科技部補助專題研究計畫成果報告
期末報告

針對多種可能隨機衰退模型之穩健型最小成本預燒實驗計劃

計 畫 類 別 ： 個別型計畫
計 畫 編 號 ： MOST 105-2221-E-006-168-
執 行 期 間 ： 105年08月01日至106年07月31日
執 行 單 位 ： 國立成功大學工業與資訊管理學系（所）

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中 華 民 國 106 年 10 月 29 日

中文摘要：由於在製作過程中不可控制的因素，產品常由兩組群體組成，分別為正常品與不良品。在產品或半成品被運送至客戶或下一工作站之前，常需要進行預燒實驗以便將一批產品或元件中的不良品挑出。未進行預燒實驗的貨物常因瑕疵品混雜其中而造成回收以及商譽上的損失。

對現今高可靠度產品而言，在短時間內不易觀察產品失效與否，因此進行預燒實驗有其困難度。一個有效的方式是觀察產品品質特性的衰退路徑以進行判定。常用來配似及估計衰退路徑的模型有Wiener 以及Gamma 隨機過程。工程師常以選定的模型推導出最佳預燒實驗計劃。然而，研究指出當選定的配似模型不同時，所推導出的實驗計劃相異極大。但是實務上常見同一產品卻有多種適合的模型可以配似。因此該選用何種預燒實驗常造成困擾。本研究針對此問題提出穩健型預燒實驗計劃。經由指派各個可能模型的先驗機率，我們可以藉由最小化加權後的成本函數推導出的預燒實驗計劃，可以適用於各項模型假設下，皆可提供相對良好的績效。進而避免模型配置錯誤時造成的損失。本研究中將討論兩種不同檢驗情境下的預燒實驗計劃，分別為使用單次以及多次檢驗數據進行預燒實驗的情況。在文中亦將以實際資料及數據驗證本文提出的預燒實驗計畫具有良好的成效。

中文關鍵詞：預燒實驗計劃、Wiener 隨機過程、 Gamma 隨機過程、加權成本函數、穩健設計

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However, based on practical examples, some products could have several potential models that can provide equivalently good fit to the same observed degradation paths. The optimal burn-in policy from each model can be significantly different from each other. Thus, an engineer may have problems when determining which policy to be used. Our goal of research is to proposed a robust burn-in policy against degradation process model uncertainty. In other words, we would like to derive policies that can be used for both models that can still provide good relative efficiency (or cost). We consider the two most commonly used degradation models, Wiener and Gamma processes. By assigning a prior probabilities regarding the true model, weighted criteria are used to find such robust burn-in test plans. We consider two possible scenarios in a burn-in test. That is, a burn-in test cutoff is determined by single or several measurements of degradation values. Numerical example based on a real data is presented to evaluate the performance of our proposed test policy.

英文關鍵詞： Burn-in test, Wiener Process, Gamma process, weighted cost function, robust design

科技部補助專題研究計畫成果報告

（□期中進度報告/☑期末報告）

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計畫類別：☑個別型計畫　　□整合型計畫
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執行期間：105 年 08 月 01 日至 106 年 07 月 31 日

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計畫主持人：胡政宏
共同主持人：
計畫參與人員：黃韻潔、林邑築、賴冠儒、蕭秉岳

本計畫除繳交成果報告外，另含下列出國報告，共 ___ 份：
□執行國際合作與移地研究心得報告
□出席國際學術會議心得報告

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中　華　民　國 106 年 10 月 01 日

附件二

科技部補助專題研究計畫成果報告自評表

請就研究內容與原計畫相符程度、達成預期目標情況、研究成果之學術或應用價值（簡要敘述成果所代表之意義、價值、影響或進一步發展之可能性）、是否適合在學術期刊發表或申請專利、主要發現（簡要敘述成果是否有嚴重損及公共利益之發現）或其他有關價值等，作一綜合評估。

1. 請就研究內容與原計畫相符程度、達成預期目標情況作一綜合評估 ☑ 達成目標 ☐ 未達成目標（請說明，以 100 字為限） ☐ 實驗失敗 ☐ 因故實驗中斷 ☐ 其他原因 說明：
2. 研究成果在學術期刊發表或申請專利等情形： 論文：☐已發表 ☐未發表之文稿 ☑撰寫中 ☐無 專利：☐已獲得 ☐申請中 ☑無 技轉：☐已技轉 ☐洽談中 ☑無 其他：（以 100 字為限）

3. 請依學術成就、技術創新、社會影響等方面，評估研究成果之學術或應用價值（簡要敘述成果所代表之意義、價值、影響或進一步發展之可能性），如已有嚴重損及公共利益之發現，請簡述可能損及之相關程度（以 500 字為限）

預燒實驗常用於產品元件進行到下一生產階段，或者是送至客戶端前篩除可能混雜於其中的瑕疵品。良好的預燒實驗計劃可降低實驗與錯誤分類的總成本。然而雖然在文獻中已有類似研究，但是目前已知研究成果皆需要選定適合產品或元件壽命相關的統計模型，對於實務上有可能因不同統計模型皆適用於同一產品壽命的情況無法直接引用。為克服此學術上尚未討論過的問題，本研究成果提出了在擬定預燒計畫前，若有不同統計模型適用於同一類型產品時，使用加權成本函數來尋找最佳化後的預燒實驗計劃。於研究成果中提出的數值結果證明，使用此方法得到的預燒實驗計劃在不同可能的統計模型下皆有不錯表現(詳細說明與範例請見報告內容)。因此，本研究成果在學術層面提出解決未在文獻中討論過的預燒實驗計劃設計方法。在實際應用方面實驗者可直接採用得到的預燒實驗計劃而較無需擔心模型選擇與配置的問題，因此在學術與實務應用上皆有其價值。本研究採用常用來配似及估計衰退路徑的模型如 Wiener 以及 Gamma 隨機過程進行討論。在未來展望與推廣研究結果上，若有不同產品適合其他統計模型，本研究提出的方法也可以包含更多可能的隨機過程模型以適用於不同產品元壽命或衰退路徑。

中文摘要

由於在製作過程中不可控制的因素，產品常由兩組群體組成，分別為正常品與不良品。在產品或半成品被運送至客戶或下一工作站之前，常需要進行預燒實驗以便將一批產品或元件中的不良品挑出。未進行預燒實驗的貨物常因瑕疵品混雜其中而造成回收以及商譽上的損失。

