186:01:28	1186,02	0,724499629	13,27
07/11/2012 10:01	07/11/2012 12:17	2:15:44	1188:17:12	1188,29	0,725901903	2,26
07/11/2012 12:17	07/11/2012 12:20	0:03:24	1188:20:36	1188,34	0,72593279	0,06
07/11/2012 12:20	07/11/2012 13:21	1:01:17	1189:21:53	1189,36	0,726562886	1,02
07/11/2012 13:21	07/11/2012 13:41	0:19:45	1189:41:38	1189,69	0,726766741	0,33
07/11/2012 13:41	08/11/2012 10:45	21:04:00	1210:45:38	1210,76	0,739782555	21,07
08/11/2012 10:45	08/11/2012 13:19	2:33:49	1213:19:27	1213,32	0,741363973	2,56
08/11/2012 13:19	08/11/2012 13:54	0:34:33	1213:54:00	1213,9	0,741722263	0,58
08/11/2012 13:54	08/11/2012 15:24	1:30:21	1215:24:21	1215,41	0,742655053	1,51
08/11/2012 15:24	08/11/2012 20:40	5:15:39	1220:40:00	1220,67	0,745904374	5,26
08/11/2012 20:40	09/11/2012 08:43	12:03:38	1232:43:38	1232,73	0,753354337	12,06
09/11/2012 08:43	09/11/2012 10:24	1:41:04	1234:24:42	1234,41	0,754392142	1,68

09/11/2012 10:24	11/11/2012 09:30	47:05:41	1281:30:23	1281,51	0,783487769	47,09
11/11/2012 09:30	11/11/2012 20:44	11:14:05	1292:44:28	1292,74	0,790425006	11,23
11/11/2012 20:44	11/11/2012 21:32	0:48:06	1293:32:34	1293,54	0,790919199	0,8
11/11/2012 21:32	12/11/2012 16:50	19:17:26	1312:50:00	1312,83	0,802835434	19,29
12/11/2012 16:50	13/11/2012 18:52	26:02:12	1338:52:12	1338,87	0,818921423	26,04
13/11/2012 18:52	17/11/2012 18:18	95:26:19	1434:18:31	1434,31	0,877878676	95,44
17/11/2012 18:18	18/11/2012 07:22	13:03:56	1447:22:27	1447,37	0,88594638	13,07
18/11/2012 07:22	18/11/2012 09:53	2:30:35	1449:53:02	1449,88	0,887496911	2,51
18/11/2012 09:53	18/11/2012 18:04	8:11:38	1458:04:40	1458,08	0,892562392	8,19
18/11/2012 18:04	20/11/2012 18:42	48:37:25	1506:42:05	1506,7	0,922596985	48,62
20/11/2012 18:42	21/11/2012 11:45	17:03:40	1523:45:45	1523,76	0,933135656	17,06
21/11/2012 11:45	22/11/2012 10:40	22:55:12	1546:40:57	1546,68	0,947294292	22,92
22/11/2012 10:40	23/11/2012 18:49	32:08:52	1578:49:49	1578,83	0,967154682	32,15
23/11/2012 18:49	25/11/2012 19:45	48:55:29	1627:45:18	1627,76	0,997380776	48,92
25/11/2012 19:45	25/11/2012 23:59	4:14:41	1631:59:59	1632	1	4,24

Failure Data of the Windows Phone Application

March			
Days	Number of Failures in the Interval	Cumulative Number of Failures	Average Failure Intensity (Number of failures/hour)
1	0	0	0
2	0	0	0
3	0	0	0
4	0	0	0
5	0	0	0
6	0	0	0
7	0	0	0
8	0	0	0
9	0	0	0
10	0	0	0
11	0	0	0
12	0	0	0
13	0	0	0
14	0	0	0
15	0	0	0
16	0	0	0
17	0	0	0
18	0	0	0
19	3	3	0,125
20	2	5	0,083333333
21	5	10	0,208333333

22	12	22	0,5
23	18	40	0,75
24	8	48	0,333333333
25	6	54	0,25
26	5	59	0,208333333
27	3	62	0,125
28	3	65	0,125
29	6	71	0,25
30	3	74	0,125
April			
Days			
1	4	78	0,166666667
2	3	81	0,125
3	4	85	0,166666667
4	2	87	0,083333333
5	5	92	0,208333333
6	2	94	0,083333333
7	3	97	0,125
8	4	101	0,166666667
9	3	104	0,125
10	1	105	0,041666667
11	2	107	0,083333333
12	10	117	0,416666667
13	9	126	0,375
14	8	134	0,333333333
15	4	138	0,166666667
16	1	139	0,041666667
17	2	141	0,083333333
18	3	144	0,125
19	10	154	0,416666667
20	3	157	0,125
21	3	160	0,125
22	3	163	0,125
23	4	167	0,166666667
24	7	174	0,291666667
25	6	180	0,25
26	4	184	0,166666667
27	2	186	0,083333333
28	1	187	0,041666667
29	1	188	0,041666667
30	3	191	0,125

