CHAPTER 5

SOFTWARE RELIABILITY ESTIMATION USING
BAYESIAN APPROACH

5.1 INTRODUCTION

Reliability is one of the most important quality attributes of commercial software since it quantifies software failures during the development process. In order to increase the reliability, a comprehensive test plan is required, that ensures all requirements are included and tested. In practice, software testing must be completed within a limited time and project managers should know how to allocate the specified testing-resources among all the modules (Chin-Yu Huang and Jung-Hua Lo 2006). Testing of software systems involves many complex problems for test managers. Important issues to be considered, include how to quantify reliability, how to design tests, cost and resource constraints, what are the implications of test failures, what tests should be re-run following corrections to rectify faults. All of these issues are related to the uncertainties involved in the quality of the software and processing of testing.

Researchers commonly need to solve a problem and make decisions based on limited information about one or more of the parameters of the problem. The types of information available to them can be

- objective information based on experimental results or observations
• subjective information based on experience, intuition, other previous problems that are similar to the one under consideration, or the physics of the problem.

The first type of information can be dealt with using the theories of probability and statistics. In this type, probability is interpreted as the frequency of occurrence assuming sufficient repetitions of the problem, its outcomes, and parameters, as a basis of the information. The second type of information is subjective and can depend on the analyst studying the problem. In this type, uncertainty that exists needs to be dealt with using probabilities. However, the definition of probability is not same as the first type because it is viewed herein as a subjective probability that reflects the state of knowledge of the analyst.

5.1.1 Bayesian Probabilities

It is common in real life to encounter problems with both objective and subjective types of information. In these cases, it is desirable to utilize both types of information to obtain solutions or make decisions. The subjective probabilities are assumed to constitute a prior knowledge about a parameter, with the gained objective information. Combining the two types produces posterior knowledge. The combination is performed based on Bayes theorem which is very useful in computing the posterior probability. Baye’s formula is a useful equation from probability theory that expresses the conditional probability of an event A occurring, given that the event B has occurred in terms of unconditional probabilities and the probability of the occurrence of the event B, given that A has occurred. This formula provides the mathematical tool that combines prior knowledge with current data to produce a posterior distribution. The prior distribution reflecting the view of the model parameters from past data is an essential part of this methodology.
It reflects the viewpoint that the past information should be incorporated say projects of similar nature etc., in estimating reliability statistics for the present and future.

If \( A_1, A_2, \ldots, A_n \) represent the prior (subjective) information, or a partition of a sample space \( S \) and \( E \subset S \) represents the objective information then the posterior probability can be computed as follows:

\[
P(A_i / E) = \frac{P(A_i)P(E / A_i)}{P(A_1)P(E / A_1) + P(A_2)P(E / A_2) + \ldots + P(A_n)P(E / A_n)}
\]

In this chapter the Bayesian approach is used in the bug removal process of the software reliability model based on the number of classified faults detected in a series of completed test and correction cycles.

5.1.2 Literature Review

Shigeru Yamada et al (1993) discuss a software reliability growth model considering imperfect debugging. Defining a random variable representing the cumulative number of faults corrected up to a specified testing time, this model is described by a semi-Markov process. Yonghua Ji et al (2005) analyze the problem of optimally allocating effort between software construction and debugging. The purpose of debugging is to locate and fix the offending code responsible for a system violating a known specification (Hailpern and Santhanam 2002). The process of debugging involves analyzing and possibly extending (with debugging statements) the given program that does not meet the specifications in order to find a new program that is close to the original and does satisfy the specifications. Thus it is the process of diagnosing the precise nature of a known error and then correcting it.
Program proving and program testing are two approaches used for indicating the existence of software faults. Program proving is formal and mathematical while program testing is more practical and heuristic. But neither of them guarantees complete confidence in the correctness of a program. Each has its advantages and disadvantages. So a metric is needed to reflect the degree of program correctness. One such quantifiable metric of quality that is commonly used in software testing is software reliability. Software reliability is a useful measure in planning and controlling resources during the development process so that high quality software can be developed.