對現今高可靠度產品而言，在短時間內不易觀察產品失效與否，因此進行預燒實驗有其困難度。一個有效的方式是觀察產品品質特性的衰退路徑以進行判定。常用來配似及估計衰退路徑的模型有 Wiener 以及 Gamma 隨機過程。工程師常以選定的模型推導出最佳預燒實驗計劃。然而，研究指出當選定的配似模型不同時，所推導出的實驗計劃相異極大。但是實務上常見同一產品卻有多種適合的模型可以配似。因此該選用何種預燒實驗常造成困擾。本研究針對此問題提出穩健型預燒實驗計劃。經由指派各個可能模型的先驗機率，我們可以藉由最小化加權後的成本函數推導出的預燒實驗計劃，可以適用於各項模型假設下，皆可提供相對良好的績效。進而避免模型配置錯誤時造成的損失。本研究中將討論兩種不同檢驗情境下的預燒實驗計劃，分別為使用單次以及多次檢驗數據進行預燒實驗的情況。在文中亦將以實際資料及數據驗證本文提出的預燒實驗計畫具有良好的成效。

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Abstract

Because of uncontrollable production variability in a manufacturing process, some units in a batch of product may not meet their design operating standards. Burn-in tests are thus conducted at the early stage of production in order to screen out latent failure products. Several burn-in methods focusing on different criteria have been proposed in literature. However, for recently highly reliable products, it is difficult to observe failure within a short burn-in test duration and thus hard to ascertain whether a unit is weak or normal. An effective way to solve this problem is to measure product's quality characteristic and make statistical inferences from the observed degradation values. Optimal burn-in test policy has also been proposed based on a specific chosen degradation model.

However, based on practical examples, some products could have several potential models that can provide equivalently good fit to the same observed degradation paths. The optimal burn-in policy from each model can be significantly different from each other. Thus, an engineer may have problems when determining which policy to be used. Our goal of research is to proposed a robust burn-in policy against degradation process model uncertainty. In other words, we would like to derive policies that can be used for both models that can still provide good relative efficiency (or cost). We consider the two most commonly used degradation models, Wiener and Gamma processes. By assigning a prior probabilities regarding the true model, weighted criteria are used to find such robust burn-in test plans. We consider two possible scenarios in a burn-in test. That is, a burn-in test cutoff is determined by single or several measurements of degradation values. Numerical example based on a real data is presented to evaluate the performance of our proposed test policy.

Keywords: Burn-in test, Wiener Process, Gamma process, weighted cost function, robust design.

1. Introduction

1.1. Introduction to Burn-in Tests

Due to high customer's expectation on high quality products, besides designing and producing reliable products, a manufacturer has to ensure that most units in a batch of product share the same good quality when they are delivered to customers. However, this is not an easy task because it is common that the population of a product is composed of two or more subpopulations with different failure rates (Bai and Kwon (1994)). For a manufacturing process, some units of a product may not meet their design operating standards due to certain production variability such as material used or manufacturing process itself (Tsai, et al. (2011)). As a result, these weak units may perform unsatisfactory and incur some potential losses such as reproduction and warranty cost. Burn-in tests are usually implemented in order to screen out latent failure products or components and to remove these unreliable units before they are delivered to the next production stage or to customers.

Several burn-in methods focusing on different criteria have been proposed in the past including maximizing residual lifetime, minimizing mission failure probability, and achieving a reliability target, etc. Meanwhile, for some special products such as integrated circuits, non-defective items can operate without failure for a long time so that the failure probability during a burn-in duration is really small. Such population is referred as limited failure population. For this type of products, Bai and Kwon (1994) suggested a economic sequential screening procedure for screening out weak components minimizing expected cost. We next summarize some recent research efforts regarding designing a burn-in test.

1.2. Literature Review

Burn-in tests have been shown as a useful and effective tool for screening out weak components before they are handed to customers at early production stage. Park (1985) examined the effect of burn-in on the mean residual life of a product. Some commonly used criteria including maximization of the mean residual lifetime (MRL), minimizing cost, achieving prescribed mission reliability, etc (see Bai and Kwon (1994) and Tsai, et al. (2011)). For example, Kuo (1984) presented a cost-optimization model from a system viewpoint for determining optimal burn-in periods for the components from a system viewpoint. Chang (2000) proposed a minimum cost burn-in model to economically determining the optimal burn-in time during decreasing failure rate phase to maximized MRL. For other concise reviews of burn-in models and methods, one can refer to Kuo and Kuo (1983), Kuo (1984), Leemis and Beneke (1990) and Block and Savits (1997).

Recently, due to continued advances in manufacturing technology, reliable products usually can operate without failure for years. Thus, it becomes difficult to observe failure data within a short test duration for a burn-in test. Alternatively, measurements of a certain product Quality Characteristic (QC) that degrades (or increases) over time are recorded at various inspection times. There are many applications showing that the lifetime of the product can be related to the level of the QC. For example, the life of an alloy can be defined when its crack (the QC) reaches size 1.6 inches (Meeker and Escobar (1998)). Elsayed (2012) mentioned, for some elastomers, which are critical materials for hoses, the life is related to its hardness measure. The product's life can be defined as the first-passage time when the QC crosses a pre-specified threshold. Research efforts and models analyzing product's degradation paths include the mixed effects nonlinear regression model (Lu and Meeker (1993)), the Gamma process model (Tseng et al. (2009) and Tsai et al. (2011)), the inverse Gaussian process model (Wang and Xu (2010)), the linear and exponential-based degradation model (Si et al. (2013)), and the Wiener Process model (Doksum and Hoyland (1992)). In this research, we focus on two commonly used models, the Wiener and Gamma degradation models. Detailed information for these two models are given in section 2.

A burn-in test can also be conducted based on data collected from degradation tests. For instance, Tseng, et al. (2003) propose a decision rule for classifying a light-emitting diodes (LED) as a normal or a weak based on the brightness of the tested lamps. Tseng and Peng (2004) proposed an integrated Wiener process to model the cumulative degradation path of the product’s quality characteristic. The optimal burn-in policy can be easily obtained. Tsai, et al. (2011) propose a mixed gamma process to describe the degradation path of the product and present a decision rule for classifying a unit as typical or weak. Ye, et al. (2012) developed a burn-in planning framework with competing risks to guide the burn-in planning for an electronic device. Comparing to burn-in tests based on go/no go (or time to failure), using degradation data for a burn-in test has some advantages including it requires shorter test time to identify weak components and it can provide lifetime assessment of the passed units (see Tseng, et al. (2003)). For other research papers discussing optimal burn-in procedures based on device degradation process, one can refer to Zhang, et al. (2015), Cha and Pulcini (2016), and Zhai, et al. (2016).

