國立成功大學「邁向頂尖大學計畫」
延攬優秀人才工作報告表
NCKU’s “Aim for the Top University Project”
Work Report Form for Distinguished Scholars

□續聘 continuation of employment  ■離職 resignation

100年7月13日更新

受聘者姓名
Name of the Employee
邱桂珍

男 Male  ■女 Female

聘期 Period of Employment
from 102年02月01日(to 102年07月31日)

研究或教學或科技研發與管理計畫名稱
The project title of research, teaching, technology development and management
An application of learning effects for assessing work performance using software reliability growth model with multiple change-points

計畫主持人
Project Investigator
謝淑蘭

補助延聘編號
Grant Number
HUA

一、研究、教學、科技研發與管理工作全程經過概述。（由受聘人填寫）
Please summarize the entire research, teaching, or science and technology R&D and management work process (To be completed by the employee)

1.研究方面

將健康照護科學研究所認知神經科學領域相關知識應用於解讀管理領域之軟體除錯工作行為分析與專案團隊績效分析與預測, 並獲得相當良好之模型適合度, 相關文章投稿於 IEEE舉辦之IEEM(The IEEE International Conference on Industrial Engineering and Engineering Management)研討會並獲接受, 因IEEE舉辦之研討會具相當之品質, 故該研討會接受之論文收錄於EI。

另在跨領域專長方面, 建置工作壓力與作夢現象線上調查資料庫以收集相關資料並分析華人工作壓力與作夢現象之相關性, 完成研究分析與撰寫文章投稿於 SCI期刊Journal of Mental Health, 目前審稿中。以上文章資料如下, 並詳列於附件1。


http://focolare.idv.tw/tinachiu/dream.htm
(二)行政方面

1. 規劃設計完成健護科學研究所 DM 與 newsletter 如下。
2. 參與健康照護科學研究所博士班跨領域課程規劃討論

3. 健康照護科學研究所外藉博士生學習輔導，陪伴參與 seminar 課程討論、針對外藉生研究需要之統計套裝軟體定期交流討論、外藉生打工、簽證展期、平安保險、房屋租賃等協助相關生活資訊收集與討論。

4. 參與協辦健康照護科學研究所研討會、演講課程協助辦理

5. 參與健康照護科學研究所所務會議並協助所務會議記錄

(三) 服務方面

1. 參與討論規劃台南市政府、成大醫院、成大醫學院全民跨領域全方位健康照護計畫規劃。根據認知神經回饋訓練可促進的生理、心理、與認知功能規劃中心運作，初期主要針對台南市民『學習疾患學習管理中心』、『情緒疾患情緒管理中心』等身心障礙者進行相關認知神經回饋訓練，及一般市民之『壓力管理中心』、『睡眠品質管理中心』透過相關認知神經回饋訓練及壓力管理、睡眠管理先進醫療器材之應用，協助市民自我壓力管理、睡眠管理，以全方位提升台南市民生活品質，促進台南市民幸福感，落實台南為『幸福城市』！概念如下。
Please evaluate the performance of research, teaching or science and technology R&D and management work: (To be completed by Project Investigator or Head of Department/Center)

1) Has the expected goal of recruitment been achieved?

2) What are the methods, professional knowledge, and progress of the research, teaching, or R&D and management work?

3) How have the research, teaching, or R&D and management results of the employed person given benefit to the project (or your unit)?

4) How has the employed person, during his or her term of employment, benefited your unit or the relevant domestic academic field?

5) Please describe the specific work performance, or the results of research, teaching, or R&D and management work:

6) Will you continue hiring the employed person? Yes No

※ This report form should be limited to 3-4 pages in principle.
※ This report form can be downloaded in http://scholar.lib.ncku.edu.tw/explain/
Abstract - Learning effects exist with regard to various behaviors, and especially work-related processes. This study measures the performance of a software testing project with time-varying effects using a software reliability growth model (SRGM), and discusses the changes in learning effects parameters with change-points in the model. We employ Chiu’s (2011) model to construct the time-varying learning effects and measure the performance of the software testing project using the data set in Huang (2010). This paper also discusses the time-lag between error-detected and error-removed that exists with different learning concepts. The results indicate that error-removed requires more cognitive learning process time, and this information can be used to help project managers mastering the staff and the process of software testing, efficiently.

