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Chapter 13
Health Monitoring for Lighting Applications

W. D. van Driel, L. M. Middelburg, B. El Mansouri, and B. J. C. Jacobs

13.1 Introduction

The history of reliability as we know it now goes back to the 1950s, when electronics played a major role for the first time [1, 2]. Now, 70 decades later, the electronic industry is facing a continuous increase of early and wear-out failures with accompanying consequences. Figure 13.1 depicts the struggle for the different high-tech industries, ranging from harsh environment suitability to long lifetime and warranty coverage. Nowadays, products with high failure rates are logged on the web leading to bad reputation for a company. In many ways, reliability is part of everyday life and part of consumer expectations. The word reliability is extensively used by the general public and the technical community, as illustrated by the following: there are over 3000 published books whose title or keywords contain the word reliability; the web of science lists some 10,000 technical papers with "reliability" as a keyword (since 1973); and the popular search engine Google lists over 12 million occurrences of "reliability" on the world wide web.

Solid state lighting applications are now at the doorstep of massive market entry [3, 4]. The penetration will grow most rapidly in the street and roadway and general service submarkets in terms of the percentage of total lumen-hour sales [5–7]. Scenarios estimate the expected future adoption of LEDs based on historical data

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Fig. 13.1 The major concern of high-tech industries: direct finance loss; delayed product release; liability and reduced consumer confidence. Each industry has its own key reliability focus areas, as listed here

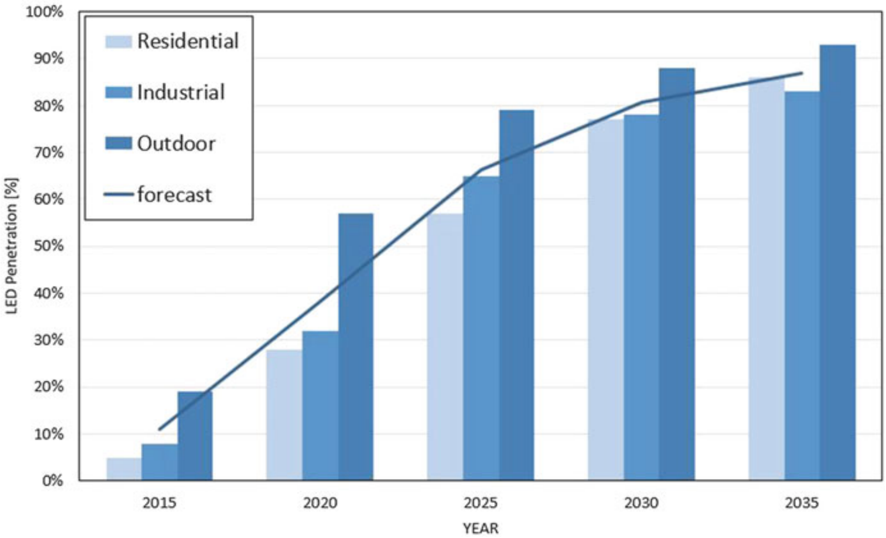

Fig. 13.2 LED penetration levels in three applications, solid line indicates overall trend (Data from [3–5]; with permission)

and the current trajectory for the technology. LEDs are predicted to comprise over 90% installed penetration by 2025 and nearly 100% by 2035. Figure 13.2 depicts the projections indicating the fact that LED penetration is growing rapidly.

Accompanied with the LED penetration, the lighting industry also experiences an exponential increasing impact of digitization and connectivity of its lighting systems [8]. The impact of this digitization is far beyond the impact on single products and extends to an ever-larger amount of connected systems. Continuously, more intelligent interfacing with the technical environment and with different kind of users is being built-in by using more and different kind of sensors, (wireless) communication, and different kind of interacting or interfacing devices. Figure 13.3 gives two examples towards these controlled and connected systems, just to highlight the possible scale of it.

Fig. 13.3 Examples of controlled and connected systems: (**a**) connected luminaires in one city and (**b**) connected luminaires in a stadium

13.2 From Traditional Test-to-Pass to Health Monitoring

Traditional lighting is shifting towards connected lighting and as a result companies are also enabled to shift more towards an information-based environment [9]. The use of information from connected sources can be described as a revolution named big data. With big data, data analytics from live connections of "intelligent" systems can be used to determine the system prognostics. Due to these changes in technology, the next generation of product data will be much richer in information [10, 11]. Reliability and availability will become enablers for product designs. Big data will bring detailed understanding of failure mechanisms, usage scenarios, technology, and optimal designs. For example, products can be outfitted with sensors that can be used to capture information about how and when and under what environmental and operating conditions products are being used. But the data can also be used for pure reliability analysis. Examples are signal-detection algorithms to detect unsafe operating conditions or precursors to system failure that can be used to protect a system by shutting it down or by reducing load to safe levels. And on top of this there can be a need to predict the remaining life of the system (or the remaining life of its most important life limiting components). This topic is named as prognostics and health monitoring (PHM). PHM refers to the process of predicting the future reliability or determining the remaining useful lifetime of a product by assessing the extent of deviation or degradation of a product from its expected normal operating conditions [12]. Today, we predict failure rates on system level following classical reliability approaches, where standardized testing and experimental failure analysis are used in order to obtain conservative bounds from the failure models. However, except in the case of reliability "incidents," there is only limited feedback with which we can judge the effectiveness of our reliability approach. Prognostics and monitoring are not just about creating a more reliable product: it is about creating a more predictable product based on real-world usage conditions. Data analytics is a necessary part of this, but it is not enough. In order to add value, product insights need to be leveraged into the technologies that are

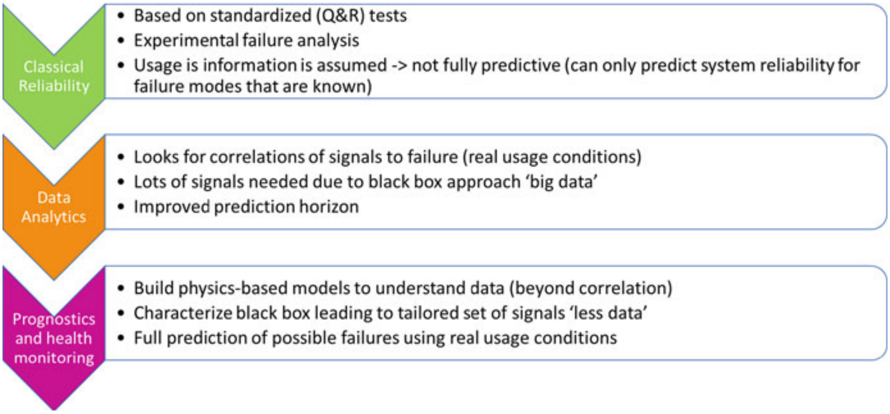

Fig. 13.4 Changing from test-to-pass to prognostics and health monitoring

used in order to differentiate from others. Prognostics and monitoring are not about troubleshooting reliability issues; rather, it is a new control point enabled by the transition to a lighting services business. It is the combination of data and deep physical (and technological) insight that will give a unique "right to win" in the lighting industry. The future possibilities for using big connected data in reliability applications are unbounded. Lifetime models that are based on this data have the potential to explain much more variability in field data than has been possible before. Figure 13.4 schematically displays the change from a classical reliability test-to-pass approach to prognostics and health monitoring.

