An efficient online time-temperature-dependent creep-fatigue rainflow counting algorithm

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ABSTRACT

Reliability assessment of the materials in real applications in which the materials are exposed to the numerous and complicated time-domain cycles has become one of the most important issues facing all reliability engineers. From offline to online useful lifetime estimations of the material, cycle counting such as Rainflow is paramount of importance. Rainflow algorithm plays the role of transferring complicated time domain cycles to the sorted set of data. This set of data applies to the lifetime model of the material and make the researchers evaluate useful life time of the materials. In this paper, a new online time-temperature-dependent creep-fatigue Rainflow counting algorithm has been proposed. In this new algorithm, online counting of half cycles, time-temperature-dependent mean temperature and creep failure mechanism have been all considered leading to the much more accurate cycle counting and reliability assessment, consequently. This study presents that consideration of the time-temperature-dependent mean temperature and creep failure mechanism can thoroughly impress the reliability assessment in the materials exposed to the temperature cycling. This feature has been validated by employing a set of experimental data of a solder joint, namely the constants of Coffin-Manson-Arhenius and Monkman-Grant, in a power semiconductor. While the solder joint has been exposed to the specified cycles, the results show that the useful lifetime of the solder joint in the power semiconductor can be estimated with 10% increase in accuracy. The results reveal the importance of the creep failure mechanism and the time-temperature-dependent mean temperature on the reliability assessment.

1. Introduction

Counting of complicated loading cycles applied to any physical systems is increasingly becoming a vital factor in the life time estimation, particularly in the thermo mechanical fatigue study. Cycle counting algorithms are attracting considerable interest due to their capability of compacting a long time history data to the somewhat sorted data expediting the analysis of the fatigue useful lifetime [1,2].

For many years, numerous cycle counting algorithms including peak counting, crossing counting, level counting, simple rate counting, Hayes method, racetrack method, simple range counting, Moshreﬁar and Azamfar method and Rainflow counting method have been applied in the various applications [3,4]. In real applications, loading cycles are not in a simple pattern to be counted. Moreover, they do comprise a long-term data which is highly involved to be either analyzed or compared. Fig. 1 depicts two sets of data (temperature), applying to a system. Regarding this figure, it is roughly impossible to analyze that how these two stresses can affect the lifetime of the system. As a reliability point of view, it is also impossible to compare these two stress patterns. However, thanks to the cycle-counting algorithm, analyzing and comparing long and complicated stresses has become possible.

The primary algorithm was established by T. Endo and M. Matsuishi in 1968 [5] based on a rain drop over a Pagoda roof as shown in Fig. 2. Each of the closed hysteresis loop is considered as a load cycle with the strain (stress) range and its corresponding mean value. For instance, after applying a specific stress to the material, it starts tensioning (from point ①) leading to the material deformation. This tension continues to point ② in which a new stress makes the material compress to point ③. Then it starts being tensioned and therefore passes point ④ leading to form a stress-strain hysteresis loop (②→③) with the strain (stress) range of |S④−③| and mean value of (S④+S③)/2. This deformation continues to point ⑤ and after that a compression stress makes the material strain decrease to point ⑥. Then a positive stress and a positive strain occurs (⑥). After that by compressing the material, a material deformation occurs and by passing through point ⑥ another stress-strain hysteresis loop is formed (with the range of |S⑥−S⑤| and mean value of (S⑥+S⑤)/2). The process will be continued till all the data has been analyzed.
As it was mentioned, there are numerous cycle-counting algorithms [3]. Among all of them, Rainflow algorithm has gained lots of attractions owing to its simplicity of implementation and insignificant errors [6–8]. As the procedure of algorithm performing point of view, Rainflow algorithm generally falls into two categories, namely, three-point and four-point [9–11].

Although McInnes and Meehan [12] have mathematically proved that the three-point and the four-point methods are both equal, the three-point algorithm gains much popularity between engineers [13]. Based on the ASTM E1049-85 standard [9], the three-point Rainflow algorithm coding was implemented by Nieslony [14] using MATLAB tools. Rainflow is based on the local maxima and minima of the time domain data history. It means that for applying Rainflow cycle counting algorithm (either in three-point or four-point cases) to the time domain data history, it primarily needs to be transferred to the local extrema. In addition, all the time domain data history has to be known which makes online cycle counting encounter to some sort of difficulties.

