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Developing Quantitative Methods for Quality and Maintenance Management in Micro-Electromechanical Systems

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Abstract: *In this research, we create and refine a computational model using Matlab software, focusing on the degradation characteristics of light-emitting devices. This work acknowledges the critical importance of burn-in procedures, quality control measures, and preventive maintenance policies in any organization. The burn-in phase serves as a fundamental step in recognizing faulty products by subjecting them to a predetermined testing period. Post the burn-in phase, a quality control system is employed, leading to the exclusion of sub-standard products. Concurrently, we establish a preventive maintenance strategy that aims at enhancing the product's performance over its lifespan. For the identification of the best choices concerning burn-in, quality control, and preventive maintenance, a cost-efficiency optimization model is formulated. The developed model is then used to assess the value of these policies, comparing original and optimal measurements using an optimization algorithm, all demonstrated through a practical case study.*

Keywords: quality, maintenance, management, quantitative methods, MEMs

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1. Introduction

The past few decades have witnessed a remarkable surge in the use of light-emitting devices, such as Light Emitting Diodes (LEDs) and Organic Light Emitting Diodes (OLEDs). The driving forces behind their widespread acceptance include their high-efficiency light output, lower energy consumption, and versatile applications spanning various sectors, including residential, commercial, and aviation lighting (Tseng, Hamada, & Chiao, 1995). However, despite their many benefits, these devices, like all electronic components, are prone to degradation phenomena. These phenomena can lead to a reduction in luminous flux output, shifts in color quality, and an overall decrease in the devices' operational lifespan (Bae & Kvam, 2006).

Due to the extensive and ubiquitous utilization of these light-emitting devices, the pursuit of methodologies that guarantee their operational reliability and longevity has become an urgent endeavor. Ensuring the durable performance of these devices is not only advantageous from an economic perspective but also vital for sustainability efforts, reducing electronic waste and conserving resources.

Historically, within the domain of reliability engineering, essential topics like burn-in, quality control, and preventive maintenance have been the subject of rigorous study. However, these investigations have typically been undertaken in isolation, each focusing on its individual impact (Mi, 1994; Cha & Mi, 2007; Shafiee, Chukova, & Yun, 2014). To date, a comprehensive model that integrates all three of these components to optimize the reliability and quality of light-emitting devices remains an underexplored research opportunity.

Against this backdrop, the focus of our current research is the development of an integrated optimization model for light-emitting devices that concurrently considers burn-in, quality control, and preventive maintenance policies. We employ a MATLAB-based computational model to probe the complex interconnections and interdependencies among these policies (Tseni, Sotiropoulos, & Georgantzinos, 2022). Our ambition is to craft a robust decision-making tool that facilitates the optimization of these policy choices, thereby boosting the reliability of the devices and curbing the total operational cycle costs.

The implications of this research are profound, with the potential to dramatically alter our understanding and implementation of integrated maintenance strategies for light-emitting devices. By unveiling the intricate interplay and dependencies between burn-in, quality control, and preventive maintenance policies, we equip engineers, managers, and decision-makers with invaluable insights. These insights can guide them in devising and implementing strategies that are both effective and efficient, enhancing device reliability while reducing costs. Following this introduction, we will delve into the specifics of our methodology, share the key results of our research, and discuss their implications.

2. Methodology

Our investigation starts by focusing on light-emitting devices like Plasma Display Panel (PDP), Vacuum Fluorescent Display (VFD), or Fluorescent Lamp (FL), that deteriorate over time as their luminosity drops below a certain percentage of the original brightness. This failure is considered as a 'light' failure, in contrast to a 'hard' failure where system components abruptly cease to function. The brightness of these types of light-emitting devices is known to degrade exponentially over their lifetime. We define this degradation as follows (Tseng, Hamada, & Chiao, 1995):

