Machine learning aided modelling of thermomechanical fatigue of solder joints in electronic component assemblies

Citation for published version (APA):

Document license:
TAVERNE

DOI:
10.1016/j.ijfatigue.2022.107298

Document status and date:
Published: 01/02/2023

Document Version:
Publisher’s PDF, also known as Version of Record (includes final page, issue and volume numbers)

Please check the document version of this publication:

• A submitted manuscript is the version of the article upon submission and before peer-review. There can be important differences between the submitted version and the official published version of record. People interested in the research are advised to contact the author for the final version of the publication, or visit the DOI to the publisher’s website.
• The final author version and the galley proof are versions of the publication after peer review.
• The final published version features the final layout of the paper including the volume, issue and page numbers.

Link to publication

General rights
Copyright and moral rights for the publications made accessible in the public portal are retained by the authors and/or other copyright owners and it is a condition of accessing publications that users recognise and abide by the legal requirements associated with these rights.

• Users may download and print one copy of any publication from the public portal for the purpose of private study or research.
• You may not further distribute the material or use it for any profit-making activity or commercial gain
• You may freely distribute the URL identifying the publication in the public portal.

If the publication is distributed under the terms of Article 25fa of the Dutch Copyright Act, indicated by the “Taverne” license above, please follow below link for the End User Agreement:
www.tue.nl/taverne

Take down policy
If you believe that this document breaches copyright please contact us at:
openaccess@tue.nl
providing details and we will investigate your claim.

Download date: 03. Aug. 2024
Machine learning aided modelling of thermomechanical fatigue of solder joints in electronic component assemblies

Vincent Voet a,b,*, Frederik Van Loock a, Christophe De Fruytier b, Aude Simar a, Thomas Pardoen a

a Institute of Mechanics, Materials and Civil Engineering, UCLouvain, 1348 Louvain-la-Neuve, Belgium
b Thales Alenia Space Belgium, 6032 Mont-sur-Marchienne, Belgium

A R T I C L E   I N F O

Keywords:
Solder joints
Cohesive zone modelling
Machine learning
Thermomechanical fatigue

A B S T R A C T

Printed board assemblies, i.e. components soldered on printed circuit boards (PCBs), are exposed to thermal cycles responsible for fatigue cracking of solder joints as a result of thermal expansion mismatch between the constituting elements. Advanced finite element simulations are performed using a traction–separation law to represent the cracking process and a temperature-dependent elasto-viscoplastic model for the joint response. Predictions are successfully assessed towards machine learning processed experimental data. In particular, the high sensitivity of thermal ageing reliability to geometric dimensions and solder joint thickness is properly captured. Additional parameters, related to the PCB substrate, are also studied, opening new avenues towards design optimization.

1. Introduction

Electronic assemblies for space applications have to meet very high standards in terms of quality and reliability. These assemblies comprise multiple electronic components soldered on printed circuit boards (PCBs). During operation, they are exposed to thermal cycling due to e.g. the satellite’s orbit and/or interrupted operating modes. Mismatches in the coefficients of thermal expansion of the assembly’s materials, i.e. those of the electronic components, tin–lead solder joints1 and PCBs, lead to cyclic deformation and fatigue damage accumulation within the solder layer [1–4]. The toughness and fatigue crack growth resistance of the soldered joint, and, therefore, the reliability of the assembly, is dominated by the elasto-viscoplastic deformation response and the damage resistance of the tin–lead solder material [5,6]. The level of reliability is also affected by the manufacturing conditions. Several soldering processes can be used such as reflow and iron soldering, leading to different thermomechanical histories, void distributions and solder joint thicknesses. The variability associated with the mounting process is significantly large, even more with manual soldering.

The reliability of solder joints has been studied for more than half a century in a wide range of industrial fields [7–9]. Several experimental methods have been developed to characterize the behaviour of electronic assemblies under cyclic thermal loadings. These include (i) micro-sectioning, where electronic assemblies are trimmed, moulded in epoxy resin and, finally, polished to be observed with a microscope and (ii) electrical monitoring, where continuous resistance measurements are conducted. Failure is detected by an increase in the recorded resistance due to the presence of a crack. Both methods are approved by the European Space Agency (via the ECSS standards), and are commonly used in the space industry.