As an example based on the codes which was composed by Nieslony [14], a sample thermal cycle as shown in Fig. 3a has been considered. Regarding Fig. 3a, cycle counting of this thermal load history is thoroughly complicated and hence necessity of utilizing Rainflow algorithm is evident. Based on the method, firstly load cycles have to be transferred to their extrema. For obtaining extrema, the method uses discrete second-order derivative of load cycles. The extrema of sample load history is also drawn in Fig. 3a. Based on the full time-temperature data (load history) and extracted extrema, MATLAB codes tried to find full and half cycles. As shown in Fig. 3b there are 16 half cycles up, 17 cycles down and 13 full cycles.

Cycle-counting algorithms, particularly Rainflow, are widely used in mechanical engineering, vibration system and power semiconductor thermo-mechanical applications [15–18]. In many applications, for online estimating lifetime consumption of an interested part in a system, an online Rainflow is undoubtedly required [19]. In the conventional Rainflow either based on the three-point or on the four-point algorithms, the whole time domain history must be specified before
starting the algorithm [20,21]. Accordingly, this method is not applicable to online lifetime estimation. In spite of its shortcomings, this method has been widely applied to the offline lifetime estimation. To the authors’ best knowledge, most studies have only tended to focus on the offline Rainflow algorithm [22–24] and a few ones have focused on the online Rainflow algorithm [2,25] and accordingly there is still a need for discussion on the online Rainflow. Generally, major flaws of these algorithms are including as follows:

- In the conventional Rainflow only the extrema (peaks and valleys) has been employed leading to lose the time data of signal and miss the real time data.
- Half cycles (not completed hysteresis loop) have to be counted only at the end of the time domain history data [26]. Evidently, it is impossible to estimate real-time useful lifetime.
- Based on the most widely-used thermo-mechanical fatigue failure model, namely Arrhenius-Coffin-Manson, mean temperature has paramount of importance in the acceptable confidence level fatigue lifetime evaluation [27,28]. In the previous Rainflow versions, the dependency of time on the mean temperature has been missed out (see Section 2).
- A neglected area in the field of Rainflow is the creep degradation. Creep mechanism plays a major role in the device/system degradation, particularly when the thermal stress ranges are sufficiently near to device melting temperature [29,30]. Therefore, the current solutions to the Rainflow algorithms are inefficient in the precise lifetime estimation.

Based on the reviewed literature, these aforementioned drawbacks of Rainflow cycles counting have not been simultaneously mitigated yet. Although online half cycle counting and time-temperature-dependency of the mean temperature were addressed by Mussallam [25] and GopiReddy [7] respectively, the other defects especially creep-included algorithm have remained.

This paper formulates a new approach to the Rainflow cycle counting algorithm and seeks to address how to tackle above-mentioned defects. The aim of this study is to broaden the current four-point Rainflow algorithm capable of considering creep mechanism, time-temperature-dependency of mean temperature and online-counting half cycles. This paper is organized as follows. Section 2 gives a brief overview of importance of creep mechanism and time-temperature-dependency of mean temperature. A new methodology is outlined in the third section. A new procedure is proposed in Section 4. Some results and conclusions are drawn in the final sections.

2. Importance of creep mechanism and time-temperature-dependent mean temperature

In this section, the importance of time–temperature-dependent mean temperature and creep mechanism will be discussed. As a sample, Fig. 4a demonstrates stress-strain curve of a material. The trace falls into two elastic and plastic regions. Stress-strain behaviors of solder for different temperatures are also depicted in Fig. 4b [30]. As it can be seen from Fig. 4b, the material temperature has a significant effect on the strain occurring inside the material. Material strain is a key factor in the fatigue aging mechanism. Accordingly, in the same stresses, the created strain in the material varies significantly by the temperature variations. In such materials that the temperature varies during its loading, the importance of considering time-temperature-dependent mean temperature has become outstanding leading to the different...
useful lifetime estimation (ULE).

Creep mechanism is one of the most critical aging mechanisms in the material in which the working temperature is sufficiently high and is above the one third of its absolute melting temperature [30]. In the most materials, a temperature increase leads to a decrease in strength of material. In the creep mechanism both the time and the temperature are paramount of importance due to its physical mechanism. Physically, creep degradation in the materials is owing to the propagation and nucleation of micro-cracks and their coalescence to meso-cracks [30,31].