13.3 Simulations for Lighting Applications

Predictive (reliability) modeling capabilities may enable the performance over time for a product. Figure 13.5 depicts the currently available toolset for lighting applications ranging from LED chip, package to complete and connected systems. Clearly, tools do exist and are used by academia and industry but direct coupling of them and inclusion of time needs further attention. On the lowest level, GaN chip is already manufactured to feature size down to several micrometer and nanometer and also modeling the light output of GaN requires knowledge from across different field such as quantum efficiency and their interaction between different loading conditions. For packaging and module level modeling, FEM is a well-established technique for predicting thermomechanical behavior of the LED packages. However, since the performance of LEDs is highly dependent on the light quality, there is a need to develop techniques that could predict the light

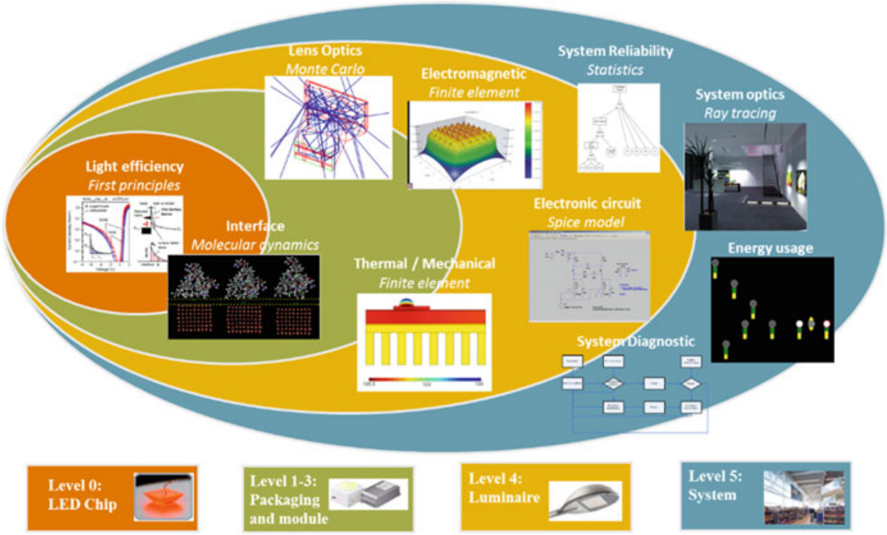

Fig. 13.5 The prediction landscape for SSL products. Coupling and inclusion of time is needed to cover reliability predictions (courtesy by C.A. Yuan, [19])

behavior in the optical system as the package degrades. Tapaninen et al. [13] presented a test case for coupling two physical aspects of an LED, optical and thermal, using specific simulation models coupled through an open source platform for distributed multi-physics modeling. They showed how to connect a Mie theory based scattering calculator with ray tracing. Alexeev et al. [14] followed this approach by connecting a ray-tracing model for the light conversion in LightTools® to a thermal model in ANSYS®. Tarashioon et al. [15] introduced a multi-physics reliability simulation approach for solid state lighting (SSL) electronic drivers. This work explored the system-level degradation of SSL drivers by means of applying its components reliability information into a system-level simulation. An automatic coupling between electrical simulations in SPICE® with thermal simulations was established in order to perform thermal-electrical reliability predictions. Sun et al. [16–18] continued this work by improving the thermal part through automatic coupling with ANSYS®. These multi-physics modeling attempts are needed to cover the grand challenge for reliability modeling in lighting applications. Simply because all failure modes and mechanisms such as electronic drift, browning, coating degradation, color shift, lumen decay, water ingress, corrosion, etc. are results of strong multidisciplinary interactions.

13.4 Lumen Maintenance

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 [20] and TM-21 extrapolations [21]. Even more, the standardization bodies like IEC [22, 23] 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, see Fig. 13.6. So, per today, commercial claims for LED-based products in terms of lumen maintenance are fully based on these LM-80 data and TM-21 extrapolations. IES LM-80-08 is an approved method for measuring lumen maintenance of LED lighting sources. The IES standard TM-21-11 provides a guideline for lifetime prediction of LED devices. It uses average normalized lumen maintenance data coming from LM-80 measurements and performs non-linear regression for lifetime modeling. There is a risk in doing lumen maintenance predictions relying only on the behavior of the average LED degradation. It cannot capture the dynamic and random variation of the degradation process of LED devices.

Alternative approaches are rare as only few other publications build upon the TM-21 method. Fan et al. from the CALCE institute of technology [24] have used the degradation-data-driven method (DDDM) which is based on the general

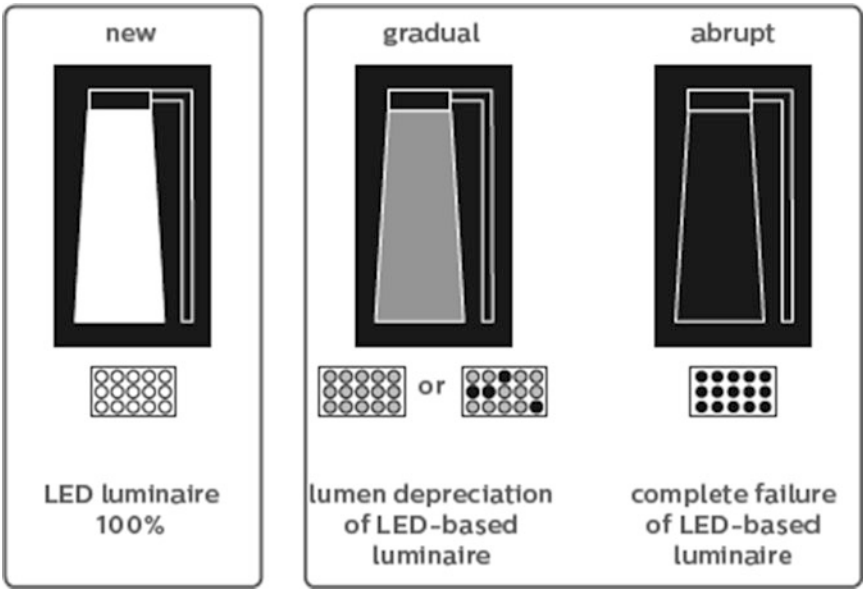

Fig. 13.6 Over time performance of an LED-based system

degradation path model. They use it to predict the reliability of HP LEDs through analyzing the lumen maintenance data collected from the IES LM-80-08 lumen maintenance test standard. Their method can get much more reliability information out of the data (e.g., mean time to failure, confidence interval, reliability function). In an accompanying paper, Fan et al. [25] describe a particle filter-based (PF-based) prognostic approach based on both Sequential Monte Carlo (SMC) and Bayesian techniques. These techniques are used to predict the lumen maintenance life of LED light sources. Also, here the alternative approach achieves better prediction performance, with an error of less than 5% in predicting the long-term lumen maintenance life of LED light sources. Lall et al. [26] follow up on this approach by using Bayesian Probabilistic Models for the assessment of the onset of degradation in solid state luminaires. The failure threshold decay rate has been calculated using an Arrhenius model, neglecting the effects of current density and humidity. The statistical approach is quite valid but also seen as complicated. Quan et al. [27] describe an in-situ method to monitor the lumen degradation of LED packages. They conclude that the luminous flux of the LEDs shows a steady and slow depreciation, but no proper statistical analysis was performed on their measured data. Huang et al. [28–30] investigated the degradation mechanisms of mid-power white-light LEDs. In their studies, a modified Wiener process was employed for the modeling of the LED devices' degradation, following the earlier work of Tsai et al. [31]. Using this method, the dynamic, random variation, as well as the non-linear degradation behaviors of the LED devices were described. They applied the Hallberg-Peck's model to describe the effects of temperature and humidity on LED degradation, thereby ignoring the crucial effects of the current density on this degradation.

Another alternative approach, used in this work, is to study the "degradation" data of each LED individually [32]. It means that for each individual LED a model as stated in Eq. (13.1) is fitted. Then, we can predict L70 values for each LED and turn degradation values into failure times. The mixed effects model is one of the most popular approaches in degradation analysis [33–35]. 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 [36]. Here, the method by Meeker and Weaver [33] to analyze a large set of LM80 data is chosen. In our approach, we have gathered LM80 sets of High Power (HP) LEDs, see table below. In total, we analyzed approximately 27,000 data points (Table 13.1).

