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DOI
10.1109/EuroSimE.2018.8369895

Publication date
2018

Document Version
Final published version

Published in
2018 19th International Conference on Thermal, Mechanical and Multi-Physics Simulation and Experiments in Microelectronics and Microsystems, EuroSimE 2018

Citation (APA)
Jacobs, B., van Driel, W. D., & Schuld, M. (2018). Lumen maintenance prediction for LEDs: New insights. In *2018 19th International Conference on Thermal, Mechanical and Multi-Physics Simulation and Experiments in Microelectronics and Microsystems, EuroSimE 2018* (pp. 1-4). IEEE. https://doi.org/10.1109/EuroSimE.2018.8369895

Lumen maintenance prediction for LEDs - new insights

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Abstract

Commercial claims for LED-based products in terms of lumen maintenance are fully based on TM-21 extrapolations using LM-80 data. We presented an approach based on statistical data analytics, following the work from Yu & Tseng, at EuroSimE2015. Since then, more LM80 test data came available both for High Power (HP) and Mid Power (MP) LEDs. In this paper, we will present the results of further investigations, where we have taken the work from Meeker into account. This is needed as some commercial claims are based on 10 years of warranty and some service bids provide periods of 20 to 25 years of operation.

1. Introduction

The debate on producing commercial claims for LED-based products in terms of lumen maintenance is still not settled. Most companies base their product lifetime claims fully on LED-level LM80 data [1] and TM-21 extrapolations [2]. Even more, the standardization bodies like e.g. IEC [3, 4] have agreed that such an approach is allowed. Here, the lumen maintenance lifetime is defined as the time when the maintained percentages of the initial light output fall below a failure threshold. In earlier publication, we have mentioned that there may be a risk in doing this as TM-21 only relies on the behavior of the average LED degradation, instead of taking into account the degradation of all individual LEDs [5, 6, 7]. In [5] we have presented a more profound statistical analysis that makes the step from TM-21 extrapolation to lumen maintenance on product level. We investigated different approaches able to perform lumen maintenance extrapolations. For that, we have analyzed several LM80 data sets from a statistical point of view [6, 7]. In [7] we proposed an alternative statistical approach to estimate lumen depreciation of LED's. Our analysis of a series of LM80 data sets did show the strength of the described method as the resulting unique fitted parameters describe the lumen maintenance of the LED over a long period. In principle we found that there is also no need for a limitation based on the so-called 6x rule from TM-21. The method we used, was based on the statistics defined by Yu & Tseng [8].

In this same book chapter [7], we also proposed the use of an even more complex stochastic models that can properly describe the degradation path for LEDs. Here, the big challenge is to get accurate estimates of a product's lifetime which, obviously, strongly depends on the appropriateness of modeling its degradation path. A typical degradation path consists of mean degradation curve and its error term (measurement error). There are two approaches available in the literature. First, the mixed effects model is one of the most popular approaches in degradation analysis [9, 10, 11]. In order to describe the unit-to-unit variations of the test units, the unknown parameters of the mean degradation path are described in terms of the mixed (or random) effects. Often the mixed effects formulations do not take the time-dependent error structure into consideration. Therefore, the stochastic process formulation, or Gauss-Markov method can be an alternative approach to model the product's degradation path. Dealing with those more complex models, to find the maximum likelihood estimates (MLEs) of the unknown parameters, the mixed effects model is computationally intensive. STATA or R can be used. However, on-hand procedures do not always guarantee that the precise parameter estimations can be obtained. Besides the mixed and Gauss-Markov approaches, the application of Bayesian methods may be promising [12, 13]. Bayes allows a reliability engineer to incorporate one's prior knowledge about the unknown parameters of the model into data analysis to provide important improvements in precision. Based on previous experiments an engineer may specify priors for the effects of temperature and/or current. As generally well-known such priors are key components in a Bayesian model specification and should be chosen carefully.

In this paper we have chosen to use the method by Meeker and Weaver [11] to analyze a large set of LM80 data. The method is denoted as repeated measures accelerated degradation test (RMADT) and finds significant contributions in other industries for describing degradation of e.g. metals and carbon.