On the contrary to the low-cycle fatigue damage process, namely load cycles, creep degradation is time-dependent and highly impressed by the dwelling time period [32]. For expressing lifetime model of the materials on the creep failure mechanism, Monkman-Grant (MG) model has been extensively used [33]:

\[ \dot{\varepsilon} = \frac{C_{MG}}{t} \]  

(1)

where \( \dot{\varepsilon} \) is the stable creep strain rate, \( C_{MG} \) and \( \beta \) are constant and material-dependent. One can find time per unit creep damage as follows:

\[ d_c = \frac{1}{t_c} = \left( \frac{\dot{\varepsilon}}{C_{MG}} \right)^{1/\beta} \]  

(2)

Accumulated creep damage during the dwelling period under the same condition gives as

\[ D_c = \Delta t \left( \frac{\dot{\varepsilon}}{C_{MG}} \right)^{1/\beta} \]  

(3)

where \( \Delta t \) is the dwelling time. Creep strain rate is a function of environmental temperature, applied stress, dwelling time [33]. There are many correlations that can express the creep strain rate such as Anand, sine-hyperbolic and Dorn [34]. Eq. (4) is a simplified Dorn equation of the creep strain rate and the stress correlation.

\[ \dot{\varepsilon} = A \sigma^n \exp \left( -\frac{Q}{RT} \right) \]  

(4)

where \( A, n \) are both constant and material-dependent, \( R \) and \( Q \) are the gas constant (J·mol\(^{-1}\)·K\(^{-1}\)) and the internal energy (J·mol\(^{-1}\)) and \( T \) is the absolute temperature of the material in Kelvin.

It was previously mentioned and also revealed from the Eq. (1) that the creep failure mechanism is time dependent which means that the longer time the material exposed to the roughly constant temperature, the more degradation occurs. Based on Monkman-Grant model, the dwelling time \( \Delta t \) is a key factor in calculating the creep useful lifetime. Previous works have only been limited to the high/low cycle fatigue by considering only the stress swings and the mean stresses and failed to purpose the dwelling times in which the material have been rested in the roughly constant temperature. Fig. 5 demonstrates a thermal stress as a function of time. As it is shown in the thermal stresses, there can be a lot of dwelling time in which the material is exposed to. Thus, it is thoroughly important to also consider the creep failure mechanism in cycle counting algorithm (red dashed border in Fig. 5).

3. Online time-temperature-dependent creep-fatigue rainflow counting algorithm

As it was mentioned in the conventional Rainflow, only the extrema (peaks and valleys) have been employed. This leads to lose the time data of the signal and miss the real time data and half cycles have to be counted only at the end of the time domain history data. In addition, the dependency of the time on the mean temperature and creep degradation have been neglected. Accordingly, a real time method needs to be considered the time-temperature-dependent mean temperature, creep degradation and online half cycle counting. In this study, a novel efficient online time-temperature-dependent creep-fatigue Rainflow counting algorithm has been proposed. While time-temperature dependency on mean temperature will be discussed in the first subsection, the new proposed methodology will be launched in the second subsection. Finally, this method will be applied to a case study.

3.1. Time-temperature-dependent mean temperature evaluation

Fig. 6 demonstrates four thermal points in a specific thermal cycle which is constituting a full thermal cycle. \( T_1-T_4 \) are the temperatures and \( t_1 \) to \( t_4 \) are their corresponded times (See also points ①–④ in Fig. 2b). \( t_{FC} \) is the time at which the thermal cycle is completely formed. Based on the Rainflow algorithm, \( T_2 \) and \( T_3 \) formed a thermal full cycle. As previously mentioned, strain-stress curve of almost all materials are temperature dependent (see Fig. 4b). Therefore, one can find that the time between the thermal points at which full thermal cycles (local hysteresis loop) occur is undoubtedly important for the mean temperature evaluation.