Table 13.1 LED dataset details

LED	If [A]	Tcase [degC]	Read points
1	0.7; 1.0	55; 85; 105	1680
2	0.35; 0.5; 0.7; 1.0; 1.5	55; 85; 105; 125	3880
3	0.5; 0.7; 1.05; 1.2	55; 85; 105	4200
4	1.5; 2.1; 3.0	55; 85; 105	1950
5	0.35; 0.7	55; 85; 105	2500
6	1.5; 2.1; 3.0	85; 105	1300
7	0.5; 0.7	85; 105	1550
8	0.5; 0.7; 1.0;	55; 85; 105; 120	3850
9	0.7; 1.2; 1.5	55; 85; 105; 120	2880
10	0.5; 0.7; 1.0; 1.5	55; 85; 105; 125	2277

The degradation of lumen for an LED at time t [h] and accelerating factors temperature T [°C], and current I [A] is given by:

$$\Phi(t) = \exp\left(-\alpha t^{\beta}\right) \tag{13.1}$$

With

$$\alpha = CI^{n} \exp\left(B/\left(T + 273.15\right)\right) \tag{13.2}$$

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

We can use the linear mixed-effects models available in Stata. 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 are 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:

$$Y = \ln\left(-\ln\left(\Phi(t)\right)\right) = \beta \cdot \ln(t) + B/\left(T + 273.15\right) + n \cdot \ln(I) + \ln(C) + \varepsilon \tag{13.3}$$

With:

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

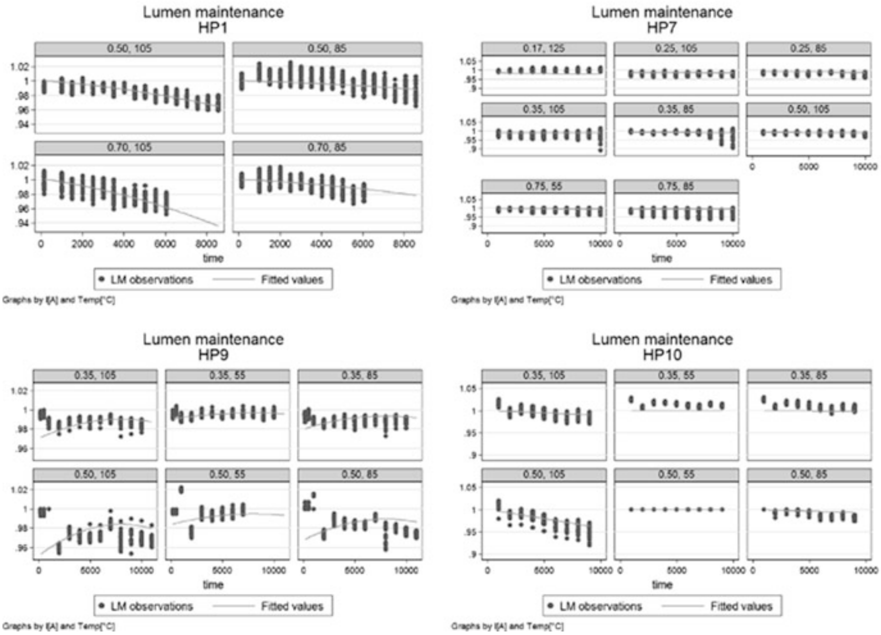

Fig. 13.7 Four typical degradation curves for the HP LEDs analyzed

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

$$(\ln(C), \beta)' \sim N_2\left(\theta, \begin{pmatrix} \sigma^2_{\ln(C)} & \rho\sigma_{\ln(C)}\sigma_\beta \\ \rho\sigma_{\ln(C)}\sigma_\beta & \sigma^2_\beta \end{pmatrix}\right) \tag{13.4}$$

Figure 13.7 depicts four typical degradation curves of the LED LM80 data, including the fitted behavior (following Eq. (13.2)). 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 given that higher stress conditions lead to higher lumen decrease. There can be multiple reasons for such non-theoretical behavior, e.g.:

- Insufficient data integrity
- Large noise over signal values

Table 13.2 Fitted parameter values for all HP LEDs

LED	β	C	B	n
1	1.47	88.0	−7501	1.83
2	0.87	1.32E − 5	451	1.86
3	0.44	2.42E − 3	−537	−0.08
4	0.83	2.30E − 7	1562	NA
5	0.67	2.11E − 5	388	0.18
6	0.30	74.8	−3729	1.16
7	0.12	0.15	−1530	−0.45
8	1.31	1.64E − 8	−678	−0.48
9	−0.30	1175.5	−2776	1.41
10	1.06	1.55E9	−11,889	3.83

Values cursive are unrealistic. NA means parameter cannot be fitted due to lack of data

Table 13.3 Material properties used in the FE model

Material	FR4 PCB	Silicon	Solder 60Sn-40Pb
Heat capacity [J/(kg*K)]	1369	703	150
Thermal conductivity [W/mK]	0.3	163	50

– Not using reference samples
– Corrections during the measurements (for instance at 6000 h)
– Differences between test houses
– Exposure to chemical incompatible substances from air pollutants or from outgassing of neighboring materials

Table 13.2 lists 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 13.3 clearly identifies that this is 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 0.35 eV, 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.

Based on the average data, the overall lumen maintenance behavior of the LEDs is depicted in Fig. 13.8 (L80 values). These are gradual degrading function that can be used to forecast the remaining life at any moment of time, with a given temperature and current.

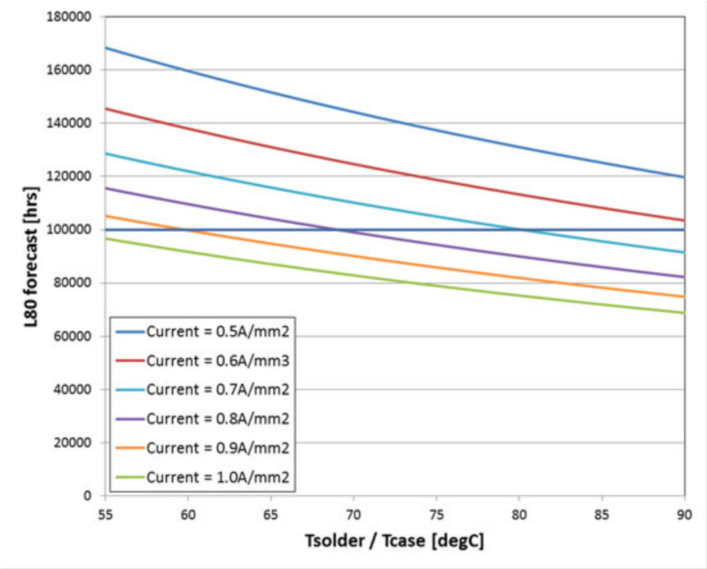

Fig. 13.8 Lumen maintenance L80 curves as function of the temperature for given current densities

13.5 Model Verification

The above-mentioned models and algorithms need to be verified. On a single LED level, LM80 tests are used to verify these models. On a system level, the verification is more complex. Here, a series of lifetime tests are being executed.

Twenty pieces of a retrofit LED lamp are put on test, see Fig. 13.9 on the left the "10 mm free air" sleeve test and on the right the prediction versus measurement.

A second verification concerns an LED module, tested now for 10,000 h. The test chamber is shown in the left picture, the verification in the right picture but only up to 6000 burning hours (Fig. 13.10).

Then a final verification is done on luminaire level. Total burning hours are 12,400 h. LED configuration is 16 HP Cree LEDs. The comparison of the prediction model to the measurement results is shown below (Fig. 13.11).

In conclusion, this verification shows that:

- The prediction models are pessimistic, it tends to give an early warning.
- B50 (50% of the population) is within 4%.

The implement hardware algorithm gives a total burning hour of (based on model, B50L94.7) 14,900 h.