Keywords - Time-varying Learning Effects, cognitive learning effects, behavior learning effects, Software reliability, Non-Homogeneous Poisson Process (NHPP), Change-points.

I. INTRODUCTION

While learning effects have been discussed in many research areas, they have rarely been quantified. Chiu et al. (2008) considered constant learning effects in a software reliability growth model (SRGM), and were able to explain S and exponential-shaped software testing behaviors simultaneously. Inoue and Yamada (2011) discussed a two-dimensional software reliability growth modeling framework with change-points, which is assumed to depend on the testing-time and testing-effort factors simultaneously. Huang and Hung (2010) applied queuing models to describe the fault detection and correction processes during software development and provided an extended infinite server queuing model with multiple change-points to predict and assess software reliability. In addition, time-varying learning effects were considered in Chiu’s (2011) model, which is used in the current work to examine the performance of a software testing project when using the an SRGM with multiple change-points in the changeable testing environment, and also to examine the different kinds of learning effects that occur in relation to error-detected and error-removed behavior in the software testing process. The results of this paper can help project managers to better control their staff, processes, reliability, and the work situations in the software testing project, simultaneously.

II. METHODOLOGY

A. Model development

The proposed models consider multiple change-points, since different testing environments or different project teams may be used to discuss the issue of software reliability based on Chiu’s (2011) model. This model is an SRGM that includes linear and exponential functions to describe the time-varying learning effects in the software testing/debugging process, and traces the software reliability using time-varying learning effects. This study considers changes in the testing environment or project team, and so the mean value functions will have change-points caused by the different learning effects functions.

The following notations will be used throughout this study:

- $a$: the expected number of all potential errors in the software system
- $\alpha$: the autonomous errors-detected factor
- $\eta$: the learning factor
- $\eta_l(t)$: the learning effect function with linear learning effects
- $\eta_e(t)$: the learning effect function with exponential learning effects
- $\xi$: the accelerative factor with time of the learning effects
- $\theta_j$: the change-point
- $f(t)$: the intensity function that denotes the fraction of the errors detected at time $t$
- $F(t)$: the cumulative function that denotes the fraction of the errors detected within time $(0,t)$
- $m(t)$: the mean value function of the software error detection process, which is the expected number of errors detected within time $(0,t)$
- $m_l(t)$: the mean value function with linear learning effects
- $m_e(t)$: the mean value function with exponential learning effects
- $R(x|t)$: the conditional software reliability, which is defined as the probability that no error is detected within the time interval $(t,t+x)$

Generally, the software testing/debugging process is modeled as an error counting process. A counting process
\( \{N(t), \ t \geq 0\} \) is said to be an NHPP with intensity function \( \lambda(t) \), where \( N(t) \) follows a Poisson distribution with mean function \( m(t) \), and this probability can be formulated as follows:

\[
\Pr(N(t) = k) = \frac{[m(t)]^k e^{-m(t)}}{k!}, \ k = 0,1,2,... \quad (2.1)
\]

The mean value function \( m(t) \), which is the expected number of errors detected within time \((0,t)\), can be expressed as:

\[
m(t) = \int_0^t \lambda(x)dx. \quad (2.2)
\]

The conditional software reliability \( R(x/t) \) is defined as the probability that no error is detected within the time interval \((t,x)\), given that an error occurred at time \( t \) \((t \geq 0, x > 0)\). Therefore \( R(x/t) \) can be formulated as:

\[
R(x/t) = e^{-\left[m(t+x)-m(t)\right]}. \quad (2.3)
\]

Note that the value of conditional software reliability is approximated to 1 when \( t \to \infty \).