Without considering the time between the thermal points, mean temperature can be readily calculated by \( \frac{T_3 + T_2}{2} \). However, it is not acceptable for the materials in which their strain-stress curves are temperature dependent. In the other words, the time of the complete formation of the local hysteresis loop is thoroughly important in the mean temperature calculation (see Fig. 2b). Based on Fig. 6, thermal cycle has been completed in \( t_{FC} \). Therefore, a whole time of the full cycle is \( t_{FC} - t_2 \). The mean temperature between the points \( t_2-t_3 \) and \( t_3-t_4 \) are \( \frac{T_2 + T_3}{2} \) and \( \frac{T_3 + T_4}{2} \). The time-weighted mean temperature of this full cycle is the average of these two mean temperatures in terms of their associated times. Accordingly, an equivalent mean temperature can be calculated as follows [7]:

\[ T_{\text{mean}}^e = \frac{t_4-t_2}{t_{FC}-t_2} (\frac{T_4 + T_2}{2}) + \frac{t_3-t_1}{t_{FC}-t_2} (\frac{T_3 + T_1}{2}) \]  

(5)

where \( T_{\text{mean}}^e \) is the new equivalent mean temperature and

\[ t_{FC} = \frac{t_2 + T_1}{T_3 - T_2} (t_4 - t_3) + t_3 \]  

(6)

It is clear that by increasing \( t_4-t_2 \), the equivalent mean temperature will be also increased which has to be taken into account in reliability assessment of the materials. Thus, in the proposed Rainflow algorithm

![Fig. 5. Thermal stress as a function of time including fatigue and creep phenomena.](image)
this equivalent mean temperature will be employed to increase accuracy of reliability evaluation.

3.2. Developing of newly proposed online time-temperature-dependent creep-fatigue Rainflow counting algorithm

To mitigate the previous mentioned problems, a newly introduced online counting cycle will be discussed in this section. In addition to considering the creep degradation and the time-temperature-dependent mean temperature, the proposed method is capable of counting half cycles at the exact times they occur. Input data including stress (e.g. temperature) and their corresponding times should have been inserted to the proposed algorithm as a real time vectors. There are two flexible buffers which are being in charge of temporarily memorizing of maxima and minima respectively. In addition, there are also three pointers for specifying the maxima and minima precession/inferiority, size of two flexible buffers.

Fig. 7 depicts schematic block diagram of proposed algorithm. The key algorithm is based on the four-point Rainflow method but applying some new features to address the above-mentioned challenges. T is the input temperature vector which is updated online by inserting new data to the algorithm. t is the corresponding time vector which is also simultaneously updated. These two vectors are considered as the input data at the top of the algorithm in Fig. 7. $S_{\text{min}}$ and $S_{\text{max}}$ are defined as a flexible buffer allocated for minima and maxima respectively. $P_{\text{min}}$ and $P_{\text{max}}$ are the pointers indicating the length of $S_{\text{min}}$ and $S_{\text{max}}$ respectively. These two pointers make the algorithm be simply implemented. j is also an indicator which shows whether or not local maximum or minimum is coming. If $j = 1$, local minimum will be coming and if $j = 0$, maximum will be coming as a next input data. H is creep hysteresis band.

Once, input data inserted the algorithm will be started. The first step is to check that enough inputs have been coming or not. In this case, because the algorithm is based on the four-point method, at least four inputs are needed. However, for the local extremum checking, there is another need to have the fifth inputs to judge whether or not the fourth point is the extremum. Accordingly, the size of T as an input data has to be 5 at any time to make it possible to run the algorithm. The auxiliary variable k is in charge of validating the number of enough inputs for the creep and extremum checks.

After that creep check will be done. In this step, the algorithm checks whether or not two consecutive inputs are roughly equal to each other. For this purpose, a creep hysteresis band (H) is defined. It means that if the difference of two consecutive inputs lay between the creep hysteresis band, absolute lower of them will be removed from the input data, then it is also left-shifted and the algorithm waits for the new input. At the same time, the mean temperature of these two points ($T_m = \frac{(T^* - T^**)}{2}$) is considered as a creep temperature which is needed in the creep degradation mode (see Fig. 5). Moreover, the time period between these two points is also reported which is needed in the creep degradation mode ($t_c = t'' - t^*$). The procedure of creep check has been indicated in Fig. 7 as a red dashed-line border on the right corner of the figure.

