RUL Estimation for Package Failure of Power Electronic Devices Using Integral Mean of Precursor Signal

Zhonghai Lu[1], Chao Guo[1], Pol Ghesquiere[2], Kai Kriegel [2], and Gerhard Mitic [2]

[1] *KTH Royal Institute of Technology, Stockholm, Sweden*
{*zhonghai, chaoguo*}*@kth.se*

[2] *Siemens, 81739 Munich, Otto-Hahn-Ring 6, Germany*
{*pol.ghesquiere, kai.kriegel, gerhard.mitic*}*@siemens.com*

ABSTRACT

Package failure like bond-wire lift-off is one common cause of failure for discrete power electronic devices such as Schottky diodes. To estimate their Remaining Useful Lifetime (RUL), forward voltage drop is often used as the precursor signal. Prior researches use the direct forward voltage feature and its derived features to construct neural networks for RUL prediction. These features can reflect the instant health condition of the device in the current time or time window, but miss to represent the accumulated effect of gradually decreasing health conditions. In the paper, we formulate the integral mean feature of forward voltage drop and propose to use it to conduct RUL estimation. By the integral mean feature, we are able to capture the device's health condition in an accumulated fashion. Our experiments show that our approach is superior in generalization performance when compared to the forward voltage feature and its statistical features based neural networks for RUL estimation.

1. INTRODUCTION

The demand for reliability of discrete power electronic devices such as Schottky diodes and Insulated-Gate Bipolar Transistors (IGBTs) is constantly increasing as functional safety must be ensured in harsher environments and in safety-critical autonomous applications, e.g., automated vehicles, industrial robotics, etc. To enable prognostic health monitoring and management, predicting Remaining Useful Lifetime (RUL) of power electronic devices is not an option but a must.

In the paper, we study the RUL estimation problem for package failure of Schottky diodes encapsulated in the common transistor outline TO220 package. We focus on the bound-wire lift-off failure, because it is the dominating failure mode for TO220 devices (Otto & Rzepka, 2019). Our RUL estimation is data driven, meaning that a machine learning model is trained to establish the relationship between RUL and its precursor signal, which is an indicator of the device failure. For the bond-wire liftoff failure of power diodes, a well-defined precursor signal is the forward voltage drop, V_f. As a common practice, we use aggregated aging data from power cycling tests for model training and inference.

Previous data-driven RUL estimation of power electronic devices and modules extract various features from the original precursor signal to facilitate the RUL estimation. These features are derived from mathematical transformations of the original time-series signal. These include time-domain statistical features (Ismail, Saidi, Sayadi, & Benbouzid, 2020) such as mean, standard deviation, entropy, etc., classic frequency-domain features such as power spectrum, and those features after convolution e.g. using convolutional layer for hidden feature extraction (X. Li, Zhang, & Ding, 2019). Statistical time-domain features give summative information about the time-series data in each profiling time window. Frequency-domain features give basic information about the frequency components embedded in the precursor signal, which are not accessible in time-domain analysis, The convolution operation can help to extract hidden features, but interpreting the extracted features is often difficult. Nevertheless, none of the existing features attempts to relate the device's RUL to the damage accumulation of the device. This is not satisfactory because the failure of a device is typically not the result of instant damage, but the result of damage accumulation.

In the paper, we develop the concept of *integral mean* of precursor signal and propose to use it as a relevant feature to study the RUL of power diodes. The integral mean is the mean of the integral of the forward voltage drop, V_f. We give a mathematical definition for this derived feature, show how to use the integral mean as the input feature to construct an RUL estimation model using Recurrent Neural Network

(RNN), and demonstrate that it can improve the estimation model's accuracy when compared to the time-domain statistical features.

The remainder of the paper is organized as follows. Section 2 discusses related work. We present the concept of the integral mean of precursor signal in Section 3 and apply it to construct RNN model for RUL estimation in Section 4. Experimental results using latest industrial power cycling tests are reported in Section 5. Finally, we conclude in Section 6.

2. Related Work

Lifetime modeling and RUL estimation of power electronic devices and modules can be broadly classified into *model-based*, *data-driven*, and *hybrid* approaches. An overview was presented in (Ciappa, 2008). Hanif *et al.* made a comprehensive survey in (Hanif, Yu, DeVoto, & Khan, 2018). Recently application of artificial intelligence for power electronic systems was surveyed in (Zhao, Blaabjerg, & Wang, 2021).

