Damage-Based Lifetime Modeling for Power Electronic Devices

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Abstract

Lifetime modeling is an essential tool for ensuring the reliability of systems. The purpose is to estimate the time before the power electronic device failure so that downtime can be reduced and costly failures can be avoided in industry. This paper will first quantify the cumulative damage in the power cycling test using Junction Temperature Swing and Maximum Junction Temperature, and then formulate the cumulative damage-based lifetime model of power electronic devices. This model assumes that the lifetime is linear to the inverse of the cumulated damage, and shows superior performance in experiments compared with the well-known LESIT model.

1. Introduction

Power electronic devices have been widely used in various industries, such as renewable energy, electronic automobiles, and consumer electronics. Reliability evaluation of the power electronic devices is critical for maintaining the whole system, as they are likely to be exposed to severe conditions, e.g., high current, high voltage, and abrupt temperature fluctuations. They can cause electrical and thermal stress within the structure, leading to the malfunction of the devices. Therefore, lifetime modeling of the devices is crucial for prognosis and health management of the systems.

The failure modes of power electronic devices can be classified into two categories, namely, chip-related failure and package-related failure, which are mainly caused by electrical stress and thermal-mechanical stress, respectively. Many lifetime models have been proposed for the latter failure mode and a popular one is established in (Held, Jacob, Nicoletti, Scacco, & Poech, 1997), which includes a Coffin-Manson related term and an Arrhenius term. The model exhibits the physical relevance between package degradation and two load features, Junction Temperature Swing (ΔT_j) and Junction Temperature ($T_{j,m}$). However, there are few lifetime models based on damage accumulation mechanisms. Considering that the thermal-mechanical fatigue accumulates over cycles leading to the eventual failure, we propose a cumulative damage-based lifetime model that focuses on the package-related failure and quantifies the damage with the two features mentioned above.

The rest of this paper is organized as follows: Section 2 provides a review of related work on power electronic devices' lifetime models, Section 3 describes the proposed damage-based lifetime model, Section 4 presents the dataset and experiment results, and Section 5 discusses the conclusions and future work.

2. Related Work

Lifetime modeling of power electronic devices and modules has a long history of research. Two major streams of investigation are the *data-driven* and *model-based* approaches. The data-driven approach uses machine learning to train a lifetime model from empirical data. It is a pure data mining technique without looking into the failure mechanism. By contrast, the model-based approach intends to investigate the failure mechanism so that a lifetime model can be established in consideration of the failure mechanism. While the data-driven approach becomes more and more popular nowadays due to the new wave of artificial intelligence, the model-based approach has been classical and developed continuously. Our work belongs to the model-based approach. In the following, We give a short review of the main model-based approaches.

The analytical lifetime models are constructed by considering the physical structure and the failure mechanisms of the device (Busca et al., 2011). The objective of the models is to predict the number of cycles to failure, i.e., the lifetime N_f of the devices that have similar operation conditions as the training devices. Due to the mismatch of the coefficients of thermal expansion of adjacent materials, the plastic strain can occur on solder joints and it is assumed as the major reason for device failure (Oh, Han, McCluskey, Han, & Youn, 2015). The Coffin-Manson model was proposed in (Ciappa, 2002). The Coffin-Manson-Arrhenius model (Manson & Dolan, 1966; Held et al., 1997), also called $LESIT$ model in some literature (Otto & Rzepka, 2019), extends the Coffin-Manson model by incorporating an Arrhenius term. The Norris-Landzberg equation (Norris & Landzberg, 1969) and the Bayerer's model (often called CIPS08 model) (Bayerer, Herrmann, Licht, Lutz, & Feller, 2008) were proposed by examining additional test conditions such as heating time, load current, etc. In (Kovačević, Drofenik, & Kolar, 2010), a Physics-of-Failure model was developed, which can physically explain the dependency on the various temperature properties.