May			
Days			
1	6	197	0,25
2	4	201	0,166666667
3	13	214	0,541666667
4	3	217	0,125
5	3	220	0,125
6	3	223	0,125
7	4	227	0,166666667
8	5	232	0,208333333
9	13	245	0,541666667
10	6	251	0,25
11	16	267	0,666666667
12	8	275	0,333333333
13	4	279	0,166666667
14	5	284	0,208333333
15	14	298	0,583333333
16	3	301	0,125
17	1	302	0,041666667
18	7	309	0,291666667
19	6	315	0,25
20	6	321	0,25
21	10	331	0,416666667
22	2	333	0,083333333
23	2	335	0,083333333
24	4	339	0,166666667
25	8	347	0,333333333
26	8	355	0,333333333
27	6	361	0,25
28	8	369	0,333333333
29	3	372	0,125
30	2	374	0,083333333
June			
Days			
1	2	376	0,083333333
2	9	385	0,375
3	9	394	0,375
4	8	402	0,333333333
5	14	416	0,583333333
6	12	428	0,5
7	5	433	0,208333333

8	8	441	0,333333333
9	9	450	0,375
10	9	459	0,375
11	3	462	0,125
12	2	464	0,083333333
13	3	467	0,125
14	2	469	0,083333333
15	8	477	0,333333333
16	8	485	0,333333333
17	7	492	0,291666667
18	11	503	0,458333333
19	22	525	0,916666667
20	16	541	0,666666667
21	20	561	0,833333333
22	11	572	0,458333333
23	6	578	0,25
24	1	579	0,041666667
25	26	605	1,083333333
26	64	669	2,666666667
27	42	711	1,75
28	42	753	1,75
29	42	795	1,75
30	18	813	0,75
July			
Days			
1	12	825	0,5
2	24	849	1
3	9	858	0,375
4	5	863	0,208333333
5	23	886	0,958333333
6	21	907	0,875
7	15	922	0,625
8	10	932	0,416666667
9	9	941	0,375
10	9	950	0,375
11	12	962	0,5
12	12	974	0,5
13	14	988	0,583333333
14	15	1003	0,625
15	37	1040	1,541666667
16	35	1075	1,458333333

17	25	1100	1,041666667
18	13	1113	0,541666667
19	12	1125	0,5
20	31	1156	1,291666667
21	38	1194	1,583333333
22	62	1256	2,583333333
23	43	1299	1,791666667
24	54	1353	2,25
25	43	1396	1,791666667
26	26	1422	1,083333333
27	20	1442	0,833333333
28	36	1478	1,5
29	31	1509	1,291666667
30	26	1535	1,083333333
August			
Days			
1	25	1560	1,041666667
2	19	1579	0,791666667
3	25	1604	1,041666667
4	38	1642	1,583333333
5	27	1669	1,125
6	23	1692	0,958333333
7	25	1717	1,041666667
8	11	1728	0,458333333
9	11	1739	0,458333333
10	11	1750	0,458333333
11	6	1756	0,25
12	10	1766	0,416666667
13	10	1776	0,416666667
14	6	1782	0,25
15	6	1788	0,25
16	6	1794	0,25
17	12	1806	0,5
18	6	1812	0,25
19	38	1850	1,583333333
20	11	1861	0,458333333
21	8	1869	0,333333333
22	20	1889	0,833333333
23	15	1904	0,625
24	11	1915	0,458333333
25	16	1931	0,666666667

26	19	1950	0,791666667
27	7	1957	0,291666667
28	0	1957	0
29	0	1957	0
30	0	1957	0

The Dataset Grouped Per Version

a) Skype

Version 1 Version 2 Version 3

Days	Number of Failures	Days	Number of Failures	Days	Number of Failures
1	2	1	10	1	1
2	3	2	13	2	4
3	5	3	18	3	7
4	7	4	12	4	15
5	8	5	8	5	12
6	13	6	7	6	9
7	5	7	11	7	5
8	3	8	10	8	9
9	1	9	8	9	7
10	5	10	6	10	10
11	2	11	4	11	8
12	0	12	0	12	6
				13	4
				14	3
				15	3
				16	0

b) Vtok

Version 1 Version 2

Week	Number of Failures	Week	Number of Failures
1	1	1	4
2	1	2	9
3	2	3	16
4	3	4	9
5	4	5	8
6	6	6	7
7	8	7	11
8	13	8	5
9	8	9	3
10	4	10	2
11	9	11	1
12	7	12	3
13	6	13	2
14	7	14	0
15	7		
16	0		