Then the local extremum extraction is obtained. The extremum extractions are based on discrete derivative. Thus, the direction of two consecutive slopes is taken into account as a local extremum determination. For checking the fourth point, it is necessary to know the fifth point (checking the slope direction). That is why, the enough number of inputs is considered to be five. If two consecutive points do not form a local extremum, absolute lower temperature is removed from the input vector, then it is also left-shifted and the algorithm goes at the beginning and waits until new input data is coming. Otherwise, after checking all points, algorithm exits from creep and extremum check and continue at $\Phi$ (top right corner of Fig. 7).

After creep and extremum checks and for the first data which is coming out from $\Phi$, it is necessary to define two flexible buffers, namely $S_{\text{min}}$ and $S_{\text{max}}$, and determine the kind of the first extremum for activating pointer j. If the first local extremum is minimum, j will be 1. Otherwise it becomes 0. In this step the first two extrema are inserted to their corresponding flexible buffers and the pointers, namely $P_{\text{min}}$ and $P_{\text{max}}$ become both 1 (“First data” conditional block diagram in Fig. 7, yellow highlighted area).

Next, four-point Rainflow algorithm has been applied to the first four input data. If the absolute inner stress swing ($\Delta T_2 = |T_2 - T_1|$) is simultaneously lower than the two outer stress swings ($\Delta T_1 = |T_1 - T_2|$ and $\Delta T_3 = |T_3 - T_2|$), full cycle occurs. Thus, one can consider $T_2$ and $T_3$ as a full cycle with the stress cycle of $\Delta T_4 = |T_4 - T_3|$ and the mean temperature of $T_{\text{mean}}$ which is calculated by (5). In this case, depending on the kind of extremum $T_3$ is replaced by the first element in flexible buffers. If the number of elements in flexible buffers is greater than one, then $S_{\text{min}}$ or $S_{\text{max}}$ have to be sorted up. Then, $T_2$ and $T_1$ will be removed from the input data vector and T is also left-shifted. The procedure of full cycle counting is indicated by the red highlighted area on the left of Fig. 7. And algorithm will wait for two new inputs. Of course, these two inputs must pass through the creep and extremum checks.

However if full cycle is not formed, algorithm tries to find the half cycles (the two rightmost flowchart in Fig. 7, green highlighted area). On one hand, when the first extremum is a local minimum, the procedure will be as follows. $S_{\text{min}}$ is right-shifted and $T_2$ will be laid on $S_{\text{min}}$ [1] (new input). The elements number of $S_{\text{min}}$ increases by one and accordingly, $P_{\text{min}} = P_{\text{min}} + 1$. After that the first two elements of minimum buffer compare with each other and if the value of new input is lower than the older one, algorithm reports $S_{\text{min}}$ [2] (old minimum) and $S_{\text{max}}$ [1] as a half cycles. Then, it crosses out the old minimum ($S_{\text{min}}$ [2]) from minimum buffer and left-shifts it. Now, because of this removing we have $P_{\text{min}} = P_{\text{min}} - 1$. This half cycle determination procedure is continuing while only one member exists in $S_{\text{min}}$. Then $T_1$ will be removed from T and it is left-shifted. Then, j has to be interchanged because the next extremum is certainly maximum (thanks to extremum check). Algorithm now is waiting new input data.

On the other hand, when the first extremum is a local maximum, the procedure will be as follows. $S_{\text{max}}$ is right-shifted and $T_3$ will be laid on $S_{\text{max}}$ [1] (new input). The elements number of $S_{\text{max}}$ increases by one and accordingly, $P_{\text{max}} = P_{\text{max}} + 1$. After that the first two elements of maximum buffer are compared with each other and if the value of new input is greater than the older one, algorithm reports $S_{\text{max}}$ [2] (old maximum) and $S_{\text{min}}$ [1] as a half cycles. Then, it crosses out the old maximum ($S_{\text{max}}$ [2]) from maximum buffer and left-shifts it. Now, because of this removing we have $P_{\text{max}} = P_{\text{max}} - 1$. This half cycle determination procedure is continuing while only one member exists in $S_{\text{max}}$. Then $T_1$ will be removed from T and it is left-shifted. Then, j has to be interchanged because the next extremum is certainly minimum (thanks to extremum check). Algorithm now is waiting new input data. In both cases, it is clear that buffers have been dynamically changed based on the input data.
3.3. Case study