The LESIT model has been extensively used to estimate the lifetime of power devices and modules. Since it does not directly model the device damage, it cannot give a clear trend analysis between device damage and device failure. In the paper, our lifetime modeling is based on damage and we show a clear decreasing trend between damage and lifetime.

3. Damage-Based Lifetime Modeling

The main source for the package-related failure of power electronic devices is the thermal-mechanical stress (Hanif, Yu, DeVoto, & Khan, 2019). Shear stress can occur between different materials due to the mismatch of coefficients of thermal expansion. The proposed damage-based lifetime model incorporates a damage accumulation law that quantifies the cumulative damage caused by each thermal cycle, leading to the eventual failure of the devices.

3.1. Damage per cycle

Since thermal-mechanical stress is directly related to temperature, we propose using two features to measure the damage caused per cycle, namely Junction Temperature Swing ΔT_j, and Maximum Junction Temperature $T_{j,max}$. While ΔT_j measures the absolute difference value between the maximum and the minimum junction temperature of the device during a single thermal cycle, $T_{j,max}$ represents the maximum temperature the device junction reaches in a single thermal cycle.

The damage in cycle n can be expressed as:

$$D_c(n) = \Delta T_j(n) \cdot T_{j,max}(n) \tag{1}$$

where $\Delta T_j(n)$ and $T_{j,max}(n)$ represents the value of ΔT_j and $T_{j,max}$ in cycle n. The variable $D_c(n)$ signifies the level of thermal-mechanical damage to the device in cycle n.

3.2. Hypothesis of the relationship between damage and lifetime

Our hypothesis is that lifetime is linear to the inverse of average damage:

$$N_f \propto \frac{1}{\bar{D}_c} \tag{2}$$

where the N_f is the lifetime of the device and $\bar{D}_c$ is the average damage in each cycle throughout the lifetime. As a result, we can express N_f as

$$N_f = b + \frac{c}{\bar{D}_c - a} \tag{3}$$

where three parameters, a, b, and c, are used to describe the relationship. Specifically, a is used to shift the model on the D_c-axis, b is used to shift the model on the N_f-axis, and c represents the expected change in N_f for a one-unit increase in $\frac{1}{D_c - a}$. By introducing them, the model can adjust the rate of change of N_f with respect to $\frac{1}{D_c}$ and have freedom on both axes. We will empirically verify this hypothesis in Section 4.3.

3.3. Cumulative damage based lifetime model

Having the damage per cycle variable D_c, the damage through the whole lifetime of the device can be quantified in an accumulative way. Assuming lifetime is linear to the inverse of cumulated damage, we have

$$N_f \propto \frac{1}{\sum_{n=1}^{n=N_f} D_c(n)} \tag{4}$$

The damage based lifetime model can then be formulated as

$$N_f = \beta + \frac{\gamma}{\sum D_c(n) - \alpha} = \beta + \frac{\gamma}{\sum[\Delta T_j(n) \cdot T_{j,max}(n)] - \alpha} \tag{5}$$

where parameters α, β and γ can be obtained from experimental measurements. Similarly, the three parameters are used to adjust the rate of change of N_f with respect to $\frac{1}{D_c}$ and increase the degree of freedom on both axes.

4. Experiments and results

4.1. Power cycling test

The Power Cycling (PC) test is an accelerated lifetime experiment for power electronic devices. During the test, the devices are applied with periodic switching-on/off current load, resulting in periodic heating and cooling, and relevant measurements are recorded continuously.

Figure 1 illustrates the power switching on/off pattern and temperature profile in PC tests. The device is subjected to a constant current causing internal heating, and after a time interval of t_{on}, its junction temperature reaches $T_{j,max}$. Then the load current is turned off and the device is exposed to certain cooling conditions to decrease the junction temperature. After a time interval of t_{off}, the temperature cools down to the lowest level whereafter another thermal cycle begins. In practical operation, however, $T_{j,max}$ of the devices displays

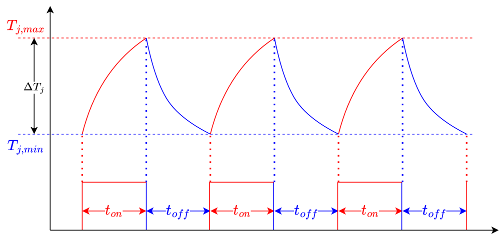


Figure 1. PC thermal cycling diagrammatic illustration.

cycle-to-cycle variation and as a result ΔT_j may slightly fluctuate. Generally, the described heating-cooling process repeats thousands or even tens of thousands of cycles until the device fails.