1.3. Motivation

Meeker and Escobar (2008) (see page 642) showed a data set for the percent increase in operating current of GaAs lasers tested at 80oC. Tsai et al. (2011) mentioned that an important quality characteristic of a laser device is its operating current. The degradation paths of 15 lasers were plotted in Figure 1 in Tsai et al. (2011). They then used this dataset and fitted a Gamma process model to it. Because the plot showed that the 15 lasers can be grouped into weak and normal units, optimal burn-in policy was proposed according to the estimated parameters from this data. However, their proposed burn-in policy depends strongly on the assumption that the degradation paths should follow the proposed Gamma process model. On the other hand, if the assumed Gamma model is not correct, the obtained optimal policy, although still feasible, might not be a good one. In fact, in the data analysis section of Tsai et al. (2011), they also tried fitting a Wiener process model to the laser data and observed that the resulting optimal burn-in policy is very different from the one obtained from Gamma model. Although there are several model selection indices suggested in literature, it is still not easy to choose a correct model in practice for a given set of model. A more likely situation is that there are several potential models that can provide equally well fit to the product's degradation paths. This causes a problem for engineers when conducting a burn-in test because burn-in policies from different models can be significantly distinct. To solve this problem, we plan to propose a robust burn-in policy that performs well for both models. In other words, instead of choosing a specific model and obtain optimal burn-in policy accordingly, we will propose policies that can be used for both models. The proposed plans are obtained by a weighted criterion. We assume that an engineer has certain prior information regarding the true degradation process.

Thus, it is possible to assign prior probabilities for each possible model. An objective function based on the given prior probability is then used to obtain robust burn-in policies. Details are discussed in Section 3.

2. Model Assumptions

In this section, we present models considered in this research that are used to describe a degradation path. Three possible stochastic processes, Wiener and two different Gamma process models, are presented. These models are used for obtaining burn-in policies in the next section.

2.1. *Wiener Process Model*

First of all, let $L(t)$, $t \geq 0$, denotes the value of a degradation path of a specific QC of the product. Because of the random nature of the measured value, we model the measured degradation process value (possibly transformed) by random variables. The first model considered is the Wiener process model. A general form of this model is:

$$L(t) = \eta t + \sigma B(t), \tag{3}$$

where η is the drift rate, σ is the diffusion coefficient, and $B(\cdot)$ is a standard Brownian motion (see, for example, Oksendal [3]).

Tseng and Yu [1] and Yu and Tseng [2] used this model to describe transformed degradation paths for a particular light emitting diode (LED) lamp. Previous research had indicated that, for electronic products, lifetime distributions tend to be bimodal from a mixture of two distributions (e.g., Alexanian and Brodie, [4]; Jensen and Peterson [5]) : One represents the normal (main) products while the other represents the weak products (freaks). Thus, it is reasonable to use the following model for describing the degradation paths of the products before conducting a burn-in test :

$$L(t) = \begin{cases} \eta_1 t + \sigma B(t), \text{ for weak unit} \\ \eta_2 t + \sigma B(t), \text{ for normal unit} \end{cases} \tag{4}$$

where $\eta_1 > \eta_2 \geq 0$. A well-know property about Wiener process is that if we define the lifetime of a product as the first threshold-crossing time of its degradation path, then the lifetime distribution is a inverse Gaussian (IG) distribution. We next introduce the Gamma process model used in this paper.

2.2. Gamma Process Model

The second model used in this research is the gamma process model (Lawless & Crowder [6]). To model a degradation process that fits a Gamma process, we follow the approach used in Tsai et al. (2011). For fixed a fixed time, t, and a increment of time, Δt, we assume that

$$\Delta L(t) = L(t+\Delta t) - L(t) \sim \text{Gamma}(\Delta g(t) = g(t+\Delta t) - g(t), \nu), \tag{5}$$

where $g(\cdot)$ is a monotone increasing function and parameter $\nu > 0$. $\text{Gamma}(\Delta g(t), \nu)$ denotes a gamma distribution with shape parameter $\Delta g(t)$ and scale parameter ν. The probability distribution function of $\Delta L(t)$ is then:

$$Y = \Delta L(t) \sim f\left(y\right) = \frac{1}{\Gamma(\Delta g(t))v^{\Delta g(t)}} y^{\Delta g(t)-1} \exp\left(-\frac{y}{v}\right), \quad y > 0. \tag{6}$$

Similar to the previous assumption, before conducting a burn-in test, the degradation paths often tends to be bimodal, arising from a mixture of weak and normal groups. We assume there exists a proportion of weak product before a burn-in test. Then, we can use the following model for describing the degradation path of the mixed products:

$$\Delta L(t) \sim \begin{cases} \text{Gamma}\left(\Delta g(t), v_1\right), \text{ for weak unit,} \\ \text{Gamma}\left(\Delta g(t), v_2\right), \text{ for normal unit,} \end{cases} \tag{7}$$

The Gamma model is more complex than the Wiener model because the mean degradation value at a given time is the product of two parameters. We assume that the degradation paths of typical and weak groups have the same shape parameter (Mahmoud and Moustafa, [8]). Under our current assumption, the mean degradation value of a weak unit is larger than that from a normal unit at any time. Therefore, we should have $\Delta g(t)v_1 > \Delta g(t)v_2$. The condition shows that, on average, an weak item degrades faster than an item in the typical group.

3. Optimal and Robust Burn-In Policy under Different Models

In this section, we first summarize the optimal cutoff point, as well as the optimal burn-in policy, for each model proposed in section 2. Then, we compare the relatively efficiency (cost) when the degradation process is wrongly specified. Using the obtained efficiencies, we proposed our objective function to obtain the robust burn-in policy.

3.1. *Optimal cutoff points*

Recall that in our model assumptions in section 2, for each model, a weak component is assumed having greater expected cumulated degradation value than that for a normal component for every given time. Therefore, if one would like to classify one unit at a specific time based on its degradation value, the general rule is to compare the degradation value to a cutoff point and classify a unit as a weak one if its cumulated degradation value is large. That is, define a region in which the observed degradation value of a unit is greater than the cutoff, i.e., $R_1 : L(t) \geq \xi(t)$. The decision rule is to conclude that a unit is a weak one when the observed degradation value falls in R_1. The choice of the cutoff point is usually determined by minimizing the misclassification probabilities or costs. In this research, we consider the minimum cost rule because the minimum misclassification probability rule can be shown is a special case. Two types of misclassification scenarios are considered. (i) Type-I error: categorize a normal unit as a weak one with corresponding cost C_α. (ii) Type-II error: categorize a weak unit as a normal one with corresponding cost C_β. In addition, multiply the prior probability to each type of misclassification, the general formula of expected misclassification cost

(MC) is $\mathrm{MC}(\xi(t),t)=C_{\alpha}n(1-p)\times\Pr\left(L(t)\geq\xi(t)\right)+C_{\beta}np\times\Pr\left(L(t)\leq\xi(t)\right)$.