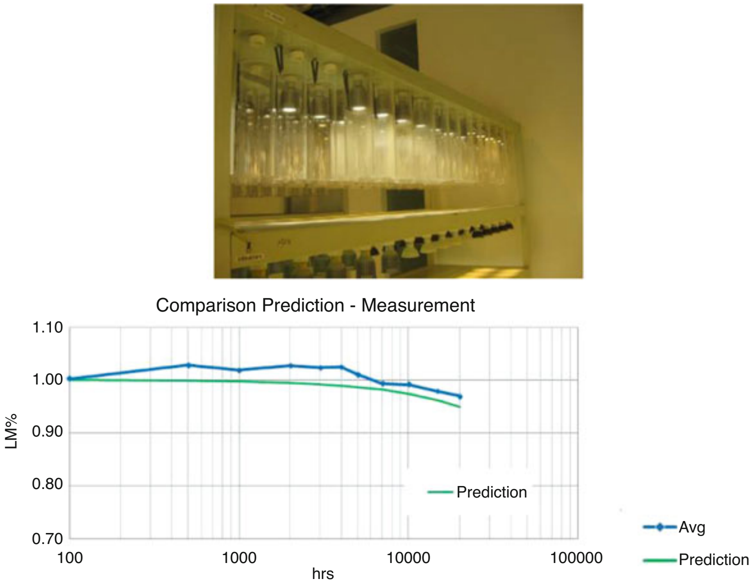

Fig. 13.9 Model verification using retrofit LED lamps

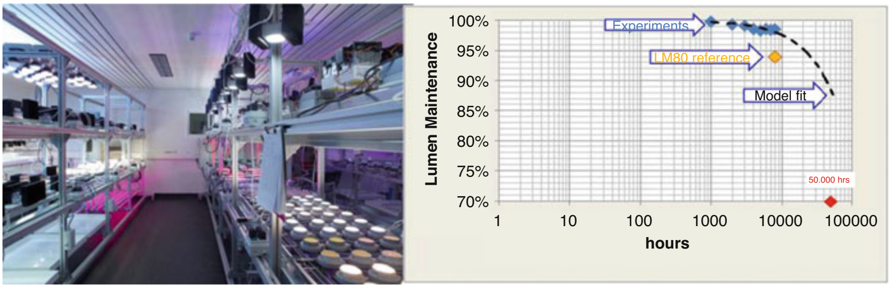

Fig. 13.10 Model verification using an LED module

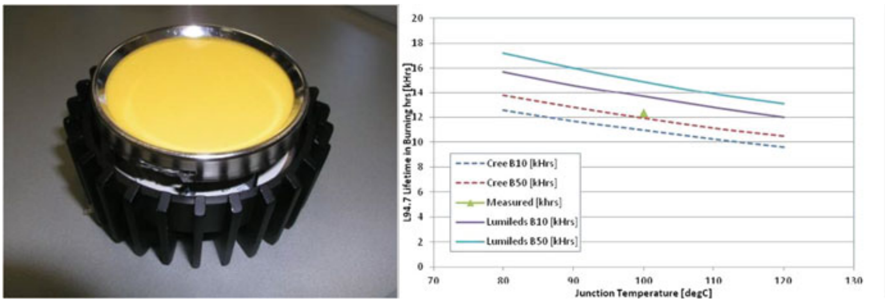

Fig. 13.11 Comparison of the prediction model to the measurement results

13.6 Uncertainty

Lighting systems are composed of many components (electronics, LEDs, custom components) assembled in a specified architecture and subjected to a certain user profile. With the smart lighting demonstrator in mind, it is important to be able to predict the failure of the components with a certain acceptable level of uncertainty. Here the starting point are the failure time distributions of the separate components, and how these distributions depend on physical circumstances such as current, temperature, relative humidity, burning hours, and switches per day. The output consists of system failure percentiles over time for several failure criteria, lumen output over time, and Paretos describing what failures are most important. The distributions of the components are assumed to be true, and all output is conditional on this assumption. For instance, the failure time of an electronics may be $T\sim$ Weibull (α, β) where we take the given values of α, β for granted. However, in practice, these may be estimated from a life time test with limited sample size, so that the sampling uncertainty is actually larger: if you would do the same test with new systems, you would get different estimates for α, β. Note that in many cases there is an additional layer: α may depend on temperature and current via additional coefficients. The question that needs to be answered is: *what are the impacts of sampling uncertainty of component parameters on the spread of system failure probabilities?*

Currently the system failure probability is considered at a given time, e.g., L70 at 50 kh. These are in fact properties derived from probability distributions of the system. Here one is to add a statement to the value of B50L70 of how certain that value is in view of the uncertainty of the components' lifetime, in the form of say a 95% confidence interval that reflects that uncertainty. There are various random quantities: for each component, and then usually a few physical failure mechanisms (e.g., for LEDs: solder failure, wirebond failure, speed of gradual decline of flux). If L70 is the random variable for the point in time at which the system crosses the 70% of initial output level, we can view L70 as a function of those many random variables (per component, per failure type):

$$\begin{aligned} L70 &= f\left(X_1, \ldots, X_p\right) \\ X_1 &\sim \text{Distribution }\left(\alpha_1, \beta_1\right), \ldots \end{aligned} \tag{13.5}$$

The uncertainty on the many parameters of the input such as α_1, β_1 may be modeled as (α_1, β_1) following some multivariate distribution, close to the sampling distribution. In terms of Bayesian statistics, we specify some prior distribution on parameters such as (α_1, β_1). Between components and failure types these will be independent. Under this prior distribution of the components, L70 has a prior distribution as well. Bayesian inference usually goes on by combining new data with the prior beliefs, but that step is not going on in our case: just getting to know the prior distribution of quantities like L70 will be enough.

As demonstrated above, lumen maintenance follows an exponential decay with L70 as the point in time where lumen output drops below 70% of the initial value. L70 follows a lognormal distribution as L70(location, scale), with:

- location = log(C) – n * log(current) + B/Temperature
- scale = sigma_lm from measurements

This results into the fact that the uncertainty depends on two parameters only, being location and scale. Typically, life time tests vary current and temperature and are used to estimate the regression coefficients.

The covariance between sigma and (C, n, B) will be zero, a property of the normal distribution. So, it is a 3 × 3 covariance matrix.

$$\log\left(-\log(L)\right) = \beta \log(t) + B \cdot \frac{1}{T} + n \cdot \log(I) + \log(C) + \epsilon \tag{13.6}$$

As fitted in statistical software Stata [36]:

$$\log\left(-\log(L)\right) = \underline{\beta_k} \log(t) + B_k \cdot \frac{1}{T} + n_k \cdot \log(I) + \underline{c_k} + \epsilon \tag{13.7}$$

where (c, β) follows a bivariate normal distribution per LED and k is type. Let the mean be (c_k, β_k) and write $\left(\underline{c_k}, \underline{\beta_k}\right) = (c_k, \beta_k) + \left(\epsilon_c, \epsilon_\beta\right)$. Then the model is

$$\log\left(-\log(L)\right) = \left(\beta_k + \epsilon_\beta\right) \log(t) + B_k \cdot \frac{1}{T} + n_k \cdot \log(I) + c_k + \epsilon + \epsilon_c \tag{13.8}$$

Taking $L = 0.7$ and solve for t where $\epsilon = 0$, first set $d = \log\left(-\log(0.7)\right) = -1.03$:

$$d - B_k \cdot \frac{1}{T} - n_k \cdot \log(I) - c_k - \epsilon_c = \left(\beta_k + \epsilon_\beta\right) \log(t) \tag{13.9}$$

The stochastics will be complex, assuming random components being zero, it results:

$$\begin{aligned} \text{location} = \log(L70) &= \tfrac{1}{\beta_k}\left(d - B_k \cdot \tfrac{1}{T} - n_k \cdot \log(I) - c_k\right) \\ &= \log\left(\exp\left(\tfrac{d-c_k}{\beta_k}\right)\right) - \left(\tfrac{n_k}{\beta_k}\right) \cdot \log(I) + \left(-\tfrac{B_k}{\beta_k}\right) \cdot \tfrac{1}{T} \\ &= \log\left(C_{lm}\right) - n_{lm} \cdot \log(I) + B_{lm} \cdot \tfrac{1}{T} \end{aligned} \tag{13.10}$$

The variance-covariance equals $\frac{1}{n} \cdot V$ with $n = nr$ of LEDs and V as follows:

symmetric avg$V$[3,3]