In this paper, we describe the learning that occurs in a software testing/debugging task and the time-dependent effects of this. We also explain how the time-dependent learning effects influence the process of software reliability growth. We employ Chiu’s et al. model (2008) to assess the performance of software testing projects.

\[
m(t) = aF(t) = a \left[1 - \frac{1 + \eta}{\alpha} + \frac{\eta}{\alpha} e^{\alpha + \eta \xi t}\right]. \quad (2.4)
\]

Chiu (2011) adopted two functions to deal with time-dependent situations, and these are given as (2.5) and (2.6), representing the linear and exponential growth of learning effects with time, respectively, in which \( \xi \) is the coefficient of the accelerative factor.

\[
\eta_t(t) = \eta + \xi t, \quad (2.5)
\]

\[
\eta_x(t) = \eta e^{\xi t}, \quad (2.6)
\]

Where \( \xi \) is the coefficient of the accelerative factor. The mean value function in Chiu’s et al. model (2008) can be improved with these two different learning styles, as given by:

\[
m_{1}(t) = a \left\{1 - \frac{1 + \eta + \xi t}{\alpha} + \frac{\eta + \xi t}{\alpha} e^{\alpha + \eta \xi t}\right\}, \quad (2.7)
\]

\[
m_{2}(t) = a \left\{1 - \frac{\eta e^{\xi t}}{\alpha} + \frac{\eta e^{\xi t}}{\alpha} e^{\alpha + \eta \xi t}\right\}, \quad (2.8)
\]

A. The fitting results for error-detected data of the actual data set

The fitting results for error-detected data of the data set in Musa et al. (1987) with the proposed linear learning model are shown in Figure 3.1, which includes linear learning effects and change-points at weeks 8 and 14.
The results show that at week 8, with the 1st change-point (CP), the autonomous errors-detected factor $\alpha$ remained at 0.005, the learning factor $\eta$ rose from 0.08 to 0.19, and the accelerative factor with time of the learning effects, $\xi$, increased from 0.005 to 0.008. The 2nd CP is in week 14, when the autonomous errors-detected factor $\alpha$ remained at 0.005, $\eta$ remained at 0.19, and $\xi$ rose from 0.008 to 0.0084. Finally, the $Rsq$ was 0.9976 and the $MSE$ was 15.1357.

The results of the fitting for error-detected data of the data set using proposed exponential learning model, which includes exponential learning effects, are shown in Figure 3.2, with CPs at weeks 8 and 14.

![Figure 3.2 Fitting results for error-detected data of the data set with the exponential learning model](image)

Figure 3.2 Fitting results for error-detected data of the data set with the exponential learning model

The results show that at week 8 with the 1st CP, and the inclusion of exponential learning effects, the autonomous errors-detected factor $\alpha$ remained at 0.005, the learning factor $\eta$ rose from 0.04 to 0.168, and the accelerative factor with time of learning effects, $\xi$, fell from 0.156 to 0.043. The 2nd CP was in week 14, and the autonomous errors-detected factor $\alpha$ remained at 0.005, $\eta$ fell from 0.168 to 0.12, and $\xi$ rose from 0.043 to 0.06. Finally, the $Rsq$ was 0.9980 and the $MSE$ was 12.5963.

The results show that the testing team experienced exponential learning effects, and the testing project had a change in criteria in the 8th week, when learning factor $\eta$ rose significantly lift and the changeful environment caused more unstable performance.

**B. The fitting results for error-removed data of the data set**

The fitting results for error-removed data of the data set obtained with the proposed linear learning effects model are shown in Figure 3.3, and there are two CPs at weeks 8 and 14. The results show that at week 8, with the 1st CP, the autonomous error-detected factor $\alpha$ remained at 0.005, the learning factor $\eta$ rose from 0.007 to 0.118, and the accelerative factor with time of learning effect, $\xi$, rose from 0.0022 to 0.0071. The 2nd CP is in week 14, where the autonomous errors-detected factor $\alpha$ remained at 0.005, $\eta$ rose from 0.118 to 0.146, and $\xi$ rose from 0.0071 to 0.009. The $Rsq$ was 0.9967 and the $MSE$ is 16.6722.

![Figure 3.3 Fitting results for error-removed data of the data set with the linear learning model](image)

Figure 3.3 Fitting results for error-removed data of the data set with the linear learning model

The results of the fitting for error-removed data of the data set with the proposed exponential learning model, which includes exponential learning effects, are shown in Figure 3.4, with CPs in weeks 8 and 14.