Depending on the assumed model for the observed degradation process, one can then derive the optimal cutoff point minimizing $\mathrm{MC}(\xi(t),t)$ for all time. Since both terms in $\mathrm{MC}(\xi(t),t)$ have the sample size (n) in it, the sample size can be factor out and further analysis will not be affected. Thus, in our following analysis, we ignore the sample size from the formula to avoid the need to input a number of *n*. We next summarize the optimal cutoff points for each model in section 2 and the associated minimum value of $\mathrm{MC}(\xi(t),t)$.

For the Wiener process model, the degradation path at time *t*, $L(t)$, is a normal random variable. It is then straightforward to shown that the optimal cutoff is: $\xi_{w}^{*}(t)=\dfrac{(\eta_1+\eta_2)t}{2}+\dfrac{\sigma^2}{\eta_1-\eta_2}ln\left[\dfrac{C_{\alpha}(1-p)}{C_{\beta}p}\right]$. On the other hand, for Gamma process model, the cutoff point is $\xi_{\mathrm{GM}}^{*}(t)=\dfrac{\nu_1\nu_2}{\nu_1-\nu_2}\left[ln\left(\dfrac{\nu_1}{\nu_2}\right)g(t)+ln\left(\dfrac{C_{\alpha}(1-p)}{C_{\beta}p}\right)\right]$ and the minimum expected misclassification cost is

$$\mathrm{MC}_{\mathrm{GM}}(\xi_{\mathrm{GM}}^{*}(t),t)=C_{\alpha}(1-p)\frac{\Gamma\left(g(t),\dfrac{\xi_{\mathrm{GM}}^{*}(t)}{\nu_2}\right)}{\Gamma\left(g(t)\right)}+C_{\beta}p\left(1-\frac{\Gamma\left(g(t),\dfrac{\xi_{\mathrm{GM}}^{*}(t)}{\nu_1}\right)}{\Gamma\left(g(t)\right)}\right)$$

where $\Gamma\left(a,z\right)=\int_{z}^{\infty}x^{a-1}e^{-x}dx$ is the incomplete Gamma function and $\Gamma(a)=\int_{0}^{\infty}x^{a-1}e^{-x}dx$ is the complete Gamma function.

Based on the previous discussion, we can see that the optimal cutoffs, as well as the minimum expected misclassification cost, depend strongly on the assumed model and underlying parameters. In other words, once the degradation model is mis-specified, the obtained cutoff point could be very different from the truly optimal one and the cost might be much larger than what was expected. Therefore, a burn-in policy that reduces such risk is necessary and useful. In the next subsection, we propose an objective function used to search for a burn-in rule that is less sensitive to the given degradation model.

3.2. Robust Cutoff Point

For a given set of degradation path data, if there are several possible models that can provide equally well fit to the data, it becomes difficult to choose an appropriate degradation cutoff point and thus the burn-in policy. Practically, an engineer usually has a prior assessment regarding the probability of a model being the true population model of the data. In other words, instead of specifying one specific degradation model to a given data set, we could evaluate the fitness of the possible models to the data and specify the prior probability (or weight) of each model based on the evaluation. In this research, we consider three possible models for a given set of degradation paths (one based on Wiener process and two based on Gamma process).

In our formula calculating the expected misclassification cost, we incorporate the information from the assessed weights based on an engineer's experience. We calculate the expected misclassification cost by using double expectation conditioned on a model. Specifically, our objected function is to minimize the weighted expected cost:

$$\min_{\xi_r(t)\geq 0} \; w_1 \times \frac{\mathrm{MC_{WM}}(\xi_r(t),t)}{\mathrm{MC_{WM}}(\xi_w^*(t),t)} + w_2 \times \frac{\mathrm{MC_{GM}}(\xi_r(t),t)}{\mathrm{MC_{GM}}(\xi_{\mathrm{GM}}^*(t),t)}. \tag{8}$$

subject to $0 \leq w_i \leq 1,\ i = 1 \text{ and } 2$ and $w_1 + w_2 = 1$. Each w_i represents the weight (prior possibility) about the true model being Wiener or Gamma process respectively based on prior assessment. Because we would like to obtained robust burn-in cutoff against the degradation process model specification, we here calculate the weighted ratio for Wiener and one of the Gamma processes.

In practice, if there is only little information regarding the true model available, we can set $w_1 = w_2 = 0.5$. On the other hand, if we set w_1 or w_2 zero, the problem becomes the original one without considering model misspecification. Although (8) is a one variable function, the analytical solution of its minimum point is still difficult to obtain due to the complexity of the function. Numerical algorithms are used to find the minimum solution in our examples. We next introduce an example to demonstrate how the proposed burn-in policy can help reducing the cost when the degradation path model is uncertain.

3.3. An illustrative example

We here use an example to illustrate the proposed robust minimum misclassification cost burn-in policy and compare the relative efficiency (cost) of the proposed cutoff to the original ones under different model assumptions. In this example, we used the parameter setting that were used in Tsai, et al. (2011) for a high-power semiconductor laser data. We assume $C_\alpha = 65$, $C_\beta = 90$, and $p = 0.2165$. Meanwhile, for the Wiener degradation process model, we have $\eta_1 = 0.0028$, $\eta_2 = 0.0018$, and $\sigma = 0.01092$. For GM model, the common shape parameter for weak and normal components are functions of time $g(t) = 0.0382t$, and the scale parameters are $\nu_1 = 0.0713$ and $\nu_2 = 0.0470$.

Under these parameter settings, the optimum cutoff points and its minimum cost can calculated for each model. For example, for the Wiener degradation process model, we have:

$\xi_w^*(t) = 0.0497 + 0.0023t$ and $\mathrm{MC}_w(t) = 50.9275 \times \Phi\left(-\dfrac{497+5t}{109.2\sqrt{t}}\right) + 19.485 \times \Phi\left(\dfrac{497-5t}{109.2\sqrt{t}}\right)$. The results for GM models can be obtained in a similar manner and thus omitted here for brevity. Let $w_1 = w_2 = 0.5$ and $t = 2{,}000$, the optimal solution is $\xi_r^*(2{,}000)$ can be easily obtained by minimizing (8). Notice that this solution was obtained for a given weight and measurement time. Therefore, with different values of weight and time, the solutions changes. In Figure 1, we graphically show the optimal solutions, $\xi_r^*(t)$, with $w_1 = 0.1, 0.5,$ and 0.9 versus time. In Figure 1, every $\xi_r^*(t)$ with a given w_1 and t is obtained by the optimization procedure.

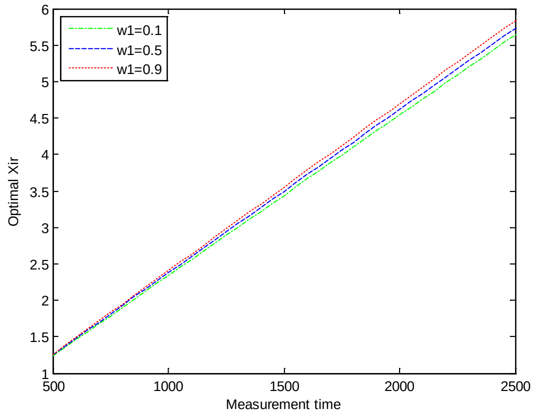


Figure 1. Optimal $\xi_r^*(t)$ when considering WM and GM models with $w_1 = 0.1, 0.5,$ and 0.9.