PC tests are the main driving force for most failure types, including wire-bond failure, die-attach degradation, and delamination of the mold compound (Otto, Rzepka, & Wunderle, 2019). By accelerating the thermal stress, PC tests can help to emulate the intrinsic thermal swings during operation in real-world applications.

4.2. Dataset

The PC test dataset (Otto et al., 2019) is used in our study. The package of discrete power electronic devices is TO-220, one of the commonly used packages in the Transistor Outline (TO) family. During the PC tests, their electrical performance and properties were monitored. According to the test conditions, 77 devices under test can be clustered into 11 groups, which is shown in Table 1.

Group	Temperature Swing $\Delta T_j(K)$	Temperature Maximum $T_{j,max}(^\circ C)$
1	76.4	176.7
2	73.0	136.3
3	106.4	175.5
4	104.8	175.0
5	135.0	170.0
6	130.1	172.7
7	130.6	164.2
8	133.4	168.9
9	105.0	145
10	106.1	141.9
11	106.0	112.8

Table 1. Test conditions for 11 groups.

4.3. Verifying the relationship hypothesis and illustrating lifetime estimation results

First, the experimental data of 77 devices in the PC tests were used to fit the parameters a, b, and c in Equation 3. Figure 2 illustrates the relationship between the average damage $\bar{D}_c$ and the lifetime N_f of devices. The inverse correlation between $\bar{D}_c$ and N_f is clearly shown in the figure. Thus, the hypothesis from the previous section is verified.

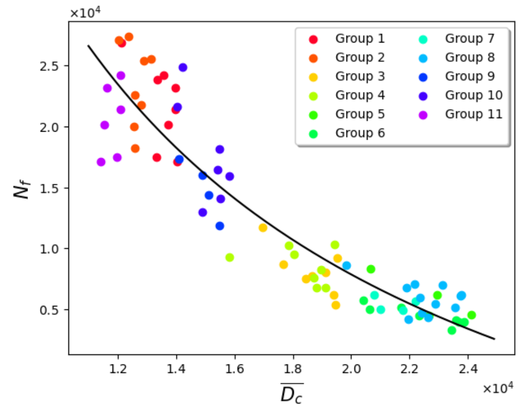


Figure 2. A scatter chart of $\bar{D}_c$ and N_f for 77 devices, and the derived regression line. The x-axis is the average $\bar{D}_c$ of the devices, while the y-axis is the number of cycles of the lifetime N_f. After fitting we have $a = -3.97 \times 10^3$, $b = -2.33 \times 10^4$, $c = 7.48 \times 10^8$. The R^2 score of the model line is 0.869.

Next, the experimental data of 77 devices in the PC tests were used to fit the parameters α, β, and γ in Equation 5. The result is shown in Figure 3, where the reciprocal relationship can be observed. The devices taking more damage would come to the end of life earlier, and vice versa.