_nl_1 _nl_2 _nl_3

_nl_1 92.889581
_nl_2 −13.417044 5.8164606
_nl_3 −29731.637 2119.4056 11051779

Now the variance of log($L70$). The stochastics come from $+(\epsilon_c, \epsilon_\beta)$. We have

$$\log(L70) = \frac{d - B_k \cdot \frac{1}{T} - n_k \cdot \log(I) - c_k - \epsilon_c}{\beta_k + \epsilon_\beta} = \frac{R}{S} \tag{13.11}$$

And can be approximated as follows:

$$\begin{gathered}
\operatorname{Var}(R/S) \approx \frac{1}{(\mu_S)^2}\operatorname{Var}(R) + 2\frac{-\mu_R}{(\mu_S)^3}\operatorname{Cov}(R, S) + \frac{(\mu_R)^2}{(\mu_S)^4}\operatorname{Var}(S) \\
= \frac{(\mu_R)^2}{(\mu_S)^2}\left[\frac{\operatorname{Var}(R)}{(\mu_R)^2} - 2\frac{\operatorname{Cov}(R,S)}{\mu_R\mu_S} + \frac{\operatorname{Var}(S)}{(\mu_S)^2}\right] \\
= \frac{(\mu_R)^2}{(\mu_S)^2}\left[\frac{\sigma_R^2}{(\mu_R)^2} - 2\frac{\operatorname{Cov}(R,S)}{\mu_R\mu_S} + \frac{\sigma_S^2}{(\mu_S)^2}\right] \\
\mu_R = d - B_k \cdot \frac{1}{T} - n_k \cdot \log(I) - c_k \\
\mu_S = \beta_k \\
\operatorname{Var}(R) = \operatorname{Var}(\epsilon_c) \\
\operatorname{Var}(S) = \operatorname{Var}(\epsilon_\beta) \\
\operatorname{Cov}(R, S) = \operatorname{cov}(\epsilon_c, \epsilon_\beta)
\end{gathered} \tag{13.12}$$

An example calculation with uncertainty in the lumen maintenance performance of the LED system is depicted in Fig. 13.12. It shows the calculated results in the

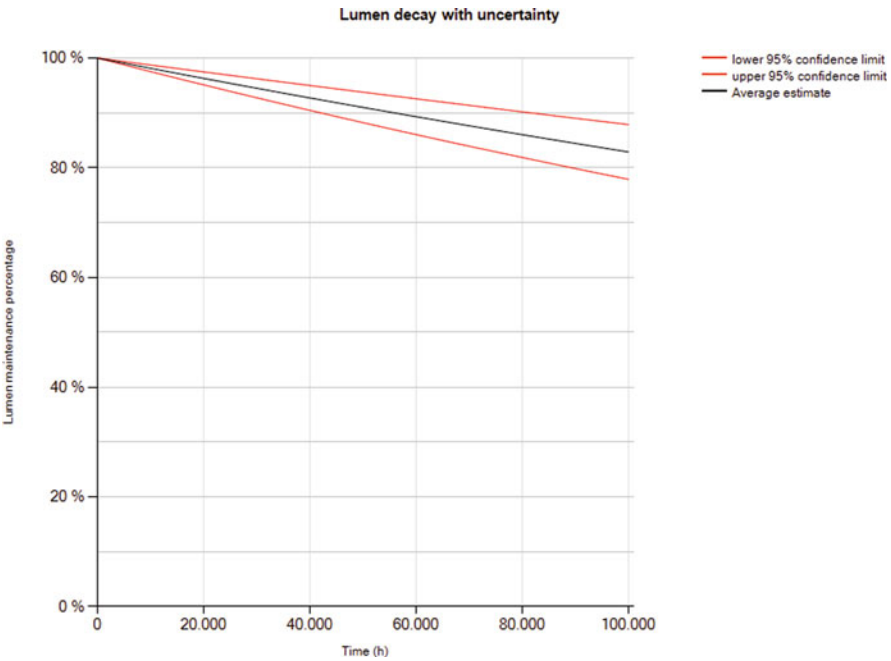

Fig. 13.12 Calculated uncertainty in the lumen decay

uncertainty of the lumen decay. It indicates that L80 at 100 kh can be met in most of the cases.

13.7 Towards a Digital Twin

Combining the algorithms with sensor data, the so-called digital twin comes into sight, which is no more than just a mathematical model of a physical object [37, 38]. Digital twin refers to a digital replica of physical assets, e.g., a luminaire, that can be used for various purposes. The digital representation provides both the elements and the dynamics of how the device operates throughout its life cycle. In the lighting case it can be the lumen maintenance over time. Definitions of digital twin technology used in prior research emphasize two important characteristics. Firstly, each definition emphasizes the connection between the physical model and the corresponding virtual model. Secondly, this connection is established by generating real-time data using sensors. Given the lumen maintenance model parameters listed above, the influence of temperature and current on the lifetime of the LED is established. These models can be diverted such that the temperature increase (coming from sensor data) directly relates to the time until failure or the remaining useful life. Here, a look-up table approach will be used, programmed into an eight-bit processor. The overall flow of the algorithm is depicted in Fig. 13.13.

13.8 Use Case: Smart Lighting

13.8.1 Introduction

Predictive and preventive maintenance are the key development targets for the smart lighting use case. Preventing and/or discovering failure modes at the earliest possible integration level will enable smart maintenance and, obviously, huge cost savings. An increase of the temperature is believed to be the signal for lumen maintenance. The smart lighting use case includes the specifications of the functionality and performance specification of the thermal, photonics/optical and light emitting sensors and their integrated packaging requirements. The use case integrates electronic components and systems addressing the challenges of the massive increase of connected sensors as the backbone of a smart digital society that needs significant reduction of energy consumption. The main functions in the demonstrator are depicted in Fig. 13.14. Four main systems can be distinguished:

1. Controls

   The controls will master the complete device by providing power from the mains. It will also serve to gate to the external world.

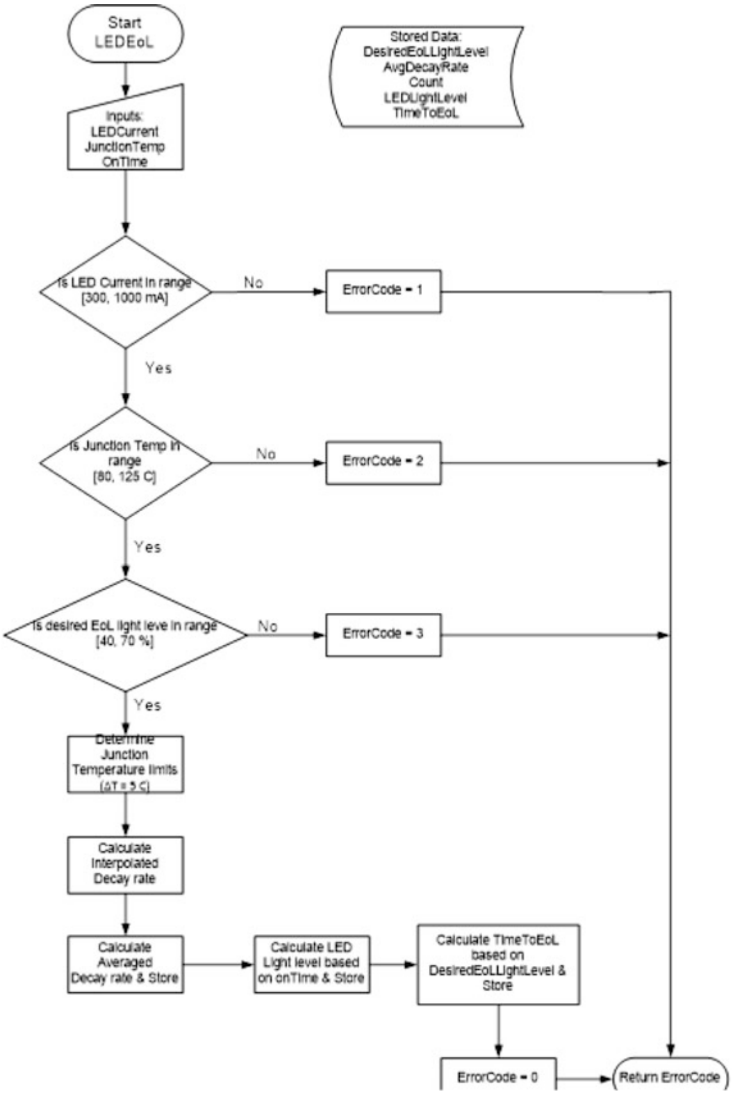

Fig. 13.13 Flowchart of getting the current status of the LED-source calculated

2. Power supply

   The power supply provides the correct power to the light source and the health monitoring device by a stable current and/or voltage to it. It will also serve to gather important signals from the light source and/or the health monitoring device.