The model-based approach seeks a mathematical relationship between the device or module's lifetime (number of cycles to failure, N_f) and its dependent variables. Such analytical models are developed from empirical data and often in relation to physics of failure. The Coffin-Manson model (Ciappa, 2002) is the original model capturing the relationship between the device's lifetime and its temperature swing ΔT. Later this model was expanded to consider other dependent variables. For example, the Coffin-Manson-Arrhenius model (Manson & Dolan, 1966) and the LESIT equation (Held, Jacob, Nicoletti, Scacco, & Poech, 1997) consider not only the temperature swing ΔT but also a reference temperature, which could be minimum T_{min}, maximum T_{max}, mean T_m, or effective T_{eff} temperature (Otto & Rzepka, 2019).

The data-driven approach uses machine learning to model the lifetime or RUL of electronic devices and modules. In (W. Li, Wang, Liu, Zhang, & Wang, 2020), Long Short Term Memory (LSTM) was proposed to monitor device aging and predict RUL. In (He, Yu, Zheng, & Gong, 2021), He *et al.* tried a few machine learning algorithms to predict RUL of IGBTs using NASA accelerated aging data sets (Celaya, Wysocki, & Goebel, 2009). Ismail *et al.* (Ismail et al., 2020) combined time-series feature extraction and Principal Component Analysis (PCA) based feature reduction with neural network to address the RUL estimation problem. To deal with solder joint degradation of electronic devices, deep neural network (Salameh & Hosseinalibeiki, 2022) was proposed to predict the useful lifetime of solder joints.

The hybrid approach combines the model-based and data-driven approaches to utilize the advantages of both by fusing physics rules into machine learning models (Chao, Kulkarni, Goebel, & Fink, 2022). To predict the RUL of IGBT modules (Lu & Christou, 2019), a particle filter based method incorporating the crack propagation physics law was developed. In (Zhao, Peng, Zhang, & Wang, 2022), the principle of physics-informed neural network was applied to estimate the parameters of the DC-DC buck converter.

3. Integral Mean of Precursor Signal

3.1. Precursor signal for wire-bond failure

For the investigated TO220 devices, wire-bond failure was the dominant failure mechanism. Forward voltage drop, V_f, is a well-qualified precursor signal to indicate this failure mode. As defined in the ECPE Guideline AQG 324 (Thoben & Reiter, 2021) and IEC standard IEC60749-34 (International Electro technical Commission, 2004), when the forward voltage drop V_f raises by 5%, it signifies that one or more of the bond-wire lift off and the device fails.

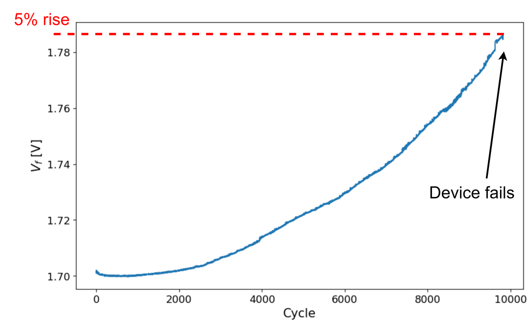


Figure 1. Precursor signal $V_f(n)$ before device failure.

Figure 1 shows a typical forward voltage drop signal up to 5% of increase for a device under power cycling test.

3.2. Integral mean of precursor signal

The integral mean is a derived variable intended to reflect that the device damage is an accumulation process. Mathematically the accumulation is the integral operation.

Given is a forward voltage signal, $V_f(t)$, where t is a real number. Its corresponding integral signal is $I(t)$, which can be expressed as follows.

$$I(t) = \int_0^t V_f(t)dt \tag{1}$$

To consider the damage accumulation over time, we further introduce the *mean of the integral* to measure the average damage accumulation, leading to a corresponding new signal $IM(t) = I(t)/t$. This is necessary because the same amount of damage may be caused in a short period or a long period. This in turn affects the length of the device's lifetime. $IM(t)$ can be expressed as follows.