$$X(t) = ln\Lambda(t) = \theta - \lambda t. \tag{1}$$

To find the best specification threshold η at the burn-in time t0, as well as forecast the reliability of light-emitting machines at a time t (t ≥ t0), we use the distribution of X(t). This distribution represents the probability that the brightness surpasses the failure threshold. Based on this, we build the cumulative function of X(t) as follows (Casella & Berger, 2002):

$$F_X(x;t) = 1 - F_\lambda\left(\frac{\theta - x}{t}\right) = 1 - \Phi\left(\frac{\ln(\theta - x) - (lnt + \mu)}{\sigma}\right), x \in (-\infty, \theta), \tag{2}$$

and the probability density function (pdf) of X(t) is then described as follows:

$$f_X(x) = \frac{1}{(\theta - x)\sqrt{2\pi}\sigma} \exp\left(-\frac{\left(\ln(\theta - x) - (lnt + \mu)\right)^2}{2\sigma^2}, x \in (-\infty, \theta). \tag{3}$$

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The reliability of a system at a given time t is then calculated as the probability that X(t) exceeds the failure limit (H) (Peng, Feng, & Coit, 2009):

$$R(t) = P(T > t) = P(X(t) > H). \tag{5}$$

We then investigate the effect of quality control on the reliability of these light-emitting devices. We begin by calculating the reliability function without any quality control:

$$R(t) = P\left(ln\lambda < \ln\left(\frac{-lnp}{t-t_0}\right)\right) = 1 - \Phi\left(\frac{\ln(t-t_0)-(\ln(-lnp)-\mu)}{\sigma}\right), t > t_0, \tag{6}$$

Next, we calculate the reliability function with quality control, i.e., after the devices have been tested and the ones with high degradation levels removed:

$$R(t|X(t_0) > \eta) = P(X(t) > H|X(t_0 > \eta) = \frac{P(\lambda < min\left\{\frac{-lno}{t-t_0}, \frac{\theta-\eta}{t_0}\right\}}{P\left(\lambda < \frac{\theta-\eta}{t_0}\right)}, \tag{9}$$

The overall aim of our investigation is to minimize the total expected cost during the expected usage time of these light-emitting devices. This total cost includes the cost of the burn-in stage, the quality cost at the production stage, and the cost of an unforeseen failure during the device's usage:

$$TC(\eta, \tau, t_0) = \frac{BC(t_0)+QC(\eta,t_0)+FC(\eta,\tau,t_0)+RC}{E[U|\eta,t_0,\tau]}. \tag{10}$$

Our optimization model seeks to minimize this total cost over the life cycle of the system, which can be articulated as follows:

$$(\eta^*, \tau^*, t_0{}^*) = argmin\{TC(\eta, \tau, t_0)\}, 0 < \eta < \theta, L_\tau \le \tau \le U_\tau, L_{t_0} \le t_0 \le U_{t_0}, \tag{11}$$

To solve this equation, we employed the Simulated Annealing Algorithm, which proved effective in dealing with such complex objective functions. (Neptune, 1999).

3. Results

Our research framework was established based on the parameters proposed by Tseng, Hamada, & Chiao (1995), which state that a bulb is classified as non-defective if it exhibits a brightness of more than 2500 lumens after a 100-hour burn-in period. Under these parameters, our model estimated the total cost per usage duration to be TC = €2.6187/hour.

The optimization model operates on three significant decision variables, namely the burn-in time (t_0), the cut-off threshold (η), and the replacement interval (τ). The practical constraints define their feasible boundaries. Utilizing the Simulated Annealing algorithm, the model identified an optimal solution with η = 7.8405, τ = 60.934 hours, and t_0 =100 hours, which considerably reduced the total cost to TC = €0.0965/hour.

We further investigated the performance of the model by adjusting the presence and absence of quality control measures while varying burn-in times. It is observed a trend where an increase in burn-in time led to increased costs.