3. Light source

   The light source produces the light that is needed in the application.

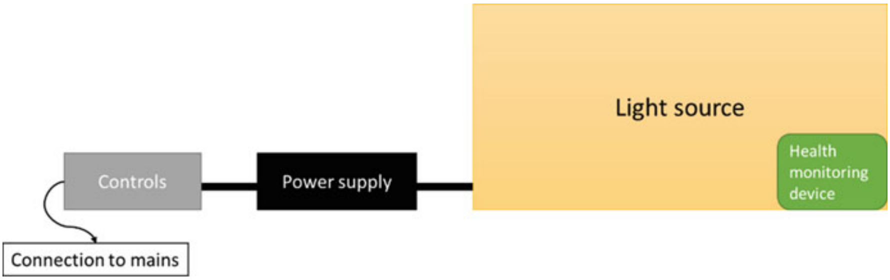

Fig. 13.14 Main functions in the smart lighting demonstrator Smight

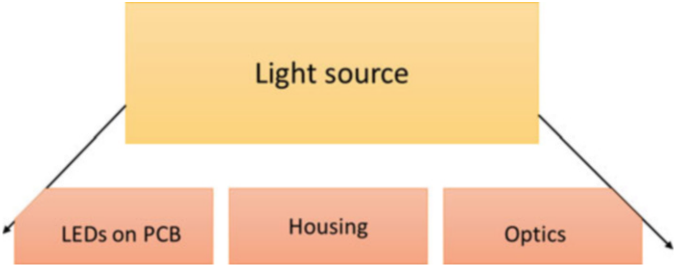

Fig. 13.15 Sub-systems in the light source function

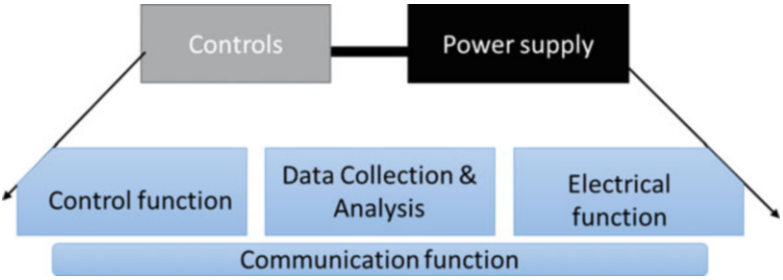

Fig. 13.16 Sub-systems in the controls and power supply

4. Health monitoring device
   The health monitoring device monitors the performance of the product.

Further breakdowns of the above main systems are depicted in Figs. 13.15, 13.16, and 13.17.

1. Light source
   We will use a typical light source consisting of several LEDs on a printed circuit board, placed in a housing and surrounded by optical elements. Optical elements are reflective materials and an exit window.

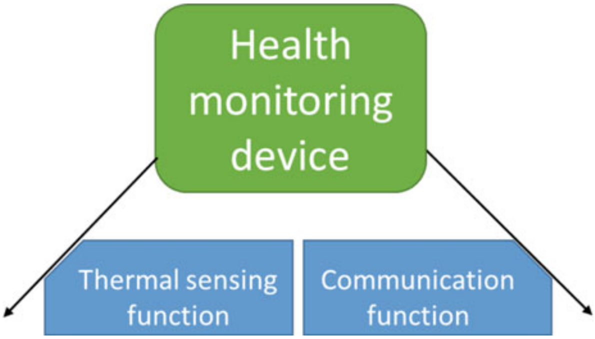

Fig. 13.17 Sub-systems in the health monitoring device

2. Controls and power supply

   We can specify the control and power supply to provide the control and electrical function. On top of this either one of the two should include the algorithms in order to collect and analyze the data coming from the health monitoring device. Finally analyzed data should be provided to the external world for maintenance purposes.
3. Health monitoring device

   The add-on health monitoring device should cover the maintenance and thus provide the thermal sensing function. It should also communicate the data to the power supply.

13.8.2 Simulations: LED on PCB Level

A finite element (FE) simulation model of the LED light source is created to identify the hotspots and the optimum position of the thermal sensor. The junction temperature and the thermal conductivity of the surrounding substrate material are of great influence on the thermal behavior. When this behavior is identified extensively, this information can be used to optimize the system design and to use for lifetime prediction by the application of temperature sensors. The expected results are an improved design for reliability due to optimized chip-layout, minimization of thermal interfaces, material resistance, and stresses.

Doing thermal simulations on LED systems deliver important information on where the thermal hotspots do arise, and at which locations the temperature sensors should be placed for adequate thermal monitoring. Information about temperature at different locations in the system can be related to the LED junction temperature, but also the temperature of the surrounding environment.

With the aid of a COMSOL FEA model consisting of an LED die and an LED package put together on a PCB board consisting of a predefined material using solder paste. Such a scenario mimics a practical situation, where usually multiple

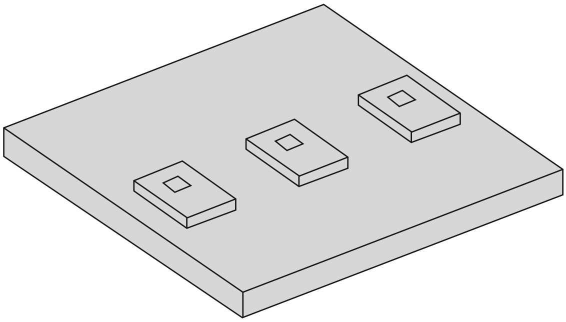

Fig. 13.18 Details of the model

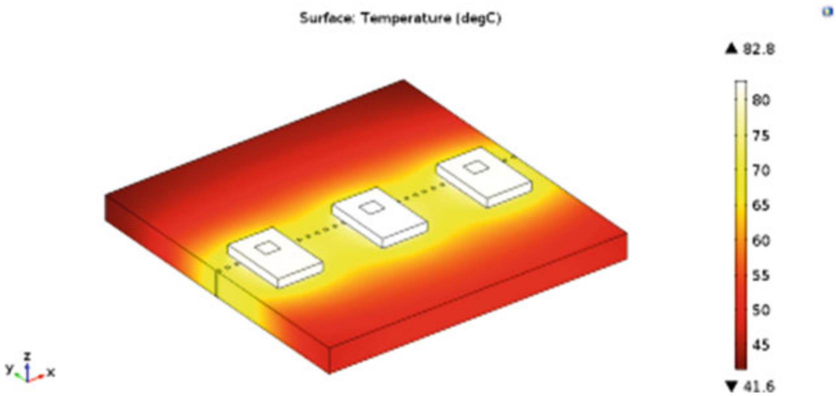

Fig. 13.19 Calculated thermal behavior on PCB level

LED packages are placed on a single PCB board to increase light output of 1 luminaire.

In this thermal problem, the two main figures of the used materials which determine the steady state and dynamic thermal behavior are the heat capacity and the thermal conductance. In this simulation, the LED is modeled as heat source with a fixed amount of power. The values in the below table are used in the simulation.

For finding the optimal position of the other LED dies and temperature sensors to be used for monitoring, an FE simulation is done. The model contains LED dies mounted on top of a PCB substrate using solder joints, see figure below (Fig. 13.18).

The calculated thermal behavior of the LEDs at a power of 0.3 W is given in the figure below (Fig. 13.19).

As can be seen the LEDs generate a significant amount of heat which also raises the temperature of the PCB underneath it, requiring a proper heatsink. The LEDs should be placed far enough from one another to reduce further heating. Figure 13.20 shows the temperature for the LEDs as a function of distance.