$$IM(t) = \frac{1}{t}\int_0^t V_f(t)dt \tag{2}$$

Definitions in Eq. 1 and 2 are general for real-numbered continuous signals. For time series data from power cycling tests, they are discrete sequences. Correspondingly, we give the discrete version of Eq. 1 and 2 in Eq 3 and 4, respectively, where $n \in \{1, 2, 3, \cdots\}$ is the power cycle.

$$I(n) = \sum_{i=1}^{n} V_f(i) \tag{3}$$

$$IM(n) = \frac{1}{n} \sum_{i=1}^{n} V_f(i) \tag{4}$$

As an example, Figure 2 shows the corresponding integral

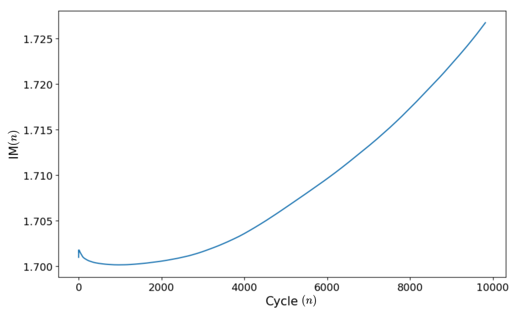


Figure 2. Integral-mean signal $IM(n)$.

mean signal $IM(n)$ of the $V_f(n)$ signal in Figure 1.

4. RNN-Based RUL Estimation Models

We use RNN to build the RUL estimation model. Compared to MLP and CNN, it has an internal memory structure that can better deal with sequential data. Compared to LSTM, RNN is simpler and thus beneficial for implementations in resource-constrained embedded systems.

4.1. RUL estimation model using integral mean feature

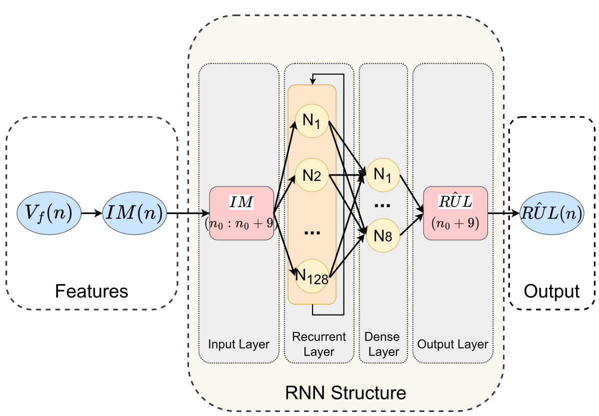


Figure 3. Integral-mean feature based RNN model.

Figure 3 shows an RUL estimation RNN model with the integral mean feature. For our RUL estimation problem, signal $V_f(n)$ is used as the precursor signal. After transformation, we obtain the integral mean feature $IM(n)$. It is fed to the RNN input layer with a timestep of 10. The second layer, fully-connected recurrent layer, has 128 neurons. The third layer is a fully-connected dense layer and has 8 neurons. The output of the model is generated via the output layer, which consists of a single neuron. We can write the basic mapping function as $RU\hat{L}(n) = RNN(IM(n))$. "$RU\hat{L}(n)$" indicates the estimated value of RUL at time n, which is in contrast to the true RUL value at time n, $RUL(n)$.

4.2. RUL estimation model using statistical features

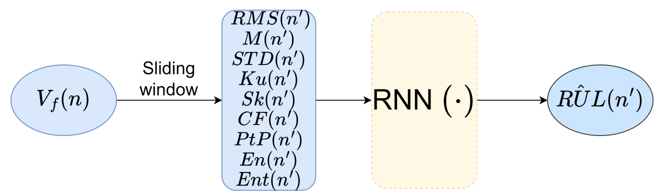


Figure 4. Statistical features based RNN model.

For clarity and comparison, we also draw the baseline RNN model for RUL estimation using extracted time-domain statistical features in Figure 4. The precursor signal is still $V_f(n)$, which is used to generate statistical features using a sliding window. There are nine statistical features extracted from $V_f(n)$, which are root-mean square (RMS), mean (M), standard deviation (STD), kurtosis (Ku), skewness (Sk), crest factor (CF), peak-to-peak average ratio (PtP), energy (En), and entropy (Ent) (Ismail et al., 2020). With this feature extraction, the dimension of the input feature vector is increased from one to nine, leading to a large increase in the model complexity (the number of input neurons increases from 1 to 9). One can use PCA to reduce the dimension, but PCA is not lossless. To keep the extracted features intact, we will use the whole nine features in our comparative experiments.

