Towards Prognostics & Health Management in Lighting Applications

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ABSTRACT

Philips Lighting's revenue is largely influenced by the change from component supplier to supplier of systems, solutions and services. Philips Lighting differentiates from competition by providing high quality and reliable products as we learned in our traditional lighting business and which we continue in our actual LED lighting business. Reliable products start with understanding the physics-of-failure by using accelerated test approaches such as (Highly) Accelerated Life Testing. A classical reliability approach is to use the results from these tests, verified by failure analysis, to obtain conservative bounds from the failure models, and predict failure rates on a system level. A next step beyond this classical approach is to use data analytics in our installed base to determine degraded performance. The data for this analysis can come either from live connections to 'intelligent' systems, or from actively retracted (working) products from the field. This allows us to move into the prognostics (PHM) regime where a detailed understanding of failure mechanisms, usage scenarios, technology and design come together.

Until recently costs for implementing PHM in Lighting products or systems was outranging possible cost benefits. Nowadays this is reversing rapidly by the exponential increasing impact of digitization and connectivity of the Lighting Systems. The impact is far beyond the impact on single products, but 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. Especially in professional systems, where many years of use has to be warranted and where system size, cost and complexity are continuously increasing, PHM is required. Where online debugging and adding new features or functions is already common practice, PHM should provide tools to keep the system within its quality and reliability targets. In the presentation we show our road towards prognostics and demonstrate PHM work being done in different professional Lighting applications as Public Lighting, Office & Industry Lighting and Retail Lighting. While data analytic tools are still premature, first results are achieved and improvement tracks are being defined. We will conclude with our strategy and vision on how to embed cost-effective PHM into lighting applications.

1. CHANGE OF RELIABILITY METRICS IN CONNECTED LIGHTING SYSTEMS

Starting our journey in large connected lighting systems almost a decennium ago we already quickly learned that the classic reliability metrics are not one to one applicable for these new systems.

1. 1 LIGHT POINT AVAILABILITY

Where for one light point reliability states the probability for survival after a specific period over time, for thousands of light points connected together this claim as isolated statement is not useful anymore. When thousands of light points are connected it makes no sense to define system, or network failure, as failure of just one single light point in the system. It makes more sense to define light point availability, indicating the fraction of light points operating in the controlled network over time:

$$PoLs\_\ Availability\ (t) = \frac{operational\ PoLs\ (t)}{\#\ PoLs\ in\ System\ (t=0)} \qquad (1)$$

Typically for a networked and connected system this availability differs from the classical definition of System Availability where System Availability is defined as the fraction of time that a system provides the service for which it is specified. This deviates significantly from PoL_ Availability as we introduced above. Where the formal System Availability depends on planning and duration of repair, the PoLs_Availability can be referred as 'without repair' or 'including repair'. Repair here should be seen as system maintenance. In connected Lighting Systems the PoLs_Availability not only depends on the Lighting units reliability, but also on the reliability of sensors, controllers, communication devices, gateways, routers, etc. Also it will depend on the robustness of Software and on the System Architecture which can determine how 'deep' a HW unit failure or SW fault impacts the Lighting System.

1.2 FAILURE CLASSIFICATION

Modern connected Lighting Systems can include many more features then was ever possible before. Also features which do not relate to the lighting system uniquely. Additional features can relate to monitoring the total electrical installation, or to temperature, humidity, CO2 level, or occupancy. Even occupancy combined with location can be monitored, as is now being implemented in the new indoor positioning system. With the many features it is not possible anymore to refer a few reliability parameters. There are many more, as they can refer to each added system feature. Also not all failure modes have equal weight. Whereas in conventional lighting we focused only on critical failure modes at product level, in the large connected system failure modes can be blocking, high severity, medium severity or low severity. As such, software 'graceful degradation' mechanisms are built in to adapt the system to transform a higher severity failure to a lower severity failure mode.