![Figure 3.4 Fitting results for error-removed data of the data set with the exponential learning model](image)

Figure 3.4 Fitting results for error-removed data of the data set with the exponential learning model

The results show that at week 8, with the 1st CP the autonomous errors-detected factor $\alpha$ remained at 0.005, the learning factor $\eta$ rose from 0.06 to 0.1, and the accelerative factor with time of learning effect, $\xi$, fell from 0.1 to 0.06. The 2nd CP is in week 14, and the autonomous errors-detected factor $\alpha$ remained at 0.005, $\eta$ rose from 0.1 to 0.11, and $\xi$ remained at 0.06. The $Rsq$ was 0.9987 and the $MSE$ was 6.4653, showing almost perfect fitting.

According to the results, the testing team has exponential learning effects, and the testing project must experience a change in week 8, when the learning factor $\eta$ rise significantly.
IV. DISCUSSION

A. Comparison of the results with other models

This study compares its fitting results for error-removed data with those of other models in Huang and Hung (2010) by using the \( \text{MSE} \) comparison criteria (See Table 4.1). The proposed models are more concise and effective, and the proposed model with exponential learning effects shows almost perfect fitting for the data set, with \( R^2 \) of 0.9987 and \( \text{MSE} \) of 6.4653, better than those of the other models. As noted above, these results indicate that the staff of this software testing project experienced exponential learning effects.

Table 4.1 Fitting results using the \( \text{MSE} \) comparison criteria

<table>
<thead>
<tr>
<th>Data set</th>
<th>Model</th>
<th>( \text{MSE} )</th>
<th>Change-points</th>
</tr>
</thead>
<tbody>
<tr>
<td>Huang &amp; Hung (2010) model 1 (for error-removed data)</td>
<td>12.71</td>
<td>1st CP=11</td>
<td></td>
</tr>
<tr>
<td>Huang &amp; Hung (2010) model 2 (for error-removed data)</td>
<td>11.86</td>
<td>1st CP=11, 2nd CP=18</td>
<td></td>
</tr>
<tr>
<td>Yamada delayed S-shaped (DSS) model</td>
<td>595.28</td>
<td></td>
<td></td>
</tr>
<tr>
<td>the proposed linear learning model (for error-detected data)</td>
<td>15.14</td>
<td>1st CP=8, 2nd CP=14</td>
<td></td>
</tr>
<tr>
<td>the proposed linear learning model (for error-removed data)</td>
<td>16.67</td>
<td>1st CP=8, 2nd CP=14</td>
<td></td>
</tr>
<tr>
<td>the proposed exponential learning model (for error-detected data)</td>
<td>12.60</td>
<td>1st CP=8, 2nd CP=14</td>
<td></td>
</tr>
<tr>
<td>the proposed exponential learning model (for error-removed data)</td>
<td>6.47</td>
<td>1st CP=8, 2nd CP=14</td>
<td></td>
</tr>
</tbody>
</table>

B. Comparison of the results with different cognitive learning behavior

Based on the results reported above, this study integrated the error-detected and error-removed data in the data set and the predicted data with the proposed models to discover that the CPs imply there is a lag between error-detected and error-removed performance. A CP occurs when the time lag between error-detected and error-removed performance changed, as shown in Figures 4.1 and 4.2.

We compare the learning effects in the behaviors of error-detected and error-removed for this software testing project with the proposed exponential learning model, the traces are conformable to the performance of error-detected and error-removed, as shown in Figure 4.3.

These figures reveal that the software testing/debugging project had a change in learning effects which led to a time lag between error-detected and error-removed. It thus seems that the error-detected and error-removed performance were subject to different cognitive learning process.
organizational environment. This study also found different learning effects with regard to error-detected and error-removed behavior, managers can make better decisions for testing projects by knowing the relationships among software reliability and the autonomous error-detected factor, the learning factor, and accelerative factor with time of learning effect, by understanding how they change. The proposed models can also be used by managers to assess organization performance with regard to the overall software testing process, and to know how the learning effects influence team performance.

ACKNOWLEDGMENT
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REFERENCES