5. Experiments and Results

5.1. Experimental purpose and setup

5.1.1. Purpose

The purpose of experiments is to evaluate our proposed approach for RUL estimation. To this end, we compare three RNN models using different features. For clarity, they are notated as follows in the result figures.

- RNN(V_f): The basic RNN model featured with the forward voltage V_f.
- RNN(V$_{statistic}$): The baseline RNN model (Figure 4) featured with the nine derived time-domain statistical features of forward voltage series V_f.
- RNN(IM): Our proposed RNN model (Figure 3) featured with the integral mean of forward voltage V_f.

We use Mean Squared Error (MSE) as metric, the common criterion to evaluate the performance of regression problems.

5.1.2. Power cycling test setup

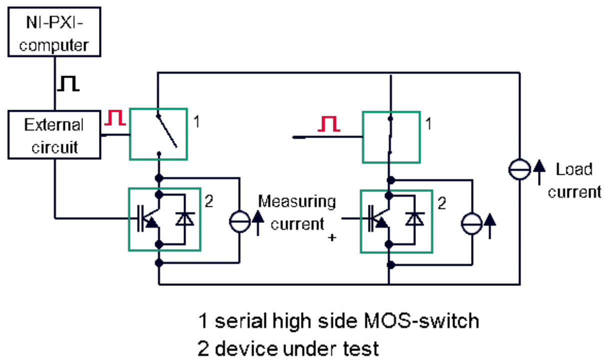


Figure 5. Schematic of power cycling test

Figure 5 draws a schematic for the power cycling test done in Siemens. The test bench is covering two devices that are electrically powered by a load current I_{load} which is switched periodically with time intervals t_{on} and t_{off} between both devices. During power cycling the temperature of the semiconductors is measured by the temperature-dependent forward voltage using a small measurement current I_{meas}. Before power cycling the forward voltage is calibrated at different temperatures up to 90° C. During power cycling all relevant electrical parameters V_{DS}, I_{load}, and thermal parameters T_j are monitored continuously.

5.1.3. Test conditions

Test Parameter	Group 1	Group 2	Group 3
Temperature Swing ΔT_j (K)	110.2	90.0	89.0
Temperature Maximum $T_{j,max}$ (°C)	167.7	155.0	147.7
Load Current I_{load} (A)	9.9	8.7	15
Switch Time t_{on}/t_{off} (s)	9 / 9	9 / 9	3 / 3

Table 1. Test conditions for three groups of devices

In the power cycling tests, six SiC-Schottky diodes were tested. They were partitioned into three groups, each with two devices. The test conditions for the three groups are listed in Table 1. Note that the three groups have different test conditions with relatively large differences in ΔT_j, I_{load}, or t_{on}/t_{off}.

5.1.4. The data set

Figure 6 depicts the original forward voltage series for the six devices. The forward voltage is increasing continuously because of gradually accumulating bond wire fatigue which is increasing the electrical resistance. Because of increased electrical resistance, electrical losses and therefore chip temperatures increase which additionally leads to higher forward voltages. Solder fatigue leading to higher thermal resistance

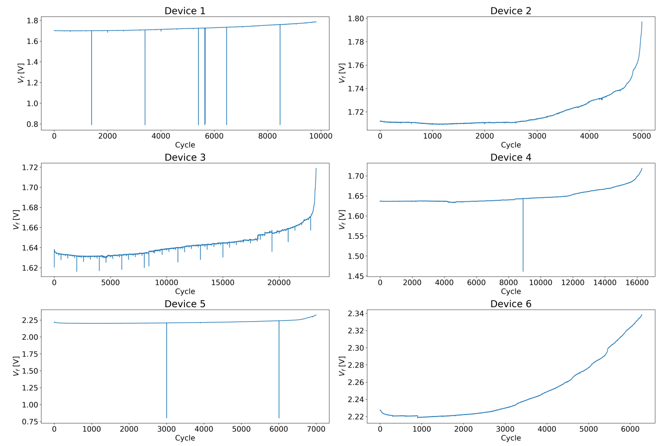


Figure 6. Forward voltage drop series up to failure.