1.3 SYSTEM AND RELIABILITY DYNAMICS

Another characteristic of a connected Lighting System is the dynamic behavior over time. Software of the installed connected Lighting Systems is continuously improved and upgraded over time. Control Software, but also data related features, fault diagnosis and failure analytic modules can be continuously improved or added. This is a very powerful feature, as it is almost impossible to predict the kind of failures which will occur in the field when rolling out new systems.

In this paper we will discuss the following 3 cases as examples of our steps into PHM.

2. CASES

Case 1. Within Philips Research, exercises to predict Light point failure and apply PHM in professional lighting started many years ago. The first case concerns professional lamps as installed in large volumes for road lighting. By analyzing the monitored technical lamp parameters together with the application conditions, an optimized lamp-replacement model has been developed which can be used to develop and optimize maintenance tools and schedules. Right at this moment this approach is extended for LED outdoor lighting, where equivalent optimized system maintenance tools are under development.

Case 2. In office lighting highly innovative systems are available where all luminaires are connected in a network over IP-cabling. Both power and data are transferred over the Power over Ethernet network. On all office desks, in corridors and in meeting rooms lighting can be controlled in user specific modes. Everywhere combined presence and light sensors are available to control the lighting levels. Local light levels can be controlled by smartphone apps. In this setup maximum energy savings can be realized while maintaining optimal comfort. Because beyond the lighting system data also the application and user data (user locations, user profiles) are available, the data can even be used to group users more efficiently for additional energy savings. These system features have high customer value, but do not relate to PHM. With all the units connected in the system and the opportunity to continue to add new features by uploading new software, also debugging and data analytics software can continuously be renewed. This adds additional opportunities to service and maintain the system over life.

Case 3. In the new networked and digitally connected lighting systems reliability is only in small part determined by reliability of the LED units. It is also determined by reliability of sensors, emitters, receivers, gateways, and not to forget the reliability of the total software. Continuously the reliability of the HW and SW modules has to be checked and validated. Also for the LED units this is a continuous activity. As LED technology is still maturing, lifetime and reliability behavior still needs significant efforts of Accelerated Lifetime Testing and field verifications. The last case is an example to evaluate the required test time to be able to predict the extreme long lifetimes as claimed for LED lighting.

3. CASES TO ILLUSTRATE STEPS INTO PHM

3.1 A lifetime prediction approach per individual light point

The aim is to analyze failures that occur in the complex outdoor lighting system when the system is installed in the field and fully operational. As there is no guarantee that real-life deployments behave as expected, unforeseen failures may occur, the installation conditions may be different from what was expected, or the system use may deviate from what was anticipated. If we can predict failures in real-life installations, the reliability of the system can be established more accurately, and the knowledge and data obtained in creating these predictions can be used to further improve the system.

The key challenge is to reliably predict lighting system (lamp, ballast, and controller) failures before they occur.

The definition of this problem is illustrated in Figure 1. For each luminaire, given historic data and a prediction range, the problem is to predict whether a failure occurs during the prediction range. This prediction model needs to be valid for each light pole. Hence, we are not predicting time to failure, but rather providing a probability of failure during a specific future time interval or fixed length, i.e. the prediction range. Typically, the prediction range is in the order of weeks or months and fixed depending on the planned use of the prediction results. It is possible to start the prediction range at the current time. Note that by using this problem definition, we have turned the problem of predicting failures into a classification problem.

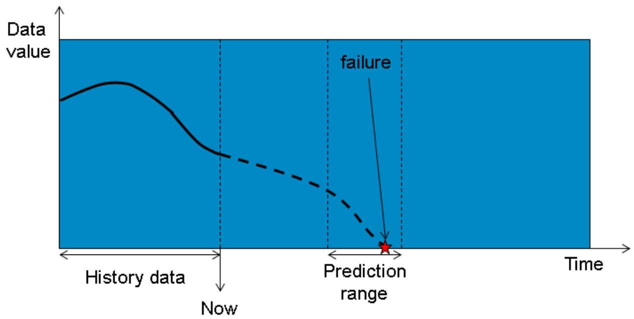

Figure 1: Failure prediction problem.