Datasets from both mid-power (MP) and high-power (HP) LEDs are used against this RMADT approach. Results are described for the datasets and conclusions given.

2. Methodology

LM80 data sets are incoming on a daily basis. The number of LED suppliers is not only growing, also the number of LED package types is significantly increasing. Although the active device (or epitaxy) can differ from type to type, the packaging materials and associated processes are not that different. From a pure data analytics point of view this means that data sets can be united, leading to statistically relevant numbers. In our approach, we have gathered LM80 sets of two distinct types: HP LEDs and MP LEDs, see table below. In total, we analyzed approximately 2x 27000 data points.

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Table 1: HP LED dataset details.

LED	If [A]	Tcase [degC]	Number of readpoints
HP1	0.7; 1.0	55; 85; 105	1680
HP2	0.35; 0.5; 0.7; 1.0; 1.5	55; 85; 105; 125	3880
HP3	0.5; 0.7; 1.05; 1.2	55; 85; 105	4200
HP4	1.5; 2.1; 3.0	55; 85; 105	1950
HP5	0.35; 0.7	55; 85; 105	2500
HP6	1.5; 2.1; 3.0	85; 105	1300
HP7	0.5; 0.7	85; 105	1550
HP8	0.5; 0.7; 1.0;	55; 85; 105; 120	3850
HP9	0.7; 1.2; 1.5	55; 85; 105; 120	2880
HP10	0.5; 0.7; 1.0; 1.5	55; 85; 105; 125	2277

Table 2: MP LED dataset details.

LED	If [A]	Tcase [degC]	Number of readpoints
MP1	0.1;0.15;0.2	55; 85; 105	3518
MP2	0.135;0.2	55; 85; 105	2115
MP3	0.15;0.2	25; 55; 85; 95	1900
MP4	0.06;0.08	55; 85; 105	3902
MP5	0.15;0.2;0.24	55; 85; 105	2147
MP6	0.165;0.2	55; 85; 105	750
MP7	0.2;	55; 85; 105	3150
MP8	0.065;0.15;0.18	55; 85; 105	539
MP9	0.1;0.15;0.2	55; 85; 105	2034
MP10	0.12;0.2	55; 85; 105	1830
MP11	0.15;0.28	55; 85; 105	2372
MP12	0.65;0.1;0.2	55; 85; 105	3112

As mentioned in the introduction, we will use the method presented by Weaver and Meeker [11], known as repeated measures accelerated degradation test (RMADT). The degradation of lumen for a LED at time t [hrs] and accelerating factors temperature T [°C], and current I [A] by:

$$\Phi(t) = exp\left(-\alpha t^{\beta}\right) \tag{1}$$

With

$$\alpha = CI^{n} exp(B/(T + 273.15)) \tag{2}$$

where C>0, n>0, and B<0

We can use the linear mixed-effects models available in Stata [14]. These models are also known as multilevel models or hierarchical linear models. The overall error distribution of the linear mixed-effects model is assumed to be Gaussian, and heteroskedasticity and correlations within lowest-level groups also may be modeled. The key to fitting mixed models lies in estimating the variance components, and for that there exist many methods. Most of the early literature in mixed models dealt with estimating variance components in ANOVA models. For simple models with balanced data, estimating variance components amounts to solving a system of equations obtained by setting expected mean-squares expressions equal to their observed counterparts.

The transformed observed lumen degradation Y at time t is:

$$Y = \ln\left(-\ln(\Phi(t)\right) = \beta \cdot \ln(t) + B/(T + 273.15) + n \cdot ln(I) + \ln(C) + \varepsilon \tag{3}$$

With:

$$\varepsilon \sim^{iid} N(0, \sigma^2)$$

We assume that the variability in the regression parameters ln(C) and β can be described by a bivariate normal distribution. This assumption reflects the LED-to-LED variability in the degradation intercepts and slopes:

$$(\ln(C), \beta)' \sim N_2\left(\theta, \begin{pmatrix} \sigma^2_{\ln(C)} & \rho\sigma_{\ln(C)}\sigma_{\beta} \\ \rho\sigma_{\ln(C)}\sigma_{\beta} & \sigma^2_{\beta} \end{pmatrix}\right) \tag{4}$$

- With θ is the mean vector. We assume that (ln(C), β)' is independent of e, and that there is no autocorrelation in time.
- Because degradation data is available for multiple Mid & High-power LEDs, we can estimate an overall model.
- The on-hand mixed effect model can be estimated by Stata.
- We refer to Weaver & Meeker [11] for a description between the degradation model and the induced failure time, e.g. assuming lumen maintenance less than 80% is not allowed.