Software reliability is a problem of major and growing practical importance though testing to high reliability, is regarded as crucial and often most expensive phase in the software development, little statistical support for such measures has been developed for complex systems. Several papers have recently appeared in software reliability. A testing strategy is proposed by Murrill (2008) that uses dynamic error flow analysis (DEFA) information to select an optimal set of test paths and to quantify the results of successful testing. An extended Markov Bayesian network is developed by Cheng Gang Bai (2005) to model software reliability prediction with an operational profile. The extended Markov Bayesian network proposed is focused on discrete-time failure data. This chapter presents Markovian approach using an intuitive process based on the experience and subjective judgments to software testing when each fault has a different probability of being detected during each review.

The Bayesian approach given in this chapter treats population model parameters as random, not fixed quantities. Before looking at the current data, old information or even subjective judgments are used to construct a prior distribution model for these parameters. This model
expresses starting assessment about how likely various values of the unknown parameters are. The Baye’s formula then make use of the current data to revise this starting assessment deriving the posterior distribution model for the population model parameters. In most of the applications, the data may not exist to validate a chosen prior distribution model. Parametric Bayesian prior models are chosen because of their flexibility and mathematical convenience.

Most Baye’s approaches (Littlewood and Verrall 1973) use prior probability based on changing failure rates after every correction cycle. This helps in the analytic simplicity of the posterior distributions. Smith and Roberts (1993) review recent uses of Markov chain and Monto Carlo methods for exploring and summarizing posterior distributions in Bayesian statistics. In software reliability sequential review model if the time taken for a testing process is divided into non overlapping intervals then those intervals could be regarded as a series of sequential reviews. Musa et al (1990), Schick and Wolverton (1978) and Goel (1985) have discussed different analytical models for assessing the reliability of software system. EI-Aroui and Soler (1996), Becker and Camarinopoulos (1990), Csenki (1990) and Jewell (1985) have applied Bayesian concept in several earlier studies on software reliability. In those studies observations of failure times are assumed to be available. But the approach in this chapter is based on the number of classified faults detected in a series of completed tests and correction cycles.

In parallel review model, faults detected during one review could also be detected during any other review. Vander Wiel and Votta (1993) derived the chance for detecting all faults in parallel independent review with capture, recapture sampling. In the sequential model the fault detected in a review can not be detected in any other review.
5.2 PROBLEM FORMULATION

Rallis and Zachary Lansdowne (2001) assumed in their analysis that each fault has the same probability of detection and the detected fault will be corrected before the next review and it is assumed that no other fault will be created during the correction cycle. These assumptions are not realistic. Faults that are probable in a single review may vary in difficulty of finding them (Arulmozhi et al 2003). Some faults may be easily detected where as some others may be found with less probability. In this work, the faults in a software system are grouped as class (1), class (2),..., class (k) and the remaining faults which are not coming under these classes as class (k+1). In the sequential independent reviews, if the faults are detected in a review they will be corrected before starting the next review, so that the same fault cannot occur in the future reviews. But when a newly developed system like software is tested in several stages before release and if a fault is observed, corrections and modifications are performed and it increases the reliability. Never the less some corrections may introduce new errors and software reliability may go down. The measure of software reliability given in this work helps to evaluate the probability that no class of faults remain in the software system by the end of last review when multiple faults are possible in each review and at the end of a correction cycle new fault may come. Using a Bayesian concept the probability based on the number of classified faults detected in each completed review cycle is evaluated.

5.2.1 Assumptions

The following assumptions are used in the analysis.

- The sequential reviews are arranged in such a way that the review j is completed before the review j + 1 starts.
The faults detected in the \( j^{th} \) review are corrected before the review \( j+1 \).

- New faults may be created during the correction process.
- The probability that a fault not being detected is independent of its class.

If \( P_{j-1}(m/A_{j-1}) \) is the prior distribution for the \( j^{th} \) review and \( M(N_{1j}, N_{2j}, \ldots, N_{K+1j}; N_j; q_{1j}, q_{2j}, q_{3j}, \ldots, q_{k+1j}) \) is the likelihood that \( N_j \) faults are detected, by Baye’s formula the posterior probability is

\[
P_j(m/A_j) = \frac{P_{j-1}(N_j + m/A_{j-1})M(N_{1j}, N_{2j}, \ldots, N_{K+1j}, m; N_j + m; q_{1j}, q_{2j}, q_{3j}, \ldots, q_{k+1j}, q_{0j})}{\sum_{r=0}^{\infty} P(r + N_j/A_{j-1})M(N_{1j}, N_{2j}, \ldots, N_{K+1j}, r; N_j + r; q_{1j}, q_{2j}, q_{3j}, \ldots, q_{k+1j}, q_{0j})}
\]

(5.1)

where \( P_j(m/A_0) = P(m) \)

(5.2)

As discussed by Rallis and Zachary Lansdowne (2001) and Arulmozhi et al (2003), the posterior distribution from any given inspection becomes the prior distribution with respect to the next inspection and so the above formula is appropriate and is applied to the next inspection.