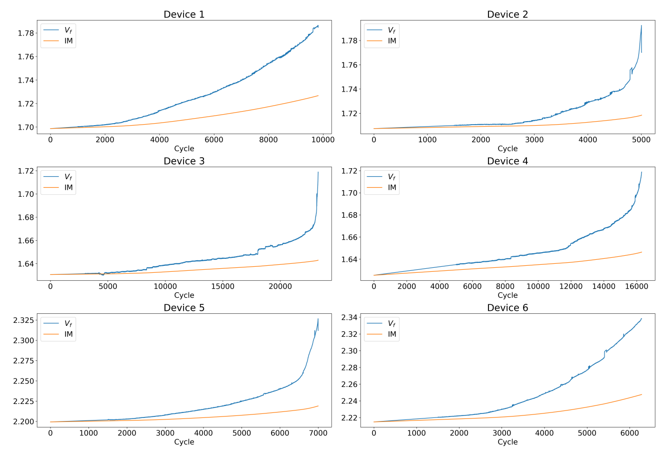


Figure 7. Preprocessed forward voltage drop series and their integral mean for the six devices.

can speed up those mechanisms. Only during a short period of time at the beginning of the power cycling experiments, the temperature is decreasing because of decreasing thermal resistance of the thermal interface material due to alignment by thermo-mechanical impact.

After removing outliers coming from incorrect measurements and replacing data from the warm-up period with stable values, the V_f signals and their IM signals are illustrated in Figure 7. These signals are then normalized to the range [0, 1] and ready for RNN modeling and inference.

5.2. Experimental results

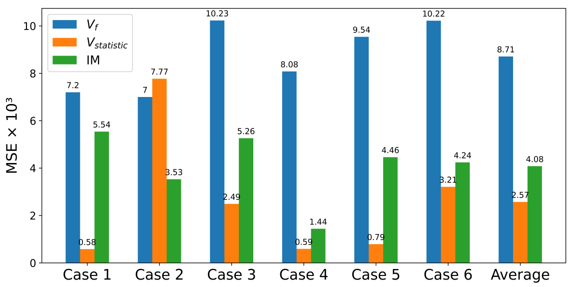
Case	Train dev.	Test dev.	Case	Train dev.	Test dev.
1	2, 3, 4, 5, 6	1	4	5, 6, 1, 2, 3	4
2	3, 4, 5, 6, 1	2	5	6, 1, 2, 3, 4	5
3	4, 5, 6, 1, 2	3	6	1, 2, 3, 4, 5	6

Table 2. Split the dataset for cross-validation

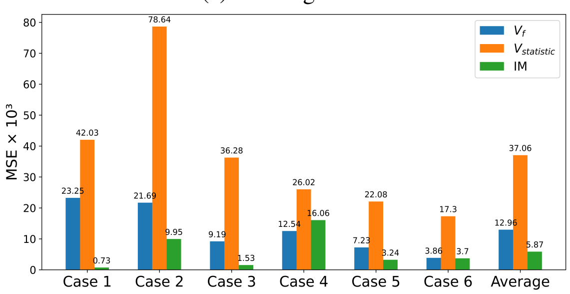
We conducted RUL estimation by k-fold cross-validation, i.e., training with $k-1$ devices and testing with one device. As we have six devices ($k=6$), we have six cases shown in Table 2. The intention is to evaluate the model's out-of-sample *generalization* performance.

5.2.1. Overall performance

The training and testing MSE results of 6 cases are shown in Figure 8. All models were trained with 100 epochs when their training MSE stabilized.



(a) Training MSE



(b) Testing MSE

Figure 8. Training and testing MSE comparison of three RNN models for six cases plus Average of the six cases.

- In training, RNN($V_{statistic}$) has the best performance over the 3 models in all cases except Case 2, and it has the lowest loss on average as well. RNN(IM) has the second lowest loss in all cases and it is approximately 1.58 times larger than the loss of RNN($V_{statistic}$) but 2.13 times smaller than that of RNN(V_f) on average.
- In testing, by contrast, RNN($V_{statistic}$) has a significantly higher loss than the other two models in all cases as well as on average. However, RNN(IM) has the best test performance over all cases. On average, its loss is 2.21 times smaller than that of RNN(V_f) and 6.31 times smaller than that of RNN($V_{statistic}$).

The results show that the RNN(IM) model performs well in training and can generalize the best in testing.