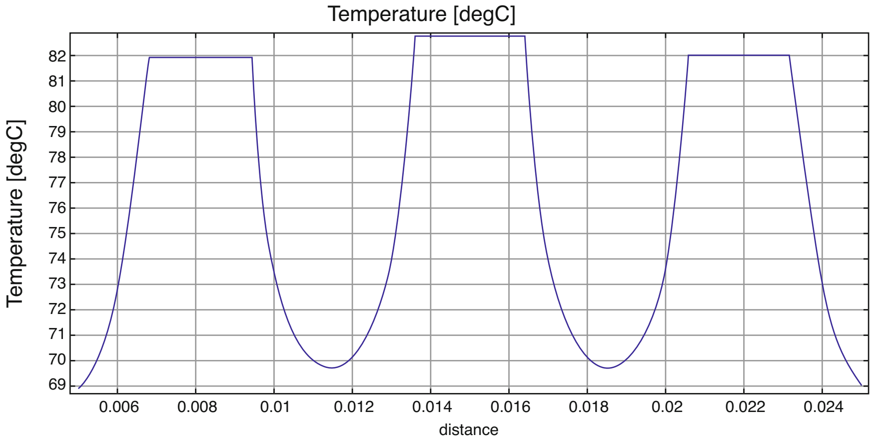

Fig. 13.20 Temperature as function of the distance, PCB level

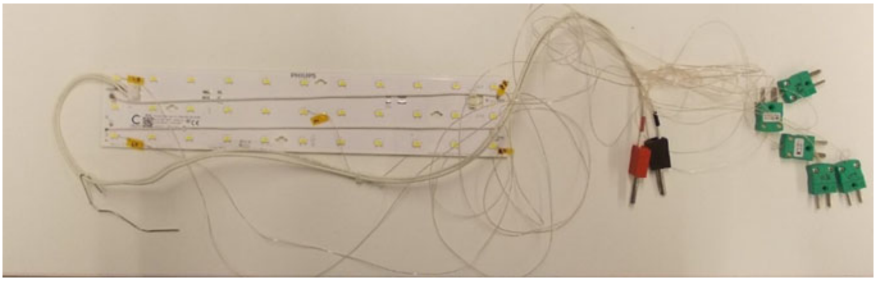

Fig. 13.21 Light source with thermo-couples as currently being tested

As can be seen from the above figure, the temperature drops outside the LEDs which shows that a minimum distance between the LEDs needs to be considered. The same can be done for placing temperature sensors near the LED as well as at a certain distance near the edge of the PCB to show the difference in the temperature distribution.

Experimental verification was done with a commercially available LED board. Figure 13.21 shows the light source with the thermo -couples placed on top. Figure 13.22 shows a temperature scan of the PCB to indicate the heat distribution from a top view. Notice the uniform distribution of temperature, which is vital to pick the location of the sensors. The resulting temperature increase is listed in Table 13.4. These results are input for the design of the thermal sensing function.

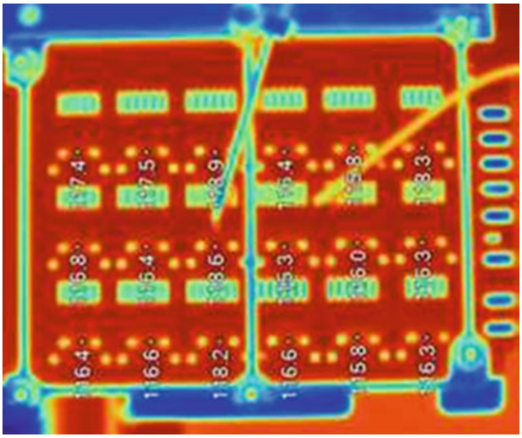

Fig. 13.22 Temperature scan of the LED light source

Table 13.4 Lifetime test results, readings for two products

Item	Product A	Product B
LED Type	Mid-power LED I	Mid-power LED II
Start date	March 04, 2015	February 02, 2016
Read point	June 29, 2016	June 29, 2016
# days testing	483	148
# on/off	69,552	102,225
Temperature increase	1.3degC	2.3degC
Temperature increase per 1000 h operation	0.15degC	1.1degC

13.8.3 Diagnostic Module

Remote diagnostics via sensing solutions and data analytics lowers maintenance costs by sending inspection and repair crews only when and where needed, improving operational efficiency. Based on the luminaire health status, its operation can be adapted to preserve the right light and schedule preventive maintenance. Also, service offerings can be tailored based on usage patterns and geographic conditions of the lighting network enabling more accurate lifetime predictions of luminaires.

The diagnostic module adds the sensors to luminaires (LED-based product). It is used for incident detection and failure analysis by monitoring environmental conditions that influence the luminaire life time. The module consists of (see also Figs. 13.23 and 13.24):

- An Onboard MCU for failure detection and sensor data aggregation
- Sensor data available to a DALI master (e.g., the IoT Client)
- Compatible with a DALI enabled LED driver

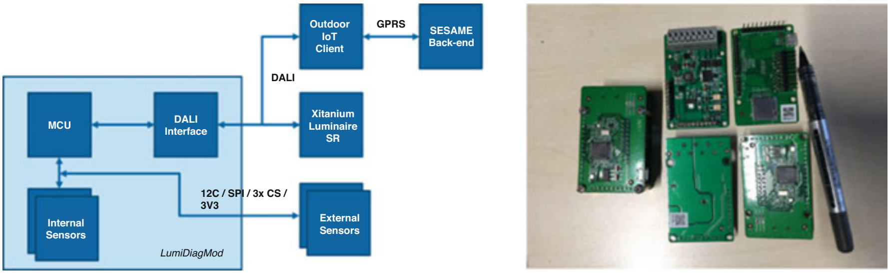

Fig. 13.23 Prototype of the diagnostic module

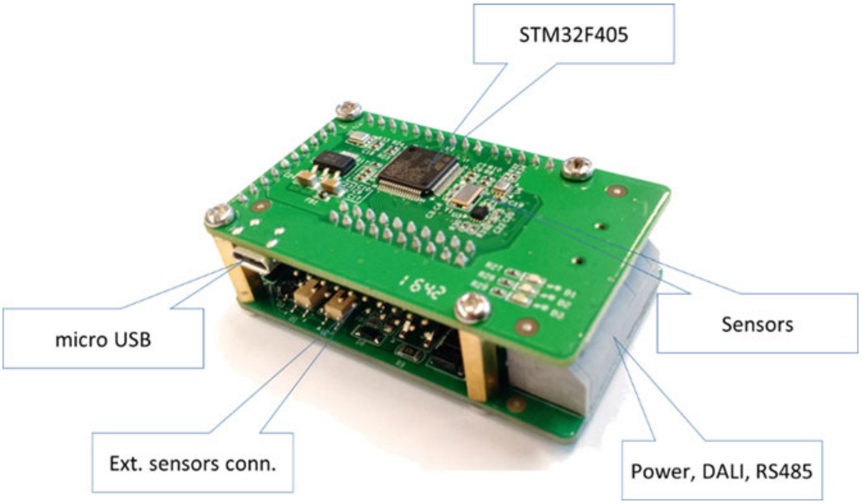

Fig. 13.24 View on the prototype (light source is not visible)

13.8.4 Integration into Test Beds

System integration in order to demonstrate the concept is done in an outdoor test bed, depicted in Fig. 13.25.

The details of this test bed are:

- Temperature as function of days is monitored
- Almost 1 year testing performed
- Under worst case conditions, where the thermal performance is worsened as to provoke failures

The results are shown in Fig. 13.26. As the figure shows, indeed the temperature increases prior to failure demonstrating the concept of health monitoring.