The results are described in next paragraph.

3. Results

3.1 High-power LEDs

Figure 1 depicts four typical degradation curves of the HP LED LM80 data, including the fitted behavior (following equation (2)). The different graphs represent different setting of current and temperature. For each LED a model can be found, having all conditions in it. Looking at the figures, a wide variety of degradation can be found, e.g.:

- Remain stable at the low-stress conditions
- Increase then decrease
- Gradually increase
- Gradually decrease

Also, it is not a given that higher stress conditions lead to higher lumen decrease. There can be multiple reasons for such none-theoretical behavior, e.g.:

- Insufficient data integrity
- Large noise over signal values
- Not using reference samples
- Corrections during the measurements (for instance at 6000hrs)
- Differences between test houses
- Exposure to chemical incompatible substances from air pollutants or from outgassing of neighboring materials [7, 15]

Table 3 list all the fitted parameters for the HP LED dataset. The ranges for the parameters underline the differences in degradation behavior, as mentioned above. Looking at the parameters one can state the following:

- β: TM-21 assumes that this parameter should be 1.0. Table 3 clearly identifies that this a strong approximation as the data set finds realistic values in the range of 0.1-1.5 with an average of 0.8.
- C: this is a scaling factor and all values can be the found. An average value makes no sense.
- B: this value is the temperature acceleration, the average value of 4091 reflects an activation energy of 0.35eV, which is quite reasonable.
- n: reflects the influence of current, negative values can be discarded. In the current data set we find realistic values in the range of 0.2-3.8 with an average value of 1.7. It is known that current acceleration for HP LEDs can be quite substantial.

In Table 4, the co-variances are listed. The co-variance describes the LED-to-LED variability in the degradation intercepts and slopes for HP LEDs.

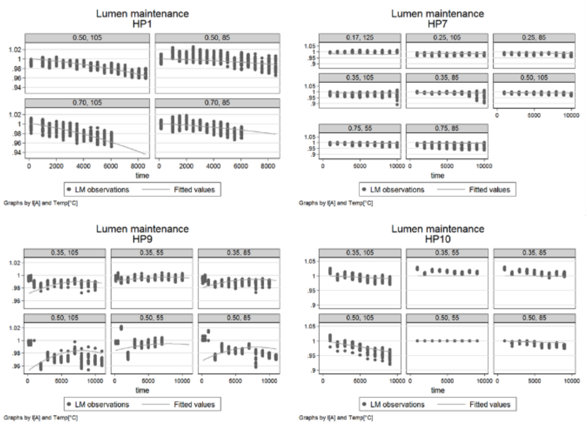

Figure 1: Four typical degradation curves for the HP LEDs analyzed.

Table 3: Fitted parameters values for all HP LEDs. Values cursive are unrealistic. NA means parameter cannot be fitted due to lack of data.

LED	β	C	B	n
HP1	1.47	88.0	-7501	1.83
HP2	0.87	1.32E-5	*451*	1.86
HP3	0.44	2.42E-3	-537	*-0.08*
HP4	0.83	2.30E-7	*1562*	*NA*
HP5	0.67	2.11E-5	*388*	0.18
HP6	0.30	74.8	-3729	1.16
HP7	0.12	0.15	-1530	*-0.45*
HP8	1.31	1.64E-8	-678	*-0.48*
HP9	*-0.30*	*1175.5*	-2776	1.41
HP10	1.06	*1.55E9*	-11889	3.83

Table 4: Co-variances for the HP LEDs, as given by equation (4).