5.2.2. Performance illustration

To give insights on the overall performance improvement, we visualize details for RUL estimation of Case 1. Figure 9 compares the model training performance for all 5 train devices and 1 test device.

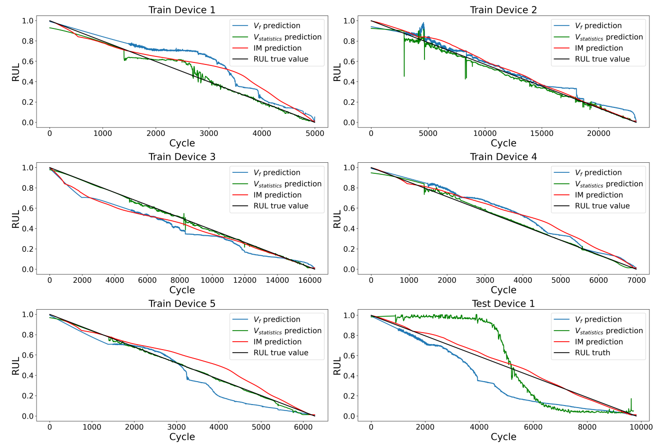
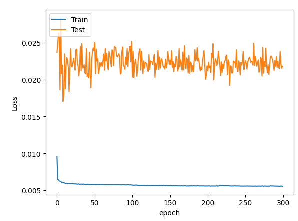
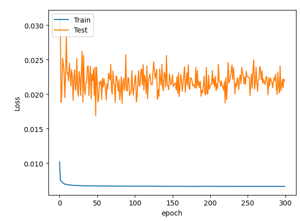


Figure 9. Training and testing performance illustration of the 3 RNN models for Case 1.

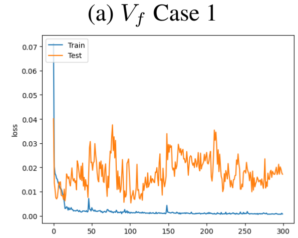
5.2.3. Epoch-wise performance monitoring



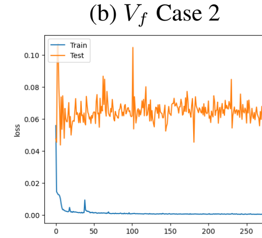
(a) V_f Case 1



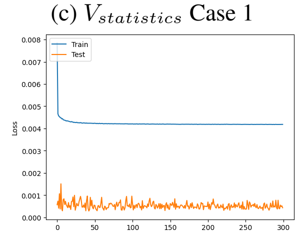
(b) V_f Case 2



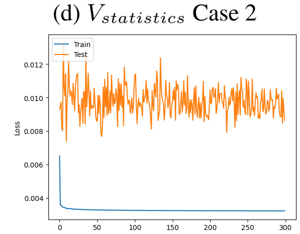
(c) $V_{statistics}$ Case 1



(d) $V_{statistics}$ Case 2



(e) IM Case 1



(f) IM Case 2

Figure 10. Training and testing MSE over training epochs for three RNN models in Case 1 and Case 2.

Figure 10 depicts the three models' training and testing MSE with respect to training epochs in Case 1 and Case 2. The testing loss is normally higher than the training loss, except in Case 1 where the RNN(IM) has a lower testing loss. We can observe that, even though RNN($V_{statistic}$) has the smallest training MSE, it does not overfit in the normal sense of training MSE decreasing but testing MSE increasing. Rather its training performance stabilizes after a certain epoch but its testing performance fluctuates, like the other two models. Compared with the other two models in testing, our RNN(IM) always has a lower loss. This indicates that the model using the IM feature can generalize better throughout different devices under different test conditions.

6. Conclusion

We have proposed a new feature, *integral mean of precursor signal*, to conduct RUL estimation of discrete power electronic devices. This feature intends to capture the accumulated damage of the device because the average damage accumulation can be mathematically expressed as an integral mean operation. With the same RNN structure for RUL estimation, we have compared this feature to a state-of-the-art counterpart using time-domain statistical features. Our experiments show that it can largely improve the model generalization performance due to the nature of integral mean capturing the damage accumulation, which is less dependent on specific testing conditions. In the future, we will use the integral mean feature of the precursor signal to study other failure modes of discrete power electronic devices.