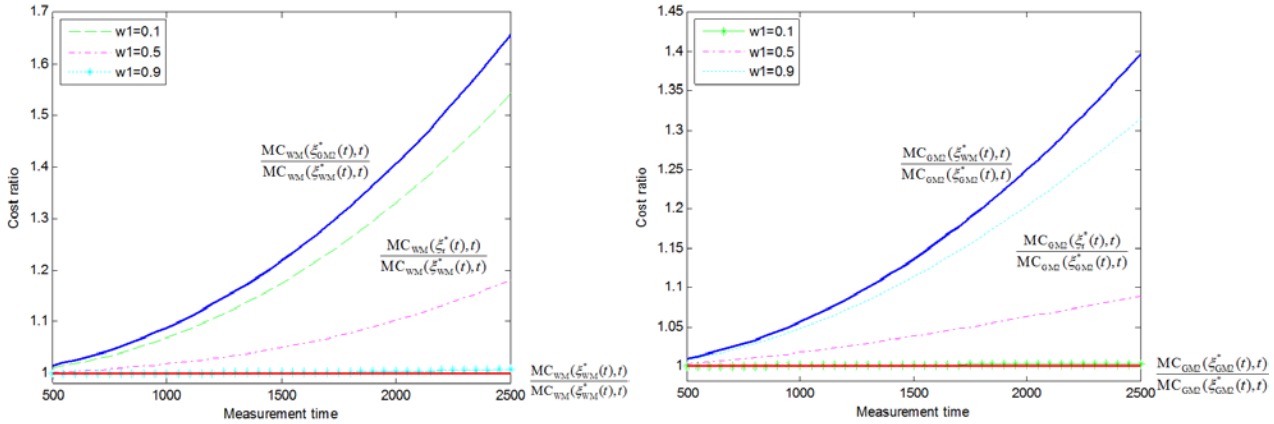
Based on Figure 1, we can see that the minimum weighted costs solutions $\xi_r^*(t)$ is a linear function of time. Therefore, we use linear regression analysis to find the formula of the optimal solutions. Closed-form solutions for $\xi_r^*(t)$ under several weights are presented in Table 1. Meanwhile, we also present the formulae of the optimal solutions, $\xi_r^*(t)$, by minimizing the weighted cost ratio objective function (?).

Table 1. Closed-form solutions $\xi_r^*(t)$ under different weights and models when considering minimizing weighted costs ratios.

	Objective function (8)		
Weights / Models	$w_1 = 0.1$	$w_1 = 0.5$	$w_1 = 0.9$
WM and GM	$0.1300 + 0.00221t$	$0.1219 + 0.00225t$	$0.1164 + 0.00229t$

In Table 1, the optimal cutoff points are described by simple linear functions. Using different weights affects the intercept and the slope of the linear function. We next calculate the misclassification cost using the proposed cutoff points and compare that to the one under model misspecification to see how the proposed plan can reduce the cost from model uncertainty.

We first assume that the Wiener process is the true model but one may wrongly fit the GM model and use it to obtain associated optimal cutoffs and costs. The obtained minimum cost (higher than expected) is then compared to the truly optimum one using correct Wiener process model and the cost ratio is calculated under different measurement times. We also calculate the cost ratios using proposed cutoffs in Table 1 with different weights. All comparison results are plotted in Figure 3(a). Assuming GM model is true but WM is fitted, the same calculation procedure is repeated and the ratios are shown in Figure 3 (b).



(a) (b)

Figure 3. Ratio of minimum misclassification costs as functions of measurement time when (a) fitting GM but WM is true. (b) fitting WM but GM is true using different weights.

Similar to what has been observed in Figure 3, fitting a wrong stochastic model to the degradation paths and use the optimum cutoff accordingly increases the expected misclassification costs significantly. Using the proposed robust cutoffs can significantly reduce the loss of cost due to model misspecification. Comparing to the true minimum costs, the increase of misclassification cost from proposed cutoffs are minor (around 5 to 10%) in all scenarios considered in Figures 3 and 4. We next present the robust burn-in policy based on the misclassification costs proposed in this section.

3.4. Robust Burn-in Policy

Based on the robust cutoffs and the corresponding misclassification costs discussed in Section 3.2, we discuss the associated burn-in policy in this section. Supposed the decision of classification of normal and weak components are determined by one measured degradation path values, the formula of the weighted expected cost is given in (8). Two additional testing costs are considered in a complete burn-in policy, test operating and unit measuring costs. We assume that to perform a burn-in test, it costs C_{ope} per unit of testing time for each test unit. Also, we assume it costs C_{mea} to measure the degradation value of a test unit. Hence, supposed there are n units in a burn-in test and the test runs up to time t, the cost associated with testing and measurement is $C_{\text{ope}} \times nt + C_{\text{mea}} \times n$. The total cost for conducting a burn-in test is then

$$C_{\text{total}}(t) = C_{\text{ope}} \times nt + C_{\text{mea}} \times n + \left(w_1 \times \text{MC}_{\text{WM}}(\xi(t),t) + w_2 \times \text{MC}_{\text{GM}}(\xi(t),t)\right). \tag{9}$$

Since the first two terms in $C_{\text{Total}}(t)$ are not related to misclassification, the minimum value of $C_{\text{Total}}(t)$ at any given time is obtained by substituting the $\xi_r^*(t)$ presented in Section 3.2. The optimal burn-in time can then be obtained by minimizing (8) with the minimum misclassification cost. Following our previous example, let $C_{\text{ope}} = 0.0009$ and $C_{\text{Mea}} = 0.0005$, Figure 4 (a) and (b) shows $C_{\text{Total}}(t)$ versus time when considering Wiener degradation process model and the two Gamma degradation process models, respectively.

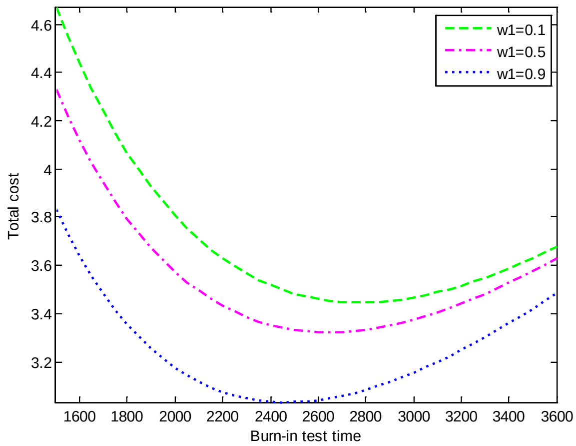


Figure 5. Total burn-in cost versus time when considering WM and GM models with different weights.