Figure 1 displays the influence of the burn-in time (t_0) on the total cost (*TC*) per usage duration, given a fixed replacement period (τ) of 30,000 hours and no quality control (η=0). The x-axis represents varying burn-in time intervals, starting from 0 hours and extending up to 300 hours, while the y-axis illustrates the corresponding total cost per usage duration. A clear positive linear trend is noticeable in the data: as the burn-in time increases, the total cost per usage duration also escalates. For instance, at 0 hours of burn-in time, the total cost is €0.1282 per hour. However, as the burn-in time elevates to 100, 200, and finally 300 hours, the total costs rise to €0.1320, €0.1358, and €0.1398 per hour respectively. This correlation suggests that extending the burn-in time in a system without quality control results in a higher operational cost, necessitating a careful consideration of burn-in time in cost optimization strategies.

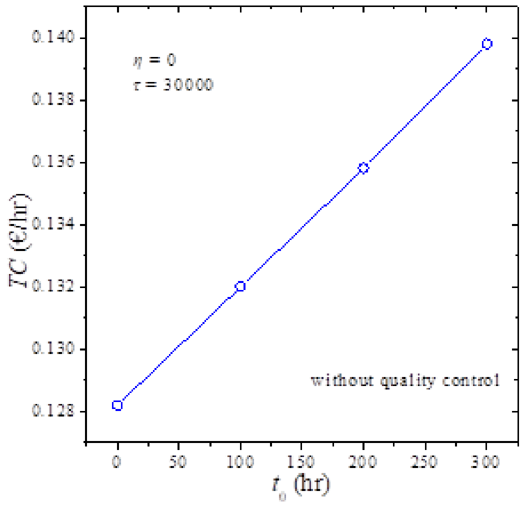

Figure 1: Variation of the total cost vs the burn-in time without quality control

Figure 2 presents the impact of the burn-in time (t_0) on the total cost (*TC*) per usage duration under the conditions of a fixed replacement period (τ) of 30,000 hours and the implementation of quality control (η = 7.8240). The x-axis portrays different burn-in times from 0 hours up to 300 hours, while the *y*-axis shows the corresponding total cost per usage duration. As can be observed from the figure, a positive linear correlation is apparent between the burn-in time and total cost, mirroring the trend observed in Figure 1. However, with quality control in place, the total cost at each burn-in time is noticeably lower than in the no-quality-control scenario of Figure 1.

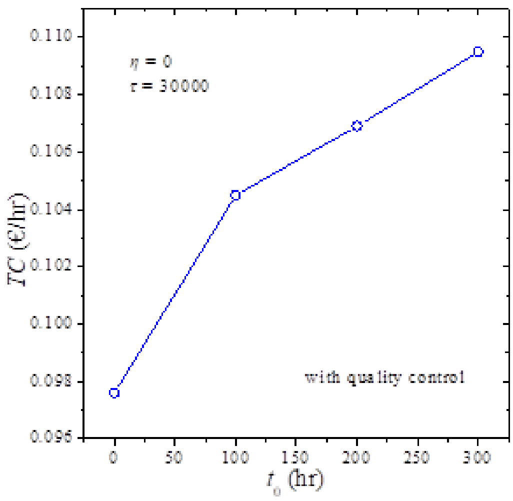

Figure 2: Variation of the total cost vs the burn-in time with quality control

For a burn-in time of 0 hours, the total cost is €0.0976 per hour, which is lower than the corresponding cost without quality control (€0.1282 per hour). This cost advantage is sustained as the burn-in time increases, with costs at 100, 200, and 300 hours of burn-in time being €0.1045, €0.1069, and €0.1095 per hour, respectively. These results underline the benefit of incorporating quality control measures in operational strategies, as they help reduce the total cost per usage duration, even when the burn-in time increases.