In this section, as an application example, the new approach has been applied to a sample load history. Fig. 8a shows a thermal cycle with 17 points. For the simplicity, the time between two adjacent points is assumed to be the same and equal to 1 sec. As it was mentioned, the enough input data is five consecutive points. The first sections of algorithm have been allocated to the creep and extremum checks. Creep
hysteresis band is assumed to be 3 °C. In the first five points, only there is one non-extremum point shown by red highlighted circle (120 °C). This point is removed from the thermal cycles as it also can be seen from Fig. 8b. Fig. 8b shows the thermal cycles after the creep and the extremum cancellation. 75 °C and 130 °C are saved in the minimum and the maximum buffers, respectively. Inner thermal swing ($\Delta T_2 = |T_2 - T_3| = 64 °C$) is not lower than the two outer thermal swings ($\Delta T_1 = |T_1 - T_2| = 55 °C$ and $\Delta T_3 = |T_3 - T_4| = 46 °C$), accordingly, full cycle does not occur. Since the first point is the minimum ($j = 1$), $S_{\text{min}}$ is right-shifted and $T_3$ lays as the first element in $S_{\text{min}}$. New temperature (66 °C) in the minimum buffer is lower than the old one and consequently old minimum temperature (75 °C) and the maximum temperature in maximum flexible buffer (130 °C) constitutes a half cycle by temperature swing of 55 °C and mean temperature of 102.5 °C. Therefore the old minimum temperature has been removed from $S_{\text{min}}$ and it has been left-shifted. Finally, $T_1$ has also been removed from $T$ and $T$ has been also left-shifted and $j \rightarrow 0$. Now, algorithm is waiting for the new temperature point. By inserting new point, $T = [130 66 112 43 45] °C$. So, the creep and the extremum checks should have been performed. Regarding the creep hysteresis band, namely 3 °C, a creep status occurs in $T_4$ and $T_5$. Based on the proposed algorithm, the lower one will be crossed out and algorithm has been going to wait for the new input data. Here $T_4$ has been removed from $T$. This creep status is indicated by green highlighted area in Fig. 8a. $j$ has been also unchanged. Algorithm, again, has been waiting for the new input data. By inserting new data, $T = [130 66 112 43 135] °C$. Inner thermal swing ($\Delta T_2 = |T_2 - T_3| = 46 °C$) is lower than the two outer thermal swings ($\Delta T_1 = |T_1 - T_2| = 64 °C$ and $\Delta T_3 = |T_3 - T_4| = 69 °C$), full cycle does occur. The algorithm reports $T_2$ and $T_3$ as a full cycle with the temperature swing of 46 °C and mean temperature of 84.4 °C.

In the full cycle calculation, the equivalent mean temperature (84.4 °C) is different from convention mean temperature (89 °C). While as it is seen from Fig. 4b, strain-stress curve is thoroughly mean temperature dependent. That is why in this proposed method time-temperature-dependent mean temperature (equivalent mean temperature) has been considered. One can follow the algorithm from Fig. 7 and obtain the associated results as listed in Table 1. Regarding the input data history (Fig. 8a), there are two creep occurrences and two non-extremum points shown as green highlighted and red highlighted regions, respectively.

4. Result and discussion

As it was mentioned in Section 2, the creep mechanism and the mean temperature both play significant roles in ULE. Accordingly, the newly proposed online time-temperature-dependent creep-fatigue Rainflow counting algorithm has been implemented to consider these two phenomena. For having a tangible comparison between the newly proposed and the conventional cycle counting, a numerical example will be considered. Power semiconductor devices have faced to a lot of thermal cycles which make them vulnerable part in the system [17]. In this case, two dominant failure mechanisms, namely fatigue and creep occurring in the die attach solder, play major roles in device degradation.

As the fatigue failure mechanism point of view, one can assume Arrhenius-Coffin-Manson as a lifetime model [35]. In addition, a degradation model can be assessed assuming linear degradation accumulation (Miner’s rule) [35–37]. The lifetime estimation methodology are described in detail in [37]. Arrhenius-Coffin-Manson’s lifetime
model expresses the number of cycles before the failure in terms of the mean temperature and the amplitude of junction temperature as

\[ N(T_m, \Delta T) = A \times \Delta T^\alpha \times \exp \left( \frac{Q}{R T_m} \right) \]  

(8)

where \( A \), \( \alpha \) are both constant and device-dependent, \( R \) and \( Q \) are the gas constant \((8.314 \text{ J mol}^{-1} \text{K}^{-1})\) and internal energy \((7.8 \times 10^2 \text{ J mol}^{-1})\) and \( T_m \) is the mean junction temperature of devices in Kelvin. \( \Delta T \) expresses the junction temperature swing of devices. Based on some experiments’ data and using least square curve fitting to that of (8), one can find that \( \alpha = -2.505 \) and \( A = 813 \times 10^6 \).