It is clear from Figure 5 that, although analytical solution is difficult to find, it is feasible to find a optimal burn-in time that minimizes the total cost by numerical method. Optimal burn-in policy is then obtained by finding the optimal burn-in time and corresponding degradation value cutoff. Notice that the policy discussed in this section is based on a measurement of degradation path.

4. Robust Burn-In Policy with Multiple Degradation Measurements

In Section 3, we discuss the robust cutoff point and the resulting burn-in policy under several possible degradation models. However, the discussion was based on the assumption that the decision is made based on one degradation measurement. In practice, there might be several measurements taken on the degradation paths before a burn-in test is finished or a decision is made. Multiple degradation values from different times are thus available for each test unit and the recorded data contains useful information for making burn-in decisions. In this section, we discuss robust burn-in test policy assuming that there are multiple degradation measurements for each test unit. We assume that each degradation path is measured at time points $t_1, t_2, \ldots,$ and t_k. For the i-th test unit, the recorded degradation values are denoted as $\mathbf{x}_i' = [x_{i1}, x_{i2}, \ldots, x_{ik}]$. Burn-in policy for each degradation model can be made based on these random vectors. We first present the robust burn-in policy for each degradation model.

4.1. Optimal *burn-in procedure for Wiener process model*

We categorize a unit into a normal or weak group based on the observed random vector with degradation values at several check points. In this section, we first assume that the data is obtained from a Wiener degradation process. To find a region R_1 (R_2) for observed degradation values in which a unit is categorized as a weak (normal) one, we use the minimum expected misclassification cost rule as that used in section 3.1. Recall that we considered two types of misclassification scenarios with corresponding costs C_α. and C_β. The formula of expected misclassification cost (EMC) is:

$$\text{EMC}(R_1) = C_\alpha n(1-p) \times \Pr\left(\mathbf{x}_i \in R_1\right) + C_\beta np \times \Pr\left(\mathbf{x}_i \notin R_1\right). \tag{10}$$

The probabilities of misclassification in the formula can be calculated by the joint probability distribution function of $\mathbf{x}_i$. Although the formula is not complex, this EMC is not straightforward to calculate because the elements in the random vector $\mathbf{x}_i$ are correlated and thus the joint probability function could be complicated. For example, the correlation between degradation values $(x_{ir}, x_{is}),\ r, s = 1, 2, \ldots k$ for a Wiener process can be found in Tseng et. al. (2003). In practice, it is easier to find regions for discrimination by considering the joint distribution of the degradation increments.

For the *i*-th test unit, let $\mathbf{d}_i' = \left[d_{i1}, d_{i2}, \ldots, d_{ik}\right]$ where $d_{ij} = x_{ij} - x_{i,(j-1)},\ j = 1, 2, \ldots k$ and $x_{i0} = 0$ (d_{ij} are degradation increments). Because of the independent property of Wiener process, the random variables in $\mathbf{d}_i$ are thus independent and the joint probability distribution can be obtained by the product of the PDFs of each random increment. Moreover, for a Wiener process, it is known that the distribution of each d_{ij} is a normal distribution. Thus, the formula of MC can be simplified than that from using $\mathbf{x}_i$ directly. The objective function (minimizing EMC) can be rewritten by replacing $\mathbf{x}_i$ to $\mathbf{d}_i$. Let $f_k(\mathbf{d}),\ k = 1, 2$ be the normal joint PDF of a random vector of degradation increments for a weak and normal unit, respectively. Then, for a Wiener degradation process, we have the following proposition:

Proposition 1: To minimize the expected misclassification cost, a unit is categorized as a weak component if the observed degradation increments fall in region R_1. The optimum region is denoted as $R_{1,w}$ where $R_{1,w} : x_k = \sum_{i=1}^{k} d_i \geq \frac{\sigma^2}{\eta_1 - \eta_2} ln\left(\frac{C_\alpha}{C_\beta}\frac{1-p}{p}\right) + \frac{(\eta_1 + \eta_2)t_k}{2}$. On the other hand, a unit is categorized as a normal one if the inequality holds in the opposite direction. A proof to this proposition is given at the final report of this research project.

This is an interesting result for a Wiener process because the classification rule with several measurements turns out only depends on the last measured degradation value. We next present the optimum classification region for Gamma degradation process.

4.2. Optimal burn-in procedure for Gamma process model

In this section, we discuss the optimum classification region assuming the degradation paths are Gamma degradation process. Similar to that in a Wiener process case, because measurements from different times are correlated, it is not straightforward to derive the joint probability distribution for degradation value vector $\mathbf{x}$. However, because of the independent increment property of a Gamma process, it is easier to analyze $\mathbf{d}_i' = \left[d_{i1}, d_{i2}, \ldots, d_{ik}\right]$ where entries in $\mathbf{d}_i$ are independent Gamma distributed random variables. To minimizing EMC, let $g_k(\mathbf{d}),\ k = 1,2$ be the product of Gamma PDFs for weak and normal units, respectively, the optimum classification region for Gamma process is presented in the next proposition.

Proposition 2: To minimize the expected misclassification cost when data is from a Gamma process, a unit is categorized as a weak component if it has observed degradation increments $\mathbf{d}_0$ falls in region R_1. The optimum region is denoted as $R_{1,\mathrm{GM}}$ where $R_{1,\mathrm{GM}} : x_k \geq \dfrac{\nu_1\nu_2}{\nu_1 - \nu_2} ln\left(\dfrac{\nu_1^{(h(t_k)-h(t_0))}}{\nu_2^{(h(t_k)-h(t_0))}} \dfrac{C_\alpha}{C_\beta} \dfrac{1-p}{p}\right)$. A proof to this proposition is also given at the final report of this research project. Because the results can be quite complex, the formula for $\mathrm{ECM}(R_{1,\mathrm{GM}})$ is not presented here. Using these results, we can develop robust burn-in procedure when there are multiple measurements available.

4.3. Robust burn-in procedure with multiple measurements

In this section, we propose robust burn-in procedure when there are multiple measurements available for each degradation path before the burn-in test is stopped. The proposed procedure is useful when there are several possible stochastic models for a degradation path. Similar to the approach used in section 3.3., we assume that the prior probability for the *i*-th possible model is λ_i. Considering the joint probability of degradation increments, $\mathbf{d}$, the objective function is to minimize the weighted ratio of misclassification cost to the minimum EMC obtained in the previous two sections. The general form of the objective function used is:

$$\min_{R_1} \sum_{i=1}^{j} w_i \frac{C_\alpha n(1-p)\Pr\left(\mathbf{d} \in R_1\right) + C_\beta np\Pr\left(\mathbf{d} \notin R_1\right)}{\mathrm{ECM}(R_{1,i})}. \tag{11}$$

To minimize (11) so that the robust region can be found, we have the following proposition.