**5.3 UNCONDITIONAL PROBABILITY FOR FAULT DETECTION UNDER ANY PRIOR DISTRIBUTION**

Let \( Q_{rp}, \ r=1,2,\ldots,k+1 \) be the probability that \( r^{th} \) class fault is detected for the first time during the \( p^{th} \) review and this event can occur only if it was detected during the \( p^{th} \) review and not detected during the preceding
p – 1 reviews. Thus \( Q_{rj} = q_{rj} \prod_{p=1}^{j-1}(1 - q_{rp}) \). Since \( Q_{rp}, r=1,2,...,k+1 \) are mutually exclusive events and \( q_{rp}, p=1,2,...,j \) are also mutually exclusive events, namely that a class of fault is detected during a particular review, the probability that \( r \) class faults are detected sometime during \( p \) reviews is
\[
\sum_{r=1}^{k+1} \sum_{p=1}^{j} Q_{rp} \cdot \text{If the detection of each class fault is independent of the detection of any other class fault then, } P_j(0/m) = \left( \sum_{r=1}^{k+1} \sum_{p=1}^{j} Q_{rp} \right)^m \text{ is the conditional probability that no fault remains after } j \text{ reviews given that the total number of faults is } m. \text{ By the law of total probability, the unconditional probability that no fault will remain after conducting } j \text{ reviews is}
\[
P_j(0) = \sum_{m=0}^{\infty} P(m)P_j(0/m) \quad (5.3)
\]

5.3.1 Unconditional Probabilities if the Prior Distribution is Poisson

The probability for \( m \) faults at the end of first review using (5.1) is
\[
P_1(m / A_1) = \frac{P(N_1 + m) M(N_{11}, N_{21}, ..., N_{k+11}, m ; N_1 + m ; q_{11}, q_{21}, q_{31}, ..., q_{k+11}, q_{01})}{\sum_{r=0}^{\infty} \sum P(r + N_1) M(N_{11}, N_{21}, ..., N_{k+11}, r ; N_1 + r ; q_{11}, q_{21}, q_{31}, ..., q_{k+11}, q_{01})}
\]
\[
= \frac{\lambda_0^{m+N_1} e^{-\lambda_0} (m + N_1)! q_{11}^{N_{11}} q_{21}^{N_{21}} ... q_{k+11}^{N_{k+11}} q_{01}^m}{(m + N_1)! N_{11}! N_{21}! ... N_{k+11}! m!} = \frac{\lambda_0^m e^{-\lambda_1}}{m!}
\]
\[
\sum_{r=0}^{\infty} \frac{\lambda_0^{r+N_1} e^{-\lambda_0} (r + N_1)! q_{11}^{N_{11}} q_{21}^{N_{21}} ... q_{k+11}^{N_{k+11}} q_{01}^r}{(r + N_1)! N_{11}! N_{21}! ... N_{k+11}! r!}
\]
where \( q_{11} + q_{21} + q_{31} + \ldots + q_{k+1} + q_{01} = 1 \Rightarrow q_{01} = 1 - \sum_{r=1}^{k+1} q_{r1} \), \( \lambda_1 = \lambda_0 q_{01} \) and the prior distribution is Poisson with parameter \( \lambda_0 \). It can be observed from (5.4) that the posterior distribution is Poisson with parameter \( \lambda_1 \). Assuming this as prior distribution, the probability of \( m \) faults at the end of second review is \( P(m / A_2) = \frac{\lambda_2^m e^{-\lambda_2}}{m!} \) with \( \lambda_2 = \lambda_0 q_{01} q_{02} \).