Comparing Figures 1 and 2 gives valuable insight into the effects of quality control measures on the total cost (TC) per usage duration. Both figures showcase the relationship between burn-in time (t_0) and the total cost, considering a fixed replacement period (τ) of 30,000 hours. In Figure 1, the absence of quality control measures is demonstrated, resulting in a steady increase in the total cost as the burn-in time increases. This upward trend underscores that without quality control, even with increased burn-in time, the system does not necessarily yield cost-effective results. The total cost per usage duration ranges from €0.1282 per hour with no burn-in time to €0.1398 per hour at 300 hours of burn-in time. On the other hand, Figure 2 provides a compelling counterpoint. Despite following the same upward trend, the implementation of quality control (η = 7.8240) results in a considerably lower total cost per usage duration at each burn-in time interval. The total cost ranges from €0.0976 per hour with no burn-in time to €0.1095 per hour at 300 hours of burn-in time. The comparison of Figures 1 and 2 underscores the financial benefit of implementing quality control measures. Even though the total cost still increases with longer burn-in times in both scenarios, the rate of increase is significantly less in the scenario that implements quality control, as seen in Figure 2. This suggests that quality control measures can help manage and mitigate the cost increases associated with longer burn-in times, providing clear cost advantages over scenarios that do not implement such measures.

Table 1 offers a comprehensive comparison between two distinct preventive maintenance strategies and their associated parameters within the degradation model framework. This comparison serves to highlight the significant impact preventive maintenance strategies have on total cost (TC), as well as other crucial variables. The first strategy, termed "Replacement upon Failure," operates on a reactive basis, with no active preventive maintenance employed. In this scenario, replacement only occurs when a failure is detected, leading to an infinite replacement period (τ = Inf). With the burn-in time (t_0) at 173 hours and the rejection threshold (η) at 7.8425, the total cost per usage duration is relatively high at €0.0956 per hour.

In contrast, the second strategy, "Age-based Preventive Maintenance" applies a proactive approach to maintenance. Here, replacement occurs at fixed time intervals or when a failure happens, whichever comes first. The data suggests that an increase in the burn-in time to 199 hours and a minor adjustment in the rejection threshold to 7.8430, coupled with a pre-defined replacement period of 30463 hours, results in a significant reduction in total cost. The total cost drops to a much more economical €0.0578 per hour.

This comparison, as shown in Table 1, underscores the value of a proactive, age-based preventive maintenance strategy. By employing this method, manufacturers can achieve substantial cost savings, reduce product failures, and significantly improve overall operational efficiency.

Table 1: Preventive maintenance strategies within the degradation model framework

Preventive Maintenance Policies	t_0	η	τ	TC
Replacement upon Failure (No preventive maintenance employed)	173	7.8425	Inf	0.0956
Age-based Preventive Maintenance	199	7.8430	30463	0.0578

4. Conclusion

This paper has presented an extensive analysis of a degradation model applied to light bulbs, as based on the parameters proposed by Tseng, Hamada, & Chiao (1995). Our initial model suggested a relatively high total cost per usage duration (TC) of €2.6187/hour. Upon employing the Simulated Annealing algorithm for optimization of the burn-in time (t_0), the cut-off threshold (η), and the replacement interval (τ), we realized a significant reduction in the total cost, bringing it down to €0.0965/hour.

Our further investigations highlighted the significant influence of quality control measures on the total cost of operations. Comparative analysis of Figures 1 and 2 demonstrated the effect of implementing quality control measures in the operational strategies. While both figures illustrated a positive correlation between the burn-in time and total cost, the implementation of quality control led to a noticeable reduction in total cost per usage duration, even with increasing burn-in times. This provides clear evidence of the financial benefits of incorporating quality control measures in operational strategies.

Further, our research spotlighted the impact of different preventive maintenance strategies on total cost. Table 1, contrasting "Replacement upon Failure" and "Age-based Preventive Maintenance" strategies, showed the considerable cost-effectiveness of a proactive approach. The Age-based Preventive Maintenance strategy, which led to a total cost of €0.0578/hour, demonstrated the potential for substantial cost savings and efficiency improvements.

In conclusion, our study underscores the criticality of strategically selecting burn-in time, employing quality control measures, and implementing a proactive, age-based preventive maintenance strategy in managing operational costs effectively. Future research in this area can delve deeper into the optimization of these factors and explore the effects of other potential influencing parameters to refine and enhance the degradation model further.

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