Linear damage accumulation, Miner’s rule has been used for evaluating the useful time of IGBT and diode [35],

\[ D_f = \sum N(T_m, \Delta T) / N(T_m, \Delta T) \]  

(9)

On the other hand, as a creep failure mechanism point of view, one can employ Monkman-Grant lifetime model which had been discussed in Section 2. ULE will be implemented based on Fig. 4. Although there are many fatigue-creep damage coupling models such as strain range partitioning, strain energy partitioning, frequency-modified strain-life equation, unified damage and mechanism-based model [38-40], here for its simplicity, the global linear damage model [41] will be assumed and express as follows

\[ D = D_f + D_c \]  

(10)

where \( D_f \) and \( D_c \) are defined by (9) and (3) respectively. From real applications point of view, there are many uncertainties either in the constant parameters of Coffin-Manson-Arrhenius and Monkman-Grant or other aspects such as mission profile. In this case, a normal distribution with the mean value of the constants parameters and deviation of 5% have been considered for these parameters. Then Monte Carlo simulation is generally used to find accumulated damages in the creep and fatigue failure mechanisms \((D_c \text{ and } D_f \text{ respectively})\). This generally leads to the Weibull distribution for these damages [42]. The semiconductor devices are assumed to be failed whenever \( D \) reaches to one with the any interested confidence level.

Based on the worldwide harmonized light vehicles test procedure (WLTP-class3), the junction temperature of power semiconductor devices is translated and depicted in Fig. 9. Based on the creep and fatigue failure mechanisms, temperature swings (cycles) are paramount of importance in the lifetime estimation. Therefore, it is assumed that the considered power devices are exposed to this temperature history. Then, newly proposed and conventional cycle counting will be applied to this junction temperature cycles and the output sorted data will be applied to the lifetime model of power devices as previously mentioned by Coffin-Manson-Arrhenius and Monkman-Grant. It is assumed that the failure occurs whenever accumulated damage, namely Eq. (10), is reached to one with 85% confidence level. The results are listed in Table 2. From this table, it is evident that considering both creep failure mechanism and time-temperature-dependent mean temperature has significant effect in ULE. Comparing conventional method to newly proposed algorithm, one can find that there is 1895 h difference in life estimation which has a significant influence in reliability assessment of devices and systems.

5. Conclusion

In this paper a novel cycle counting method was proposed. This method represents innovative alternative to the conventional Rainflow algorithm. Our method is a clear improvement on the current Rainflow cycle counting by considering online half cycle counting, time-temperature-dependent mean temperature, creep failure. Online half cycle counting created the opportunity of online counting cycle. Since strain-stress behavior of materials, especially in metals, is thoroughly temperature dependent, the equivalent mean temperature is considered making useful lifetime estimation to be much more accurate. In addition, creep failure mechanism, a very common failure mechanism in high temperature, has been also considered. The importance of this new online time-temperature-dependent creep-fatigue Rainflow counting algorithm became thoroughly evident by applying this to the translated WLTP-class3 temperature cycles in power semiconductor devices using Arrhenius-Coffin-Manson fatigue lifetime model as well as Monkman-Grant creep lifetime model. Our research is beneficial in accurate solving of fatigue and creep lifetime estimation at the same time.

Table 2
Useful lifetime of devices (hours).

<table>
<thead>
<tr>
<th>Case</th>
<th>Hours to failure</th>
</tr>
</thead>
<tbody>
<tr>
<td>Conventional</td>
<td>18,197</td>
</tr>
<tr>
<td>NP only considering equivalent mean temperature</td>
<td>17,953</td>
</tr>
<tr>
<td>NP only considering creep</td>
<td>16,623</td>
</tr>
<tr>
<td>Complete NP</td>
<td>16,302</td>
</tr>
</tbody>
</table>

NP: Newly Proposed.

References