By assuming the prior probability as Poisson with parameter \( \lambda_0 \), it is proved that the probability of \( m \) faults at the end of first review is Poisson with parameter \( \lambda_1 \). Assuming this as the prior distribution, it is proved that the probability of \( m \) faults at the end of second review is also a Poisson process with parameter \( \lambda_2 \). To prove the result for any value of \( j \) by the inductive hypothesis it is assumed that

\[
p_{j-1}(m / A_{j-1}) = \frac{\lambda_{j-2}^m q_{0,j-1}^m e^{-\lambda_{j-2} q_{0,j-1}}}{m!} \text{ with mean } \lambda_{j-1} = \lambda_{j-2} q_{0,j-1}.
\]

Therefore for the \( j^{th} \) review,

\[
P_j(m / A_j) = \frac{\lambda_j^m q_j^m e^{-\lambda_j q_j}}{m!}
\]

\[
= \frac{\lambda_j^m e^{-\lambda_j q_j}}{m!} \text{ with mean } \lambda_j = \lambda_{j-1} q_{0,j-1}.
\]

\[
\text{(5.5)}
\]

where \( \lambda_{j-1} = \lambda_{j-1} q_{0,j-1} = \lambda_0 \prod_{p=1}^{j-1} \left( 1 - \sum_{r=1}^{k+1} q_{r,p} \right) \) \( \text{(5.6)} \)
So by induction principle, the results given by (5.5) and (5.6) are true for any value of \( j \). From the result (5.5), it can be deduced that if the prior probability \( P(m) \) has the Poisson distribution with parameter \( \lambda_o \), then the confidence that no fault remains after \( j \) independent reviews with observation \( A_j \) is

\[
P_j(0 / A_j) = e^{-\lambda_j}
\]  

(5.7)

Using (5.7) in (5.3), the unconditional probability that no fault remains after \( j \) reviews is

\[
P_j(0) = e^{\lambda_0 \left( 1 - \sum_{p=1}^{j} \sum_{r=1}^{k+1} Q_{rp} \right)}
\]

and

\[
1 - \sum_{p=1}^{j} \sum_{r=1}^{k+1} Q_{rp} = \prod_{p=1}^{j} \left( 1 - \sum_{r=1}^{k+1} q_{r,p} \right),
\]

since both sides represent the probability that a fault is not detected during the \( j \) reviews. In this chapter it is proved that the probability that no fault remains after \( j \) independent reviews is same in both prior to and after observing the number of faults detected in each cycle and the conditions under which these two measures, the conditional and unconditional probabilities are the same is also shown. If the prior probability has the Poisson distribution then the above result gives how many independent reviews are required to achieve a desired confidence that all faults have been found in a given software system. By assuming

\[
\sum_{r=1}^{k+1} q_{r,1} = \sum_{r=1}^{k+1} q_{r,2} = \cdots = \sum_{r=1}^{k+1} q_{r,j} = q_j,
\]

the results obtained by Rallis and Zachary Lansdowne (2001) can be deduced from these results.

5.3.2 Multiple Types of Faults under Binomial Prior Distribution

If the prior probability \( P(m) \) has the Binomial distribution with mean \( np \), where \( n \) is estimated as the total number of bugs in the software,
then by the induction process, it is proved that the posterior probability distribution $P_j (m/A_j)$ is also Binomial. Assuming $P(m) = nC_m p^m q^{n-m}$ and using Baye’s formula given in (5.1) for multiple faults, where

$$p_i = \frac{pq_{ij}}{1-p\sum q_{ij}}, \quad q_i = \frac{q}{1-p\sum q_{ij}}$$

and $p_i + q_i = 1$.

By the inductive hypothesis it follows that

$$P_{j-1}(m/A_{j-1}) = (n-N_1-N_2-\ldots-N_{j-1})C_m p_{j-1}^{m-nN_1-N_2-\ldots-N_{j-1}}$$

where $p_{j-1} = \frac{p_{j-2}q_{j-1}}{1-p_{j-2}\sum q_{ij-1}}$, $q_{j-1} = \frac{q_{j-2}}{1-p_{j-2}\sum q_{ij-1}}$.

Therefore for the $j^{th}$ review, assuming the prior probability as $P_{j-1}(m/A_{j-1})$

$$P_j (m/A_j) = (n-N_1-N_2-\ldots-N_j)C_m \left[ \frac{p_{j-1}q_{0j}}{1-p_{j-1}\sum q_{ij}} \right]^{m-nN_1-N_2-\ldots-N_j-n}.$$ 

With

$$p_j = \left[ \frac{p_{j-1}q_{0j}}{1-p_{j-1}\sum q_{ij}} \right], \quad q_j = \left[ \frac{q_{j-1}}{1-p_{j-1}\sum q_{ij}} \right]$$

$$P_j(m/A_j) = (n-N_1-N_2-\ldots-N_j)C_m p_j^{m-nN_1-N_2-\ldots-N_j-n}$$  \hspace{1cm} (5.8)

proving the result that if the prior probability distribution is Binomial then the posterior distribution is also Binomial. It can be derived from (5.8) that if the
prior probability \( P(m) \) has the Binomial distribution with mean \( np \) then the confidence that no fault remains after \( j \) independent reviews with observation \( A_j \) is \( P_j (0/ A_j) = q_j^{n-N_1-N_2-...-N_j} \).