Acknowledgment

The research was supported in part by VINNOVA (Swedish Innovation Agency) (2020-05117), BMBF (16ME0324) via the Trust-E project of Eureka PENTA and EURIPIDES[2] programmes, and Vetenskapsrådet (Swedish Research Council) via the LearnPower project (2020-03494).

References

Celaya, J. R., Wysocki, P., & Goebel, K. (2009). *IGBT Accelerated Aging Data Set.* (NASA Prognostics Data Repository, NASA Ames Research Center, Moffett Field, CA)

Chao, M. A., Kulkarni, C., Goebel, K., & Fink, O. (2022). Fusing physics-based and deep learning models for prognostics. *Reliability Engineering & System Safety*, *217*, 107961.

Ciappa, M. (2002). Selected failure mechanisms of modern power modules. *Microelectronics Reliability*, *42*(4), 653-667. doi: https://doi.org/10.1016/S0026-2714(02)00042-2

Ciappa, M. (2008). Lifetime modeling and prediction of power devices. In *5th international conference on integrated power electronics systems* (pp. 1–9).

Hanif, A., Yu, Y., DeVoto, D., & Khan, F. (2018). A comprehensive review toward the state-of-the-art in failure and lifetime predictions of power electronic devices. *IEEE Transactions on Power Electronics*, *34*(5), 4729–4746.

He, C., Yu, W., Zheng, Y., & Gong, W. (2021). Machine learning based prognostics for predicting remaining useful life of IGBT – NASA IGBT accelerated ageing case study. In *2021 ieee 5th information technology, networking, electronic and automation control conference (itnec)* (Vol. 5, pp. 1357–1361).

Held, M., Jacob, P., Nicoletti, G., Scacco, P., & Poech, M.-H. (1997). Fast power cycling test of IGBT modules in traction application. In *Proceedings of second international conference on power electronics and drive systems* (Vol. 1, p. 425-430 vol.1). doi: 10.1109/PEDS.1997.618742

International Electro technical Commission. (2004). *Semiconductor devices mechanical and climatic test methods part 34: Power cycling.* International standard IEC 60749-34.

Ismail, A., Saidi, L., Sayadi, M., & Benbouzid, M. (2020). A new data-driven approach for power IGBT remaining useful life estimation based on feature reduction technique and neural network. *Electronics*, *9*(10), 1571.

Li, W., Wang, B., Liu, J., Zhang, G., & Wang, J. (2020, November). IGBT aging monitoring and remaining lifetime prediction based on long short-term memory (LSTM) networks. *Microelectronics Reliability*, *114*.

Li, X., Zhang, W., & Ding, Q. (2019). Deep learning-based remaining useful life estimation of bearings using multi-scale feature extraction. *Reliability engineering & system safety*, *182*, 208–218.

Lu, Y., & Christou, A. (2019). Prognostics of IGBT modules based on the approach of particle filtering. *Microelectronics Reliability*, *92*, 96-105. doi: https://doi.org/10.1016/j.microrel.2018.11.012

Manson, S. S., & Dolan, T. J. (1966, 12). Thermal stress and low cycle fatigue. *Journal of Applied Mechanics*, *33*(4), 957-957. doi: 10.1115/1.3625225

Otto, A., & Rzepka, S. (2019). Lifetime modelling of discrete power electronic devices for automotive applications. In *Ame 2019 - automotive meets electronics; 10th gmm-symposium* (p. 1-6).

Salameh, A., & Hosseinalibeiki, H. (2022, 07). Application of deep neural network in fatigue lifetime estimation of solder joint in electronic devices under vibration loading. *Welding in the World*, *66*. doi: 10.1007/s40194-022-01349-7

Thoben, M., & Reiter, T. (2021, May). Guideline for lifetime calculation of power modules annex of ECPE GUIDELINE AQG 324. In (p. Annex II.D 1-14).

Zhao, S., Blaabjerg, F., & Wang, H. (2021). An overview of artificial intelligence applications for power electronics. *IEEE Transactions on Power Electronics*, *36*(4), 4633-4658.

Zhao, S., Peng, Y., Zhang, Y., & Wang, H. (2022). Parameter Estimation of Power Electronic Converters With Physics-Informed Machine Learning. *IEEE Transactions on Power Electronics*, *37*(10), 11567-11578.