We analyzed a dataset that contains data from a connected lighting system with about 4500 luminaires, recorded from August 2011 to January 2013. The luminaires are of different types (SON, metal-Halide) distributed over numerous controllers of different types. The recorded data contains various electrical parameters, all switching and dimming behavior, and behavior faults, i.e. messages generated by the lighting system indicating abnormal behavior such as e.g. light switching problems, communication problems, system control problems, etc. Furthermore, we retrieved local weather data. A failure occurs when we detect no current, no power, no dimming level, and proper communication, while there are still commands issued to change the lamp status. Only the first instance for which this holds for a particular luminaire is regarded as a failure. We define two classes, class 0, indicating that no failure has happened, and class 1 indicating a failure occurs during the prediction range.

In order to build a prediction model, we first preprocessed the data such that all clearly wrong data is removed. Examples of clearly wrong data are e.g. negative voltage values, or excessively high energy usage values. Secondly (some) missing data is substituted with interpolated values. After constructing a cleaned dataset, we created additional derived variables for each base variable (i.e. transformations) that we think are important for predicting failures.

Next, we determined the most important variables using the Random Forest method (Breiman, 2001). The resulting importance values for all variables (base and derived variables) are shown in Figure 2, which contains about 45 variables and 30 transformations. Using the resulting most important variables, we created a failure prediction model using Random Forests (Breiman, 2001) with 5-fold cross-validation. In k-fold cross validation, the data is randomly divided into k segments and k-1 segments are used to train the prediction model, and 1 segment is used to evaluate the performance. The 5 performance results are then averaged.

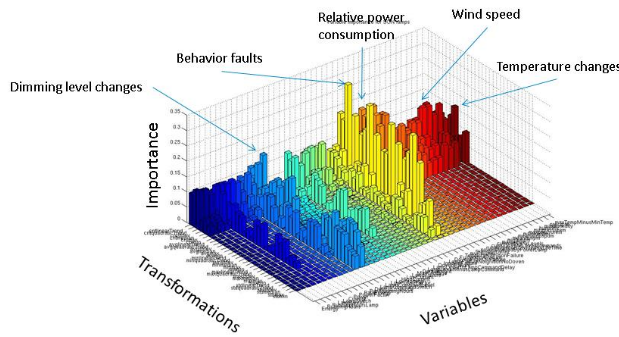

Figure 2: Variable importance.

The resulting ROC-curve (Receiver Operator Curve) is given in Figure 3. A ROC-curve shows the sensitivity (proportion of failures that are correctly identified as such) versus 1 - specificity (1 minus the proportion of non-failures that are correctly identified as such). The best possible prediction method would yield a point in the upper left corner or coordinate (0, 1) of the ROC space, representing 100% sensitivity (no missed failures) and 100% specificity (no wrongly predicted failures).

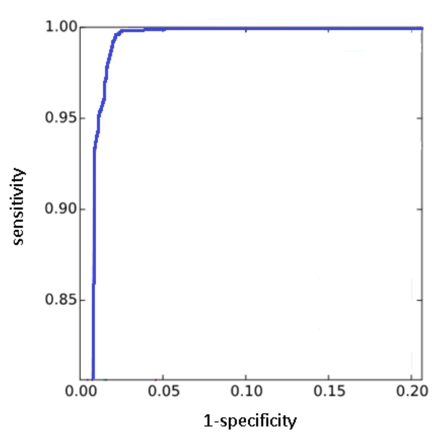

Figure 3: ROC curve.