If the prior probability \( P(m) \) has the Binomial distribution then the unconditional probability that no fault will remain after conducting \( j \) independent reviews is

\[
P_j(0) = \sum_{m=0}^{\infty} P(m) \left[ \sum_{p=1}^{j} \sum_{r=1}^{k+1} Q_{rp} \right]^m
\]

\[
= \sum_{m=0}^{\infty} \frac{n!p^m q^{n-m}}{m!(n-m)!} \left[ \sum_{p=1}^{j} \sum_{r=1}^{k+1} Q_{rp} \right]^m
\]

\[
= \left[ q + p \sum_{p=1}^{j} \sum_{r=1}^{k+1} Q_{rp} \right]^n \quad \text{and} \quad q_j^{n-N_1-N_2-...-N_j} = \left[ q + p \sum_{p=1}^{j} \sum_{r=1}^{k+1} Q_{rp} \right]^n
\]

The result obtained for \( P_j(0) \) with the prior probability distribution as Binomial gives how many independent reviews are required to achieve a desired confidence that all the faults have been detected in a given software system.

5.4 RESULTS

Tables 5.1, 5.2 and 5.3 give various confidence measures to ensure that after \( j \) reviews there is no more fault in the software if the prior distribution is Poisson with parameter \( \lambda_0 = 10 \). Table 5.1 illustrates various confidence measures to ensure that after 4 reviews, there is no more fault in
the software. The problem being modeled as multinomial, where the faults are classified according to their severity, the detection probability for each type of fault is different. The first four sub columns in Table 5.1 list the sum of probability values of detecting a fault of all kind in reviews 1, 2, 3 and 4 respectively. The last column of Table 5.1 illustrate the probability of no fault at the end of 4 reviews. A significant increase in the confidence measure is obtained for the increase in the detection probabilities in various reviews. A comparative study is done by changing the number of reviews in Table 5.2. It gives the confidence measures for 2, 4 and 6 reviews. The result in Table 5.2 indicates that the confidence measure increases as the number of reviews increases. Table 5.3 illustrates the confidence measures for the changes in the parameter values of the prior Poisson distribution.

Table 5.1  The conditional probabilities for 4 reviews with various detection probabilities

<table>
<thead>
<tr>
<th>Detection probability</th>
<th>P_4(0/A_4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Review 1</td>
<td>Review 2</td>
</tr>
<tr>
<td>0.3</td>
<td>0.3</td>
</tr>
<tr>
<td>0.4</td>
<td>0.3</td>
</tr>
<tr>
<td>0.5</td>
<td>0.3</td>
</tr>
<tr>
<td>0.6</td>
<td>0.4</td>
</tr>
<tr>
<td>0.8</td>
<td>0.5</td>
</tr>
<tr>
<td>0.8</td>
<td>0.6</td>
</tr>
<tr>
<td>0.85</td>
<td>0.8</td>
</tr>
<tr>
<td>0.95</td>
<td>0.8</td>
</tr>
</tbody>
</table>
Table 5.2  Comparison of the conditional probabilities for 2, 4, 6 reviews with same set of detection probabilities

<table>
<thead>
<tr>
<th>Detection probability</th>
<th>$P_2(0/A_2)$</th>
<th>Detection probability</th>
<th>$P_4(0/A_4)$</th>
<th>Detection probability</th>
<th>$P_6(0/A_6)$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Review 1</td>
<td>0.3</td>
<td>Review 2</td>
<td>0.2</td>
<td>Review 3</td>
<td>0.0065</td>
</tr>
<tr>
<td>Review 2</td>
<td>0.28</td>
<td>Review 3</td>
<td>0.3</td>
<td>Review 4</td>
<td>0.15</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.5</td>
<td></td>
<td>0.2</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.4</td>
<td></td>
<td>0.2</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.6</td>
<td></td>
<td>0.4</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.5</td>
<td></td>
<td>0.4</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.65</td>
<td></td>
<td>0.5</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.6</td>
<td></td>
<td>0.5</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.7</td>
<td></td>
<td>0.5</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.6</td>
<td></td>
<td>0.5</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.9</td>
<td></td>
<td>0.5</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.7</td>
<td></td>
<td>0.5</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 5.3  The conditional probabilities for 4 reviews with various Poisson parameters