Proposition 3: Given the previous defined parameters and objective function, the optimum burn-in classification rule minimizing (11) is to categorize a unit with $\mathbf{x_0}$ as a weak component if $\mathbf{x_0} \in R_1$ where

$R_1 : \dfrac{\dfrac{w_1}{\mathrm{ECM}(R_{1,w})} f_1(\mathbf{d}) + \dfrac{w_2}{\mathrm{ECM}(R_{1,\mathrm{GM}})} g_1(\mathbf{d})}{\dfrac{w_1}{\mathrm{ECM}(R_{1,w})} f_2(\mathbf{d}) + \dfrac{w_2}{\mathrm{ECM}(R_{1,\mathrm{GM}})} g_2(\mathbf{d})} \geq \dfrac{C_\alpha(1-p)}{C_\beta p}$ and categorize this unit as normal when the inequality is in opposite direction.

Proof: Let $\xi_f = \mathrm{ECM}(R_{1,w})$ and $\xi_g = \mathrm{ECM}(R_{1,\mathrm{GM}})$. Because $R_1 \cup R_2 = \Omega$, we can rewrite the objective function as to find R_1 that minimizes

$$w_1 \times \frac{C_\beta p\left(1-\int_{R_1} f_1(\mathbf{x})d\mathbf{x}\right) + C_\alpha(1-p)\int_{R_1} f_2(\mathbf{x})d\mathbf{x}}{\xi_f} + w_2 \times \frac{C_\beta p\left(1-\int_{R_1} g_1(\mathbf{x})d\mathbf{x}\right) + C_\alpha(1-p)\int_{R_1} g_2(\mathbf{x})d\mathbf{x}}{\xi_g}$$

$$= \frac{w_1 C_\beta p}{\xi_f} + \int_{R_1} \frac{w_1}{\xi_f}(C_\alpha(1-p) f_2(\mathbf{x}) - C_\beta p f_1(\mathbf{x}))d\mathbf{x} + \frac{w_2 C_\beta p}{\xi_g} + \int_{R_1} \frac{w_2}{\xi_g}(C_\alpha(1-p) g_2(\mathbf{x}) - C_\beta p g_1(\mathbf{x}))d\mathbf{x}$$

$$= \int_{R_1}\left[\frac{w_1}{\xi_f}(C_\alpha(1-p) f_2(\mathbf{x}) - C_\beta p f_1(\mathbf{x})) + \frac{w_2}{\xi_g}(C_\alpha(1-p) g_2(\mathbf{x}) - C_\beta p g_1(\mathbf{x}))\right]d\mathbf{x} + \left(\frac{w_1}{\xi_f} + \frac{w_2}{\xi_g}\right)C_\beta p$$

$$\Rightarrow \frac{w_1}{\xi_f}C_\alpha(1-p) f_2(\mathbf{x}) - \frac{w_1}{\xi_f}C_\beta p f_1(\mathbf{x}) + \frac{w_2}{\xi_g}C_\alpha(1-p) g_2(\mathbf{x}) - \frac{w_2}{\xi_g}C_\beta p g_1(\mathbf{x}) \leq 0$$

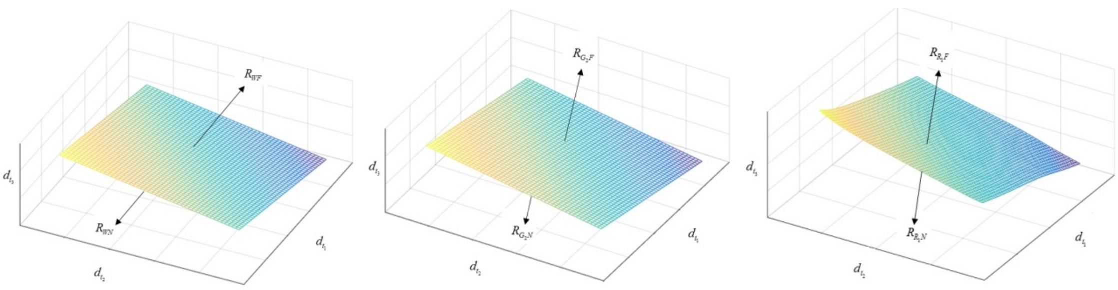
$$\Rightarrow \frac{\frac{w_1}{\xi_f} f_2(\mathbf{x}) + \frac{w_2}{\xi_g} g_2(\mathbf{x})}{\frac{w_1}{\xi_f} f_1(\mathbf{x}) + \frac{w_2}{\xi_g} g_1(\mathbf{x})} \leq \frac{C_\beta p}{C_\alpha(1-p)} \Rightarrow \frac{\frac{w_1}{\xi_f} f_1(\mathbf{x}) + \frac{w_2}{\xi_g} g_1(\mathbf{x})}{\frac{w_1}{\xi_f} f_2(\mathbf{x}) + \frac{w_2}{\xi_g} g_2(\mathbf{x})} \geq \frac{C_\alpha(1-p)}{C_\beta p}.$$

Some special cases can be easily derived by the rule proposed.

In this section, we propose robust burn-in procedure when there are multiple measurements available for each degradation path before the burn-in test is stopped. The proposed procedure is useful when there are several possible stochastic models for a degradation path.

4.4. A numerical example with multiple measurements

In this section, we provide a numerical example using the proposed proposition based on the GaAs lasers data presented in Meeker and Escobar (2008) (see page 642). Suppose there are three measurements of degradation paths available. Using parameters from Tsai, et al. (2011). We first present some illustrative graphs for $R_{1,w}$, $R_{1,GM}$, and R_1 in figure 6 (see Chen dissertation (2017)).



(a) (b) (c)

Figure 6. Illustrative graphs for $R_{1,w}$ (a), $R_{1,GM}$ (b), and R_1 (c) when there are three measurements.

Next, using the same parameters and cost settings as those presented previously, we calculate the misclassification cost and total expected test cost based on the derived R_1 in Table 2 when the true degradation path is Wiener under various test termination times *t*.

Table 2. Misclassification cost and total expected test cost based on the derived R_1.

t	500	1000	1500	2000	2500	3000	3500	4000
$MC(R_1)$	724.16	405.89	225.43	126.65	72.24	41.59	24.27	14.30
Total	932.69	737.20	681.15	673.84	701.15	748.96	808.81	875.51

It is clear from Table 2 that the total test cost is minimized at time $t = 2000$ and thus this is the optimal burn-in test stopping time. Comparing the total cost using mis-specified model (Gamma in this case), our proposed robust burn-in test policy has significantly lower total test cost. Similar observation can be obtained when we assume Gamma is the true model and using our proposed burn-in test policy. Therefore, our proposed method can be used in both model assumptions without increasing too much test cost.