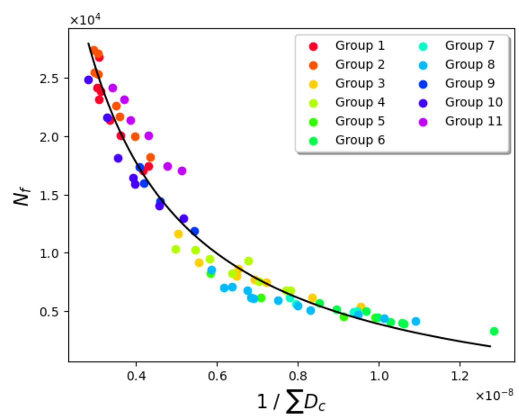


Figure 3. A scatter chart of $1/\sum D_c$ and N_f for 77 devices, and regression line of the fitted damage-based lifetime model. The x-axis is the cumulated damage $\sum[\Delta T_j(n) \cdot T_{j,max}(n)]$ of the devices, while the y-axis is the number of cycles of the lifetime N_f. After fitting the parameters, we have $\alpha = 2.23 \times 10^{-10}$, $\beta = -4.85 \times 10^3$, $\gamma = 8.55 \times 10^{-5}$. The R^2 score of the model is 0.957.

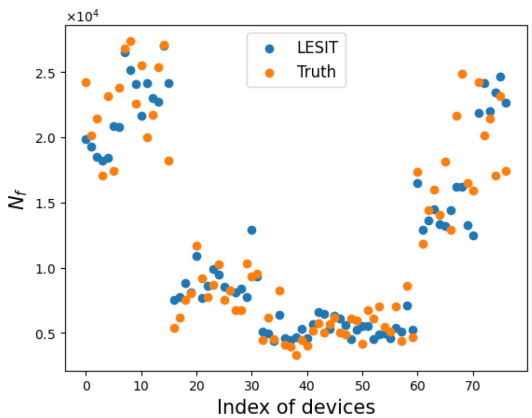
4.4. Comparative results of the LESIT model and our damage-based lifetime model

After verifying the hypothesis and illustrating the lifetime estimation results, we compare the lifetime estimated by our proposed model in Equation 5 with that by the well-known $LESIT$ model (Manson & Dolan, 1966; Held et al., 1997).

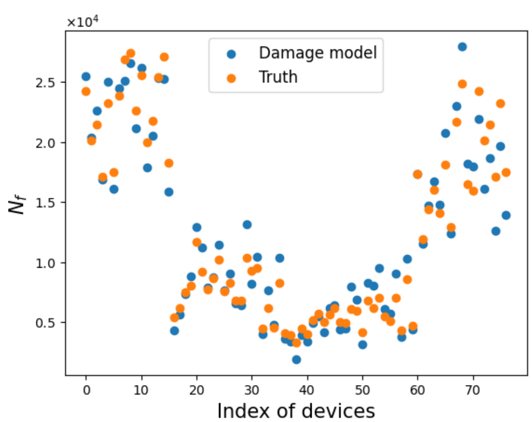
The LESIT model also reflects the relationship between the two features ΔT_j, $T_{j,max}$ and the lifetime. The equation is given in

$$N_f = A \cdot \Delta T_j^{\alpha} \cdot \exp\left(\frac{Q}{R \cdot T_{j,max}}\right) \tag{6}$$

where R is the gas constant ($8.314\ J \cdot mol^{-1} \cdot K^{-1}$), and A, α, and Q can be obtained form experimental data.



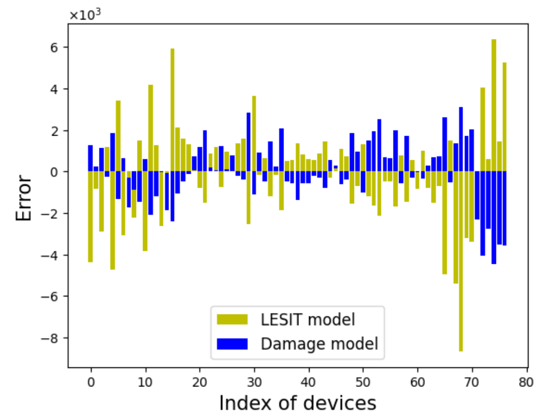
(a) The prediction of $LESIT$ equation and the actual lifetime. After fitting we have $A = 4.38 \times 10^6$, $\alpha = -2.63$, $Q = 2.26 \times 10^4$. The R^2 score of the model is 0.904.