<table>
<thead>
<tr>
<th>$\lambda_0$</th>
<th>2</th>
<th>4</th>
<th>6</th>
<th>8</th>
<th>10</th>
<th>15</th>
</tr>
</thead>
<tbody>
<tr>
<td>$P_4(0/A_4)$</td>
<td>0.926</td>
<td>0.858</td>
<td>0.794</td>
<td>0.736</td>
<td>0.681</td>
<td>0.562</td>
</tr>
</tbody>
</table>

Assuming Binomial prior distribution with parameters $p = 0.3$, $n = 50$ and $N_1 = 20$, $N_2 = 10$, $N_3 = 5$, $N_4 = 3$, Table 5.4 gives various confidence measures to ensure that after $j$ reviews there is no more fault in the software. Application of the result can be viewed from the Figure 5.1 which gives the posterior probability of not having any fault when the prior distribution is Poisson with $\lambda_0 = 10$, the number of sequential reviews is either, 2, 3, 4 or 5 and the detection probability for the class faults are the same for all reviews and varies from 0 to 1. If the detection probability of all classes of faults for each review is assumed to be 0.4, 0.6 and 0.8 then the corresponding confidence measures are depicted in the Table 5.5. The observed values shows that reviews with higher detection probabilities are more effective than those with lower detection probabilities.
Table 5.4 The conditional probabilities for Binomial parameters

<table>
<thead>
<tr>
<th>Number of Reviews ((j))</th>
<th>(q_j)</th>
<th>(P_j(0/A_j))</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>0.928</td>
<td>0.222</td>
</tr>
<tr>
<td>3</td>
<td>0.949</td>
<td>0.456</td>
</tr>
<tr>
<td>4</td>
<td>0.959</td>
<td>0.605</td>
</tr>
</tbody>
</table>

Table 5.5 Probability of no fault for various detection Probabilities

<table>
<thead>
<tr>
<th>Detection Probability</th>
<th>Probability of no fault</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Number of reviews ((j))</td>
</tr>
<tr>
<td></td>
<td>2</td>
</tr>
<tr>
<td>0.4</td>
<td>0.027</td>
</tr>
<tr>
<td>0.6</td>
<td>0.202</td>
</tr>
<tr>
<td>0.8</td>
<td>0.67</td>
</tr>
</tbody>
</table>

Figure 5.1 Probability of no fault remains versus detection probability for different sequential reviews
5.5 DISCUSSION AND CONCLUSION

In this work, the faults in a software system are grouped as class(1), class(2),……, class(k) and the remaining faults which do not come under these classes as class(k+1) depending upon their severity in detection. In the sequential independent reviews, if the faults are detected in a review, it is assumed that they are to be corrected before starting the next review so that the same fault will not occur in the future reviews. From the results obtained, it can be observed that the conditional and unconditional probabilities $P_j(0/A_j)$ and $P_j(0)$ are the same if the prior probability distribution is Poisson and Binomial. In these cases the confidence that all faults are deleted is not a function of the number of faults observed during the successive reviews but it is a function of the number of reviews, the detection probabilities and the mean of the prior distribution. This is a remarkable result because it gives a circumstance in which the statistical confidence from a Bayesian analysis is actually independent of all observed data. From the results it can be seen, Exponential formula could be used to evaluate the probability that no fault remains when a Poisson prior distribution is combined with a multinominal detection process in each review cycle.

To use all the information available old and/or new, objective or subjective, when making decisions under uncertainty makes practical sense and especially true when the consequences of the decisions can have a significant impact, financial or otherwise. A compromise between testing resources and software reliability is very essential. If more faults are exposed by testing and verification process then the additional cost for testing the remaining faults increases. So beyond some threshold value continuation of testing to improve the software reliability further is justified only if it is cost effective. There should be a trade-off between costs involved in testing and costs of finding failures during software operation. So cost analysis may be considered in future work.