Fig. 13.25 System integration into an outdoor test bed

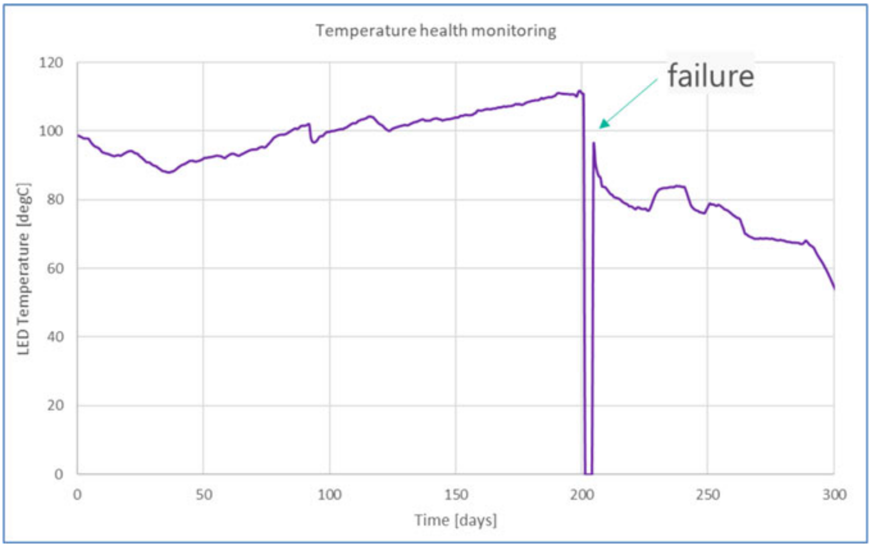

Fig. 13.26 Temperature as function of days for the test bed

A second test bed was installed at the premises of the Technical University of Graz in Austria, see Fig. 13.27. The data is generated on-line. The integrated health monitoring device is placed within the cabinet of the luminaire. The test bed has the following features.

- An environmental sensor monitors temperature, humidity, barometric pressure as well as acceleration in three axes and as vector.
- It operates autonomously and sends measured data daily to a functional email account.
- The measurement modules are small in size and thus can be integrated easily in a luminaire.
- The autonomous data measurements and transmission is independent from AC mains voltage for about 1 day thanks to an integrated energy storage battery.

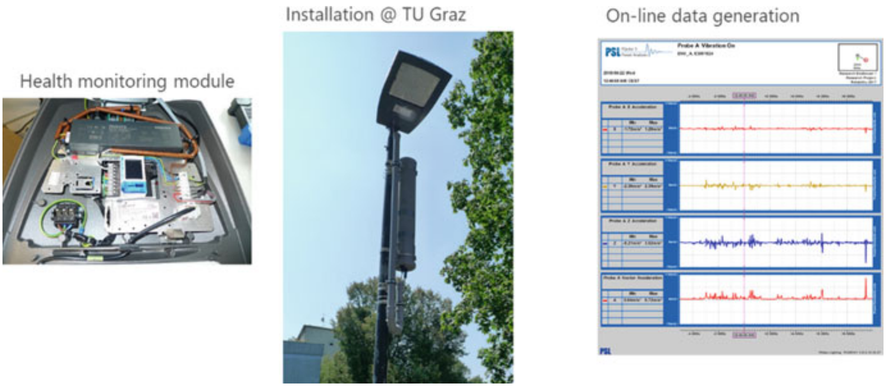

Fig. 13.27 Test bed at the Technical University of Graz

13.8.5 Life Time Prediction

With the incoming data from the test bed and the physical description of it, it is possible to predict the lifetime of these products. There are three main paradigms for solving classification and detection problems in sensor data: data-driven approach, model-driven approach, and fusion-driven approach which combines the first two approaches. Data-driven is a new way of thinking, enabled by machine learning which is learning patterns from historical data. Results are dependent on the availability of both good quality data. As more and more data has become available, developing good performing classifiers using machine learning has become more and more feasible. Data-driven approaches can be very effective for electronic systems, considering that the capability of realizing complex physical models for the system is reduced. However, in most of the cases the parameters monitored have no connections to the real failure. So there is need for a method to link the actual failure with the monitored parameters, which is the fusion-driven approach. Here, a fusion-driven method is proposed to predict the catastrophic failure of luminaires only based on historical measured time series. In this case, it is the (rising) temperature for which the failure occurrence is known by the models described in the previous chapter.

For predictive maintenance modeling, the goal is to predict whether the luminaire experiences its failure in the next few days. The prediction of catastrophic failure is defined as “Given time-series of features (such as current, energy, burning hours, etc.), for n number of days, predict if a catastrophic failure will happen within the next *m* days.” This is indicated in Fig. 13.28.

Figure 13.29 shows the mean value of five test accuracy from five machine learning algorithms over prediction days. Here the observation days are fixed to 10. With the increase of the prediction days, the mean accuracy value decreases and then back to fluctuating values. The observation infers that the effect of observation days on the accuracy is limited. Further observations are:

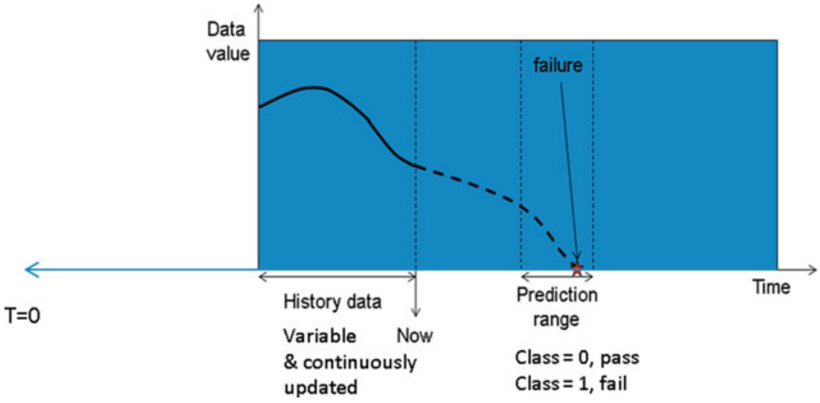

Fig. 13.28 Predicting the time frame in which the failure will occur

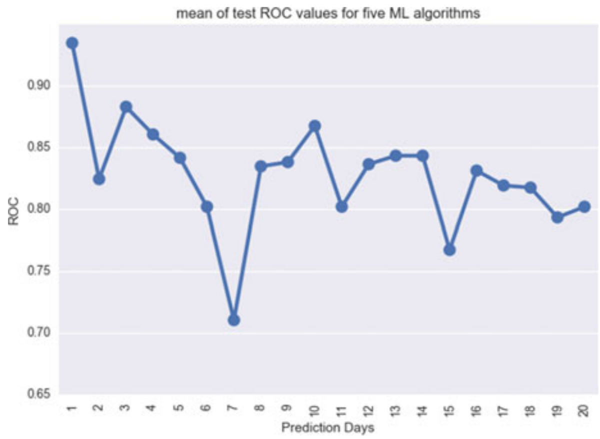

Fig. 13.29 Mean value of five test accuracy from five machine learning algorithms over prediction days

- Models show balanced accuracy of 77–83%, sensitivity (predicting failures) of 55–85%, and specificity (predicting non-failures) of 81–99% using prediction windows of 2 days. This suggests failure prediction using temperature data is feasible.
- Prediction accuracy decreases by 5–10% when the prediction window increases to 10 days.

The next step is to validate, test, and further develop algorithms using more incoming data.

13.8.6 Final Remarks

In the past 4 years, we have witnessed a substantial change in the lighting industry. Traditional companies have changed their strategy and upcoming competition has pushed down prices for LED-based products considerably. LED penetration levels increased so as the diversity of commercially available replacement products. New processes and materials were introduced, and consequently new failure modes appeared. This trend will continue as the lighting industry is getting connected and large amount of user data is being analyzed. New components are needed to deliver this functionality (sensors, actuator IoT modules) and, as such, the diversity from an architectural point of view will also increase. Gradually but slowly the term reliability will be replaced by availability and "smart" maintenance will distinguish good from bad products. In this chapter, we have presented a smart lighting use case in which the temperature rise served as indicating parameter for lumen maintenance. A fusion-driven approach combining sensor test data with a physical system description was developed. In fact, these are our first steps towards a digital twin for a connected luminaire.

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