As can be seen from Figure 3, the failure of a luminaire can be predicted well based on the selected most important variables, particularly dimming level changes, relative power consumption, behavior faults, temperature changes, and wind speed. The behavior fault messages clearly indicate upcoming more serious failures. Known important physical parameters such as relative power consumption, dimming level changes, and temperature changes are also found to be important to reliably predict failures. We also found wind speed to be an important trigger for failures. Strong wind can cause mechanical stress which mainly affects interconnects on the luminaire and system level. Our data analysis has shown this to be an effect that should be taken into account on the luminaire and system level in reliability models.

3.2 Connected office lighting

In office buildings, more than 30% of the energy is used by the Lighting system. The Lighting industry has produced many innovations over the past decades that aim to reduce this energy consumption to make buildings cheaper to operate, and reduce environmental impact. The two main contributions to energy saving are the use of more efficient light sources, and the application of lighting controls to reduce unnecessary light emission. In recent years, the introduction of LED light sources has resulted in a significant increase in light source efficiency. LED luminaire efficiencies now exceed 100 lumens/watt and keep on improving. LED based lighting is quickly replacing traditional sources like fluorescent light as the dominant technology. Next to this improvement, the application of lighting controls based on various sensor inputs such as occupancy and daylight sensors, is becoming standard. This is not only driven by ongoing reduction of the cost of sensors and other electronic components so that these can be integration in the luminaire, but also by various government driven programs to incentivize energy reduction technologies.

Where the lighting controls have been traditionally based on proprietary standards, the industry is seeing a convergence to more open and common technologies. This has led to the recent introduction of luminaires that are connected, both to other luminaires and to other building systems, via the internet protocol (IP). In fact, Lighting is one of the first systems in commercial buildings that is now becoming part of the ‘Internet of Things’.

A particular advantage of using IP connections is that cable (installation) cost can be reduced by also carrying the power to the luminaire over the IP (Ethernet) cable using the Power-over-Ethernet (PoE) standard. And because LEDs are operated at low voltage, this also increases efficiency of the luminaire by removing the need for high-voltage AC to low voltage DC conversion. Figure 4 shows a schematic of this PoE connected lighting system.

These connected lighting systems offer new possibilities in the field of reliability monitoring and prediction. The luminaires are able to measure various relevant system parameters, like voltage, current and burning hours. Moreover, the sensors embedded in the luminaires provide continuous information about the environment, in terms of climate conditions (temperature, light level) and in terms of building occupant behavior (occupancy sensors). This data is generated at luminaire level, and transmitted over the network to a central ‘lighting management server’ in the building or directly in the ‘cloud’. Here, the data is stored and analyzed, and reports are generated for the various users of the system (building management, Philips service, maintenance staff, etc).

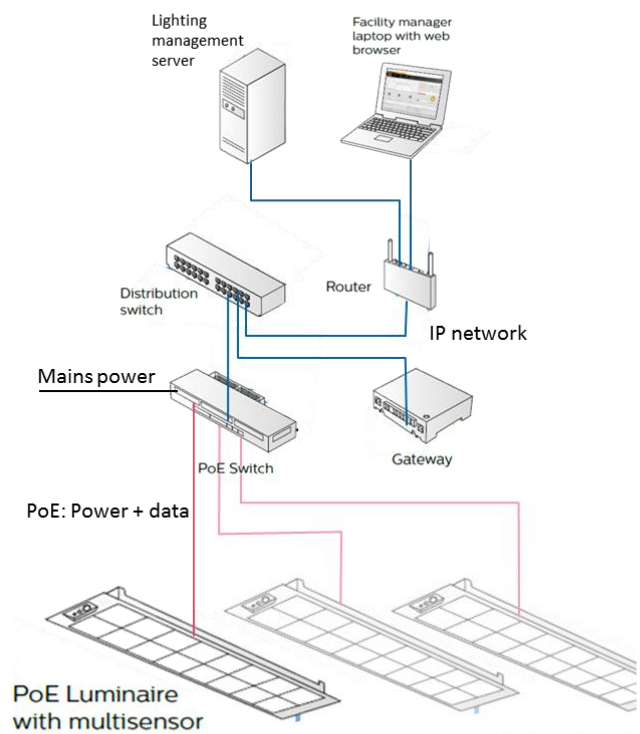

Figure 4: Power-over-Ethernet IP connected lighting system, with luminaire-integrated sensors.