Modelling approaches have also been developed to determine the reliability of electronic assemblies when subjected to thermal cycles and to justify accelerated cyclic tests by converting temperature profiles from test to operating (actual) conditions. Analytical models, such as the laws of Norris-Landzberg [10] and Engelmaier [11], have been developed to predict the reliability of a solder joint (in terms of thermal cycles to failure) for a given cyclic temperature profile, characterized by the mean temperature, temperature range, and cycle frequency. Analytical approaches are commonly used in industry, but suffer from a limited window of validity: they make use of empirical parameters with limited validity in terms of temperature range and frequency. In addition, multiple damage mechanisms may co-exist in the solder joint and govern solder failure, which proves to be challenging to capture via analytical laws [12]. Numerical models using finite element analysis with various damage criteria, based on the inelastic or total strain or inelastic work, have been proposed in the literature [3,13]. The formulation and identification of these models require an improved understanding of the thermomechanical and fatigue behaviour of the assembly. These more advanced methods are expected to overcome some of the limitations encountered by analytical approaches such as

---

1 Lead-based alloys are still used in the space industry due to the requirement of material joining methods with proven assembly reliability.

https://doi.org/10.1016/j.ijfatigue.2022.107298

Received 10 June 2022; Received in revised form 22 September 2022; Accepted 22 September 2022

Available online 27 September 2022
an extended working range. Damage mechanics approaches have been developed to get rid of the geometry dependence of fatigue laws [12]. These include cohesive zones models, which allow explicit simulations of crack propagation [14], and continuum damage methods [15,16], where damage-dependent parameters are used to dictate the constitutive behaviour of the joint material. These models offer an in-depth understanding of solder joint damage but are not taking advantage of a machine learning approach to process experimental data that allows improving the reliability of parametric studies.

Advanced numerical models rely on many material parameters and many underlying assumptions regarding the description of the failure process; hence, they have to be validated for a wide range of electronic assembly configurations. However, testing all conditions is cumbersome and very challenging from a practical point of view. This motivates the use of a machine learning algorithm to process available experimental data and isolate individual parameters of interest and hence, provide extended model parameter identification and validation capabilities. It allows a better and more reliable determination of how characteristic parameters influence joint failure.

The objective of the present study is to develop and validate an innovative approach based on experimental data collected by the company Thales Alenia Space for decades and processed through a neural network. The available data involves many variations of parameters and can hardly be used without treatment for model comparison assessments. Thermally aged assembly data mainly consists of micro-sections observed by microscopy. Data extracted from these samples are compiled and used to train and test the fully connected neural network model. The latter allows the identification of parameters and the validation of an advanced finite element model. A traction–separation law is used to simulate the fatigue crack advance. Cohesive zone elements are located at the interface between the component and the joint, in the region where cracks are prone to propagate in ceramic surface-mounted resistors. The material behaviour of the solder joint is elastic-viscoplastic with temperature dependence. Compared to most literature studies, crack initiation and propagation is captured for a large number of applied thermal cycles. Various assembly configurations are tested in the scope of the parametric study. The ultimate goal is to identify design guidelines and to estimate assembly reliability based on such an advanced thermomechanical model.

The paper is structured as follows: Section 2 presents the experimental analysis, including the description of the solder joint test method and the machine learning algorithm; Section 3 introduces the finite element model; Section 4 presents the solder joint database. One may notice the rather binary distribution, partially piled and used to train and test the fully connected neural network. The available data involves many variations of parameters and can hardly be used without treatment for model comparison assessments. Thermally aged assembly data mainly consists of micro-sections observed by microscopy. Data extracted from these samples are compiled and used to train and test the fully connected neural network model. The latter allows the identification of parameters and the validation of an advanced finite element model. A traction–separation law is used to simulate the fatigue crack advance. Cohesive zone elements are located at the interface between the component and the joint, in the region where cracks are prone to propagate in ceramic surface-mounted resistors. The material behaviour of the solder joint is elastic-viscoplastic with temperature dependence. Compared to most literature studies, crack initiation and propagation is captured for a large number of applied thermal cycles. Various assembly configurations are tested in the scope of the parametric study. The ultimate goal is to identify design guidelines and to estimate assembly reliability based on such an advanced thermomechanical model.

2. Experimental data processing

The experimental data are based on micro-sections performed on different resistor sizes, mounting processes, joint thickness and termination lengths observed by microscopy. These samples were exposed to 500 thermal cycles as defined in Fig. 1 (−55/+100 °C, 10 °C/min and 15 min dwell time, following the ECSS-Q-ST-70-61C [17] standard). The available data are processed through a machine learning approach in order to compare and validate the numerical results.

2.1. Experimental methods

A typical surface-mounted resistor soldered on a PCB is presented in Fig. 2 and a micro-computed tomography image of this assembly is also included. The resistive layer and both solder joints can be identified on the PCB. The latter is only visible through the copper paths and planes, with the fibre-reinforced polyimide matrix being X-ray transparent. The ceramic substrate (e.g. alumina) does not appear in the micrograph. The cutting plane corresponding to the micro-sectioning is also highlighted. The solder material is a tin-lead alloy 62Sn (62% of tin, 36% of lead and 2% of silver).