5. Summary

To maintain high quality level of outgoing products, burn-in tests has been implemented at the early stage of production in order to screen out latent failure products. For recently highly reliable products, an useful method is to measure the QC values of a product and decide if a unit is normal or weak based on observed degradation value. To model the observed QC degradation path, there were several useful models such as Wiener and Gamma degradation models. Optimal burn-in test policy has also been proposed based on a specific chosen degradation model.

Some examples have been presented in literature showing that several potential models that can provide equivalently good fit to the same observed degradation paths. However, the optimal burn-in policy from each model can be significantly different from each other. Thus, it becomes important to find some robust burn-in test policies that can be used in all possible degradation models without increasing overall test cost too much. In this research, we proposed a robust burn-in policy against degradation process model uncertainty. The weighted cost ratio is used as the objective function. We consider the two most commonly used degradation models, Wiener and Gamma processes. By assigning a prior probabilities regarding the true model (weights), weighted criteria are used to find such robust burn-in test plans. Two possible scenarios in a burn-in test. That is, a burn-in test cutoff is determined by single or several measurements of degradation values. Numerical example based on a real data is presented to evaluate the performance of our proposed test policy. Results show that our proposed method can be used in both models without increasing too much overall test costs.

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105年度專題研究計畫成果彙整表

計畫主持人：胡政宏	計畫編號：105-2221-E-006-168-
計畫名稱：針對多種可能隨機衰退模型之穩健型最小成本預燒實驗計劃	

成果項目					量化	單位	質化（說明：各成果項目請附佐證資料或細項說明，如期刊名稱、年份、卷期、起訖頁數、證號...等）
國內	學術性論文	期刊論文			0	篇	
		研討會論文			0		
		專書			0	本	
		專書論文			0	章	
		技術報告			0	篇	
		其他			0	篇	
	智慧財產權及成果	專利權	發明專利	申請中	0	件	
				已獲得	0		
			新型/設計專利		0		
		商標權			0		
		營業秘密			0		
		積體電路電路布局權			0		
		著作權			0		
		品種權			0		
		其他			0		
	技術移轉	件數			0	件	
		收入			0	千元	
國外	學術性論文	期刊論文			0	篇	
		研討會論文			0		
		專書			0	本	
		專書論文			0	章	
		技術報告			0	篇	
		其他			0	篇	
	智慧財產權及成果	專利權	發明專利	申請中	0	件	
				已獲得	0		
			新型/設計專利		0		
		商標權			0		
		營業秘密			0		
		積體電路電路布局權			0		
		著作權			0		
		品種權			0		
		其他			0		

	技術移轉	件數	0	件	
		收入	0	千元	
參與計畫人力	本國籍	大專生	0	人次	
		碩士生	4		本次計畫研究內容，共計有四位碩士班兼任助理參與。其中碩士助理的主要貢獻與工作內容包含文獻蒐集、程式執行、論文排版與其他行政相關事項等。由於這些訓練工作與撰寫論文過程皆為碩士班撰寫畢業論文時所需要的訓練項目。因此每位學生在參與計畫並負責完成其工作時，也可以了解論文的撰寫方式與要求。每位學生在完成工作後，皆認為對於其論文撰寫要求的了解加深，畢業生也因此順利的完成正式且高品質的畢業論文。對於學生的論文訓練幫助很大。
		博士生	0		
		博士後研究員	0		
		專任助理	0		
	非本國籍	大專生	0		
		碩士生	0		
		博士生	0		
		博士後研究員	0		
		專任助理	0		
其他成果 （無法以量化表達之成果如辦理學術活動、獲得獎項、重要國際合作、研究成果國際影響力及其他協助產業技術發展之具體效益事項等，請以文字敘述填列。）					

科技部補助專題研究計畫成果自評表

請就研究內容與原計畫相符程度、達成預期目標情況、研究成果之學術或應用價值（簡要敘述成果所代表之意義、價值、影響或進一步發展之可能性）、是否適合在學術期刊發表或申請專利、主要發現（簡要敘述成果是否具有政策應用參考價值及具影響公共利益之重大發現）或其他有關價值等，作一綜合評估。

1. 請就研究內容與原計畫相符程度、達成預期目標情況作一綜合評估

■達成目標

□未達成目標（請說明，以100字為限）

□實驗失敗

□因故實驗中斷

□其他原因

說明：

2. 研究成果在學術期刊發表或申請專利等情形（請於其他欄註明專利及技轉之證號、合約、申請及洽談等詳細資訊）

論文：□已發表 □未發表之文稿 ■撰寫中 □無

專利：□已獲得 □申請中 ■無

技轉：□已技轉 □洽談中 ■無

其他：（以200字為限）

3. 請依學術成就、技術創新、社會影響等方面，評估研究成果之學術或應用價值（簡要敘述成果所代表之意義、價值、影響或進一步發展之可能性，以500字為限）

預燒實驗常用於產品元件進行到下一生產階段，或者是送至客戶端前篩除可能混雜於其中的瑕疵品。良好的預燒實驗計劃可降低實驗與錯誤分類的總成本。然而雖然在文獻中已有類似研究，但是目前已知研究成果皆需要選定適合產品或元件壽命相關的統計模型，對於實務上有可能因不同統計模型皆適用於同一產品壽命的情況無法直接引用。為克服此學術上尚未討論過的問題，本研究成果提出了在擬定預燒計畫前，若有不同統計模型適用於同一類型產品時，使用加權成本函數來尋找最佳化後的預燒實驗計劃。於研究成果中提出的數值結果證明，使用此方法得到的預燒實驗計劃在不同可能的統計模型下皆有不錯表現（詳細說明與範例請見報告內容）。因此，本研究成果在學術層面提出解決未在文獻中討論過的預燒實驗計劃設計方法。在實際應用方面實驗者可直接採用得到的預燒實驗計劃而較無需擔心模型選擇與配置的問題，因此在學術與實務應用上皆有其價值。本研究採用常用來配似及估計衰退路徑的模型如Wiener 以及Gamma 隨機過程進行討論。在未來展望與推廣研究結果上，若有不同產品適合其他統計模型，本研究提出的方法也可以包含更多可能的隨機過程模型以適用於不同產品元壽命或衰退路徑。

4. 主要發現
本研究具有政策應用參考價值：■否　□是，建議提供機關
（勾選「是」者，請列舉建議可提供施政參考之業務主管機關）
本研究具影響公共利益之重大發現：□否　□是
說明：（以150字為限）