Figure 5 shows an example of the LED Current-Voltage (I-V) characteristic that is obtained from monitoring an office building with more than 1000 luminaires for several months, taking measurements several times per day for each luminaire, and storing these in a database in the lighting management server. The figure shows the typical exponential I-V curve for LEDs. The system consists of two types of luminaires (‘troffers’ and ‘downlights’), indicated with different colors, each with a slightly different I-V characteristic. The voltage values at 0 current show a large spread, but this is because the voltage measurement is not accurate at these currents. Also clearly visible is that the luminaires are configured with a minimum light level corresponding to 200 mA, which is corresponds to the minimum light output for office applications.

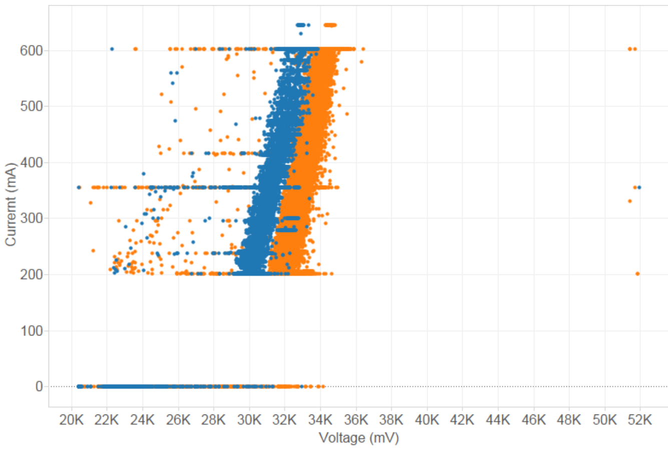

Figure 5: Voltage-current characteristic obtained from monitoring >1000 connected luminaires over one year period.

To determine the reliability of the system, we are essentially interested in two aspects: outliers to the average behavior, and trends of the behavior over time. The outliers typically indicate luminaires that do not behave according to specification, for example producing too little light, or no light at all due to an electronic (‘catastrophic’) failure.

In this example, we see a lot of outliers to the left side of the curve. These, however, do not indicate failures or other undesired behavior. In fact, these outliers correspond to luminaires that are in a transient state (from off to on) during the measurement, which makes these measurements unreliable.

There are also some measurements, corresponding to only two luminaires in this case, that show voltages that by far exceed the distribution. The voltages are close to 50V, which corresponds to the open-circuit voltage, indicating that these luminaires are not producing any light. In fact, two faulty luminaires is actually quite good for a lighting system of this size (>1000 devices), and reflects the situation that the system is relatively recently installed (a year ago), and the fact that LEDs are known for their long lifetime compared to traditional light sources. Over time, more of these failures are expected to appear. These can now be repaired very efficiently because we know exactly which luminaire (type, location) it concerns. The fully data-enabled connected lighting system enables this type of optimized maintenance that was not possible with traditional systems.

Besides the catastrophic failures, LED also exhibit gradual degradation. This manifests itself as a slow reduction in light output at fixed power, and can be observed as an increase in voltage. The measured data in our connected lighting system allows this monitoring on a global scale: all luminaires of a particular type and production date can be measured continuously to create very accurate models for the I-V curve. The shifts in these models over time, or the shift of a particular luminaire relative to the average luminaire, provide very useful information to determine the probability that a particular luminaire will fail early, or the probability that a complete building will perform at a lower efficiency than expected. Knowing this information in real-time will enable more efficient maintenance operations, giving increased up-time (availability) of the system, at reduced energy consumption.