Random-effects Parameters	Estimate	Std. Err.	[95% Conf.	Interval]
led_type: Unstructured				
var(ln_time)	1.045823	.044936	.9613564	1.137711
var(_cons)	66.86275	2.93656	61.34796	72.87328
cov(ln_time,_cons)	-8.333795	.3626095	-9.044497	-7.623093
var(Residual)	.3446933	.0042673	.3364303	.3531592

3.2 Mid-power LEDs

Figure 2 depicts four typical degradation curves of the MP LED LM80 data, same as above for HP LEDs. The different graphs represent different setting of current and temperature. Looking at these figures, for each case a substantial amount of degradation is measured. This makes the model fitting easier, fitted parameters are listed in Table 5. For MP LEDs, we find that:

- β: average value is 1.5 which is quite reasonable giving the degradation behavior of this technology.
- B: An average value of 2827 corresponds with an activation energy of 0.24 eV for MP LEDs, which is quite reasonable.
- n: current influence is found to be average 0.7, which is lower than found for HP LEDs. This is mainly due to the lower current densities in MP LEDs.

In Table 6, the co-variances are listed. The covariance describes the LED-to-LED variability in the degradation intercepts and slopes for MP LEDs.

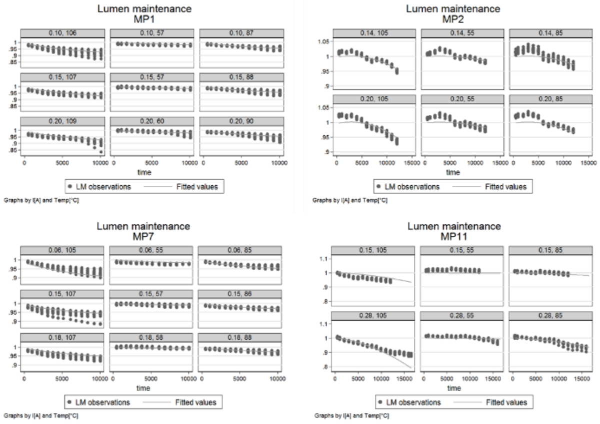

Figure 2: Four typical degradation curves for the MP LEDs analyzed.

Table 5: Fitted parameters values for all MP LEDs. Values cursive are unrealistic. NA means parameter cannot be fitted due to lack of data.

LED	β	C	B	n
MP1	0.59	4.15	-3708	*-0.14*
MP2	3.41	1.97E-12	-2673	0.53
MP3	1.93	4.15E-7	-1300	1.23
MP4	0.71	1.7E-4	-2253	0.47
MP5	0.88	0.11	-802	*-0.01*
MP6	1.34	1.05E-6	-471	*NA*
MP7	0.54	*14.9*	-4472	*-0.66*
MP8	3.30	4.05E-13	-1362	*NA*
MP9	0.92	0.66	-3502	0.38
MP10	1.03	3.36E-4	-1161	0.63
MP11	1.77	*1071.1*	-8739	1.96
MP12	1.52	2.16E-3	-3478	0.53

Table 6: Co-variances for the MP LEDs, as given by equation (4).

Random-effects Parameters	Estimate	Std. Err.	[95% Conf.	Interval]
led_type: Unstructured				
var(ln_time)	.3279413	.0142065	.3012464	.3570017
var(_cons)	27.5708	1.175706	25.36013	29.97418
cov(ln_time,_cons)	-3.001179	.1289426	-3.253902	-2.748456
var(Residual)	.0865945	.0011075	.0844508	.0887926

4. Conclusions

In this paper we describe our next steps to find appropriate statistical models able to describe LED degradation. We analyzed ten long-term datasets of HP LEDs and twelve for MP LEDs. A new model was used, the so-called repeated measures accelerated degradation test (RMADT). Fitted parameters are presented as well as co-variances between them. The results show that finding a good representation of LED degradation behavior is not easy, even impossible. Data integrity, reference samples, noise over signal are disturbing a clean degradation curve. If we take out certain data, we surely can find reasonable model parameters for both LED technologies.

Acknowledgments

This work was supported by the European project "IoSENSE: Flexible FE/BE Sensor Pilot Line for the Internet of Everything". This project has received funding from the Electronic Component Systems for European Leadership Joint Undertaking under grant agreement No 692480. This Joint Undertaking receives support from the European Unions Horizon 2020 research and innovation programme and Germany, Netherlands, Spain, Austria, Belgium, Slovakia.

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