Scanning electron microscopy (SEM) is used to characterize cross-sections of thermally aged components. Fig. 3 shows three magnifications of a typical surface-mounted resistor assembly. The crack initiates underneath the component, close to the tip of the nickel barrier (left side of Fig. 3c) and propagates towards the termination corner (on the right side of Fig. 3b), and finally, complete failure is achieved when the solder fillet is cracked. Particular attention is paid to the crack initiation region, i.e. underneath the component. In what follows, the crack length is defined in terms of percentage relative to the length of this initiation region, meaning that a length of more than 100% is required to lead to complete failure, including the solder fillet region. The heterogeneity of the solder material can be observed in Fig. 3c, with lead-rich inclusions embedded within a tin-rich matrix.

A first set of experimental results comprises data of 139 joints (i.e. 80% of the 174 joints included in this study) and is used to train the machine learning model. The 35 remaining solder joints are part of the test set to assess the model predictions. Joints are randomly distributed between both sets. More than twenty trainings have been performed to ensure that there is no significant dependency on subset selection. They contain the following information: joint thickness, component length and thickness, termination length and crack length at 500 cycles. Resistor packages belong to five size classes, 0402, 0603, 0805, 1206 and 2010 with 16, 50, 56, 46 and 6 samples that belong to each class, respectively. The first two figures indicate the component length and the last two the component width, both expressed in hundreds of inches. Both training and test sets cover the entire range of component sizes and close to the entire range of solder joint thicknesses. Fig. 4 shows the distribution of the crack lengths extracted from the solder joint database. One may notice the rather binary distribution, partially cracked samples are scarce.
2.2. Machine learning data processing

The machine learning platform Tensorflow and Keras API [18] are used. The machine learning model is divided into two submodels. The first submodel is a classification which categorizes if a joint is cracked or not and the second is a regression that provides the crack length. Both submodels are fully connected neural networks. The classification uses the rectified linear activation function and two hidden layers (consisting of 5 and 3 neurons) with a binary cross entropy loss function. The classification allows the regression to be more accurate, essentially centred around 0% cracked and 100% cracked joints (see Fig. 4).

A comparison between the classification submodel predictions and the 35 joints of the test data set is presented in Fig. 5 in terms of normalized crack length. Three predictions of the test set were incorrect, leading to an overall accuracy of about 90%. It is extremely difficult to improve the accuracy with the available data. Very similar configurations (resistor size, solder joint thickness) can sometimes lead to apparently conflicting results. Other parameters, not taken into account in the database, influence the sensitivity to cracking. These parameters, including component tilt and alignment and/or the presence of voids (size, distribution), are often difficult to characterize and control.

Predictions and measured true values of the test set can now be compared to evaluate the accuracy of the regression submodel. Fig. 6a shows that three predictions (two at 100% and one at 0%) are incorrect. The latter can be attributed to the incorrect classification of the first submodel, see Fig. 5. Regions around 0 and 100% crack lengths are readily identified. The important conclusion emerging from this analysis is that when failure starts, the crack rapidly propagates throughout the joint underneath the component. In other words, the incubation/initiation stage must be captured accurately by the thermo-mechanical model for accurate failure assessment in the scope of the present study.

Prediction errors are presented in the histogram of Fig. 6b; 85% of predicted crack lengths (30 out of 35 joints) are within plus or minus 25% of true values. Only the three misclassified predictions have errors larger than 60%. This analysis proves an overall good accuracy and sets a fair basis for validating the finite element model (Section 3).
The effect of solder joint thickness on reliability is now investigated for several resistor sizes. The predicted crack lengths extracted from the machine learning model are shown in Fig. 7 as a function of the solder joint thickness normalized by the PCB thickness. Due to the lack of available data for the largest and the smallest component sizes (i.e. 2010 and 0402), predictions must be considered with care; especially for the 2010 resistors with a normalized solder joint thickness ($t_{\text{solder}}/t_{\text{PCB}}$) larger than $10 \cdot 10^{-3}$. The component size has a major impact on reliability with increasing crack lengths for larger components. A significant change of behaviour, between thin and thick joints is clearly observed for the 0805 and 1206 sizes, indicating that thinner joints are much more prone to cracking. This example illustrates the interpolation capabilities offered by the machine learning approach and related opportunities for comparisons with numerical predictions.

3. Finite element model

The finite element (FE) model is described in this section including the geometry and meshing, the material’s constitutive behaviours, the cohesive zone description and the loading conditions. The implicit solver of the Abaqus finite element software [20] is used.

3.1. Geometry of the assembly

The component is a surface-mounted ceramic resistor with nickel terminations mounted on a copper footprint, part of a printed circuit board as shown in Fig. 8. Alumina ($\text{Al}_2\text{O}_3$) is considered as component ceramic body. The PCB material is polyimide Arlon 35N [21]. Two-dimensional plane strain