The voltage-current analysis shown above is just one example of what is possible with connected lighting systems in the domain of reliability monitoring and prediction. Others aspects are also under investigation, such as light point availability, network response times, and luminaire switching behavior. The system technical parameters are continuously analyzed against data obtained from various sensors in the system that relate to user profiles (occupancy, manual control use) and environmental conditions (temperature, daylight levels). We aim to determine if the observed system reliability is to be expected given the external circumstances and the use conditions of the particular building.

3.3 System Reliability for LED-based Products: gradual output degradation

Classical reliability approaches, such as (accelerated) test approaches combined with failure analysis, are used in order to obtain conservative bounds from the failure models and predict failure rates on a system level. One of the challenges here is to master the reliability of different systems and their components, ranging from lighting in offices, around living houses to streetlight and total cities that need to be lighted (Driel, 2012). Even further, the light needs to be controlled and maintenance or service schedules are one of our key focus areas per today. Figure 6 shows different possible lighting applications, e.g. lighting in offices, around living houses to streetlight and a total city that needs to be lighted.

Figure 6: Lighting applications, with from left to right, an office with bulbs, outdoor luminaires at residential environments, road lighting in Dubai and lighting the city of Shanghai with LED-based products.

Our reliability process follows a closed loop between acceleration testing, models, statistical predictions and market feedback.

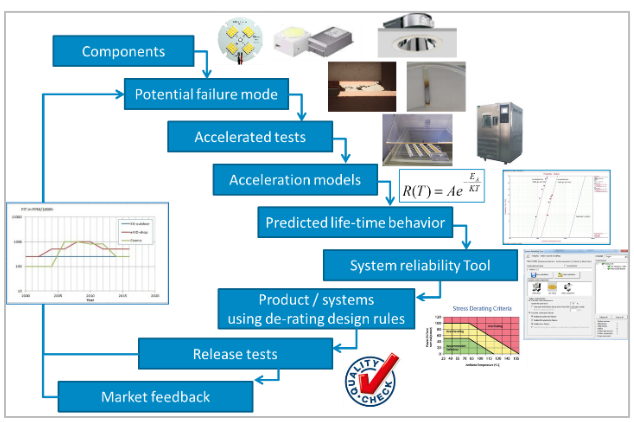

Figure 7: Philips Lighting reliability process: closing loops between supplier quality, R&D and Quality.

There are two relevant 'over time' performance values to be considered: gradual and abrupt light output degradation of a LED-based luminaire, see Figure 8. Gradual light output degradation relates to the lumen maintenance of a luminaire over time. It tells you how much of the initial lumen output of the luminaire is maintained after a certain period of time. The lumen depreciation can be a combination of degradation of optical elements used, individual LEDs giving less light and individual LEDs giving no light at all. Abrupt light output degradation describes the situation where the LED based luminaire no longer gives any light at all because the system or a critical component therein has failed.

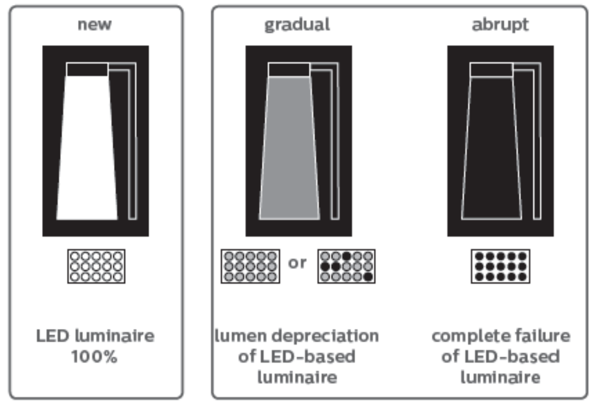

Figure 8: Over time performance of LED luminaire light output, showing difference between gradual and abrupt failure

Gradual light output degradation follows an exponential decaying function (Driel, 2012):

$$\Theta(t) = \exp(-\alpha t^{\beta}) \qquad (2)$$

Where:

- t is time in hours;
- $\Theta(t)$ is the normalized luminous flux output at time t;
- α is the decay rate constant derived by a least squares curve-fit;
- β is the shape parameter.