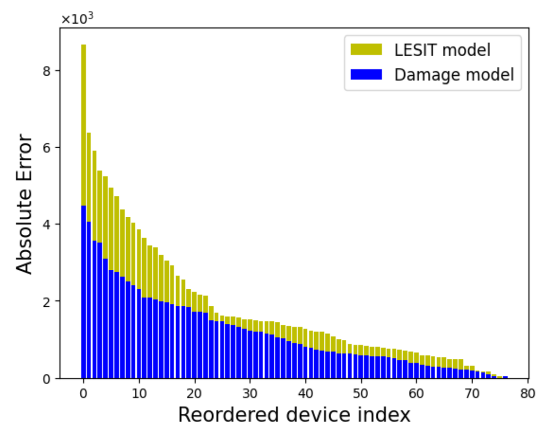
(b) The prediction of our damage-based lifetime model and the actual lifetime. After fitting we have $\alpha = 2.23 \times 10^{-10}$, $\beta = -4.85 \times 10^3$, $\gamma = 8.55 \times 10^{-5}$. The R^2 score of the model is 0.957

Figure 4. Results of $LESIT$ model and the damage-based lifetime model.

Figure 4 compares the in-sample prediction results of the $LESIT$ model and the damage-based lifetime model using the power-cycling experimental data. The figure shows that both models can fit the data well but our damage-based lifetime model achieves a higher R^2 score of 0.957, meaning it is a better fit for the data.



(a) The error of the damage-based lifetime model and the LESIT model for each device.



(b) The absolute error of the damage-based lifetime model and the LESIT model in descending order. The indexes are reordered and the same index may refer to different devices for two models

Figure 5. Prediction error of the LESIT model and the damage-based lifetime model.

Figure 5 illustrates the prediction error for each device and the prediction absolute error in descending order for both models. The error was calculated by subtracting the true value from the predicted value and the absolute error was the absolute value of the difference between the predicted value and the true value. In Figure 5b, the Mean Absolute Error (MAE) of the $LESIT$ model is 1839.99, whereas our damage-based lifetime model has a lower MAE of 1208.03. Additionally, the maximum absolute error of the $LESIT$ model is 8666.17, nearly double that of our model, which is 4484.79.

Based on the comparative results using the power-cycling dataset, the proposed damage-based lifetime model exhibits a higher R^2 score and a lower MAE, indicating its better performance than the LESIT model. In addition, the simplicity of our model and the cumulative calculation make it more suitable for online lifetime prediction in embedded real-time applications where computing and memory resources are limited.

We would also note that different packages have different lifetimes even under the same conditions. For example, the TO220FP's lifetime varies more than TO220's with the same amount of change in temperature swing (Otto & Rzepka, 2019). However, different packages exhibit a consistent relationship between the junction temperature and the lifetime, i.e., the lifetime would decrease when the ΔT_j or $T_{j,max}$ increases. The difference lies in the fact that the decrease in lifetime varies among different packages when subjected to an equal change in temperature ΔT_j or $T_{j,max}$, which can be captured by different parameters (α, β, and γ) when fitting the lifetime model.

5. Conclusion

Our study proposes a damage accumulation model for lifetime estimation of power electronic devices. The model treats the damage in a cumulative way, which is congruent with the experimental observation that the fatigue and crack within the package grow incrementally to the failure. We validate the proposed model by devices under PC tests and demonstrate its superior accuracy compared to the well-known $LESIT$ model. Our damage-based lifetime model is succinct and thus has the potential for real-time online lifetime estimation due to its compact parameter set, low computational overhead, and low memory requirements.

In the future, we will consider the impacts of other test conditions such as heating time and load current, and integrate them into our damage-based lifetime model. The model was evaluated using a dataset in which devices were subjected to constant loads. To further validate the effectiveness of the damage model, future testing will involve introducing varying loads. This will assess the model's ability to capture the damage accumulation effect in power cycles.

Acknowledgment

The research was supported in part by VINNOVA (Swedish Innovation Agency) (2020-05117) through the Trust-E project of Eureka PENTA and EURIPIDES^2 programmes.

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