Appendix B: Source Code of the JAVA Program - Extracting the Needed Information from the Crash File

```
import java.io.BufferedReader;
import java.io.DataInputStream;
import java.io.File;
import java.io.FileInputStream;
import java.io.FileNotFoundException;
import java.io.FileOutputStream;
import java.io.FileReader;
import java.io.IOException;
import java.io.InputStreamReader;
import java.io.PrintStream;
import java.io.PrintWriter;
import java.util.Arrays;
import java.util.List;
import java.util.Scanner;
public class Extract {
	/**
	 * @param args
	 * @throws FileNotFoundException
	 * @throws IOException
	 */
		public static void main(String[] args) throws IOException {
		// TODO Auto-generated method stub
		PrintStream diskWriter = new PrintStream(new File ("C:/Users/hp/Desktop/test.txt"));
		FileInputStream fichier = new FileInputStream("C:/Users/hp/Desktop/crash.txt");

		PrintWriter pw = new PrintWriter(new FileOutputStream("C:/Users/hp/Desktop/crash.txt"));
		File file = new File("C:/Users/hp/Desktop/all FB data/");
		File[] files = file.listFiles();
		String linestr;
		DataInputStream in = new DataInputStream(fichier);
		BufferedReader entree = new BufferedReader(new InputStreamReader(in));
		for (int i=0; i < files.length; i++) {
	System.out.println("Processing" + files[i].getPath() + "...");
				BufferedReader br = new BufferedReader(new FileReader(files[i].getPath()));
				String line = br.readLine();
					while (line != null)
					{
	pw.print(line + "\n");
						line = br.readLine();
						}
					br.close();
		}
		pw.close();
		System.out.println("All files have been concatenated into crash.txt");
		try {
				while ((linestr = entree.readLine()) != null) {
					if (linestr.startsWith("Identifier")) {
					System.out.println(linestr);
					diskWriter.print(linestr + "\n");
					}
				else if (linestr.startsWith("Date/Time:")) {
						System.out.println(linestr);
						diskWriter.print(linestr + "\n");
				}

				else if (linestr.startsWith("Crashed Thread:")) {
					System.out.println(linestr);
```

```
                                        diskWriter.print(linestr + "\n");
                                }
                                else if (linestr.startsWith("Highlighted Thread:")) {
                                        System.out.println(linestr);
                                        diskWriter.print(linestr + "\n");
                                }
                                else if (linestr.startsWith("OS Version:")) {
                                                        System.out.println(linestr);
                                                        diskWriter.print(linestr + "\n");
                                                }
        }
                        }
                        catch (IOException e) {
                                // TODO Auto-generated catch block
                                e.printStackTrace();
                        }
                        try {
                                in.close();
                        } catch (IOException e) {
                                // TODO Auto-generated catch block
                                e.printStackTrace();
                        }
                        entree.close();
        }
}
```

Curriculum Vitae

Name: Sonia Meskini

Post-secondary Education and Degrees:
Faculty of Science of Tunisia (FST)
Manar 1, Tunis, Tunisia
2006-2008 Math-Physics Preparatory school

The School of Engineers of Tunisia (ENIT)
Manar 1, Tunis, Tunisia
2008-2011 Engineering Diploma in Computer Science

The University of Western Ontario
London, Ontario, Canada
2011-2013 MESc in Software Engineering

Related Work Experience
Teaching Assistant
The University of Western Ontario
2011-2013

Publications:

S. Meskini, A. B. Nassif, and L. F. Capretz, "Reliability Models Applied to Mobile Applications," *Proceedings of the 7th IEEE International Conference on Software Security and Reliability Companion*, Washington, D.C., *IEEE Press*, pp. 155-162, June 2013.

S. Meskini, L. F. Capretz, and A. B. Nassif, "Can We Rely on Smartphone Applications?," *IEEE Computer*, *IEEE Press*, submitted, July 2013.

S. Meskini, L. F. Capretz, and A. B. Nassif, "Reliability Prediction of Smartphone Applications Through Their Failure Data Analysis," *19th IEEE Pacific Rim International Symposium on Dependable Computing*, Vancouver, B.C., accepted, December 2013.