The acceleration model for α follows as (Nelson, 2004):

$$\alpha = C \exp\left(\frac{-E_a}{k_B T_s}\right) I^n \qquad (3)$$

Where:

- C is a pre-exponential factor;
- E_a is the activation energy (in eV);
- T_s is the in-situ absolute temperature (in K);
- k_B is the Boltzmann's constant (8.617385x10-5 eV/K).
- I is the current;
- n is a life-stressor slope.

Using long term LM-80 testing (IES, 2008) for each individual product a model is fitted to predict L80 values, the time when 80% of the initial lumen output is remaining, which is typical for definition of failure time.

. One of the most important questions arising from a degradation experiment is how many hours an accelerated degradation experiment should last for gathering proper data to allow one to make inference about the product lifetime under the normal use condition. Here, we focus on the convergence of the quantile estimators (such as B10 or B50) to decide whether we are able to make this inference (Driel, 2016). A Maximum Likelihood (ML) procedure is used to estimate B10 (50) under certain use conditions (T, I). Lognormal and Weibull distributions are both appropriate models to fit the (estimated) lifetime data. Figure 8 demonstrates this method for LM-80 data sets coming from high-power (HP) LEDs and reveals convergence after 11khrs test time. At that point of test time, the acceleration model parameters are fitted to be: C = 8.1; n = 0.38; Ea = 0.10eV; s = 0.33. This model can now serve as reference for prognostics health monitoring (Lima, 2012).

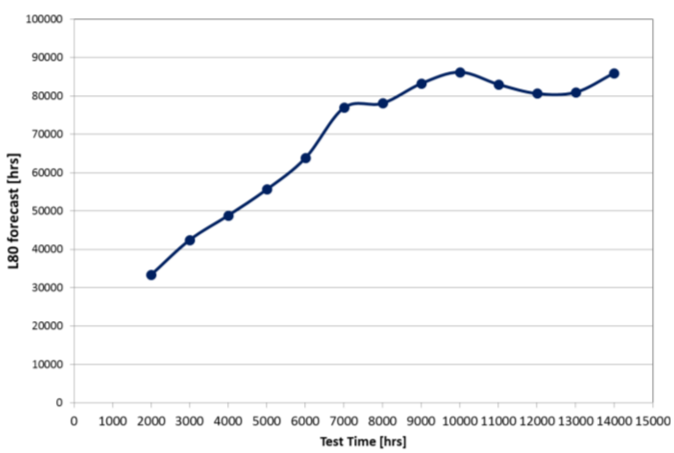

Figure 8: Predicted gradual output degradation as function of test time revealing C = 8.1; n = 0.38; Ea = 0.10eV; s = 0.33.

4. CONCLUSION

By presenting these 3 cases it becomes clear that we are paving the way for introducing PHM based techniques for large and complex Lighting systems. Our strategy and vision on how to embed cost-effective PHM into lighting applications is laid down into the so-called *PHM roadmap for Philips Connected Lighting Systems*, key points are:

- Continue (H)ALT for the critical HW in the connected Lighting Systems
- Continue retraction of HW Lighting & System components to validate failure & degradation behavior over lifetime in application
- Build validated failure & lifetime models for HW Lighting & System components
- Optimize System Architectures and Software to log HW and SW component, module, system and user data and to be able to run data analytics in the systems and on remote decks
- Build PHM methods and tools to maintain and service Connected Lighting Systems effectively

Due to the shift in the Lighting Industry towards fully networked and connected Systems, the requirement of Prognostics & Health Management is inevitable to be able to maintain and service the connected Systems in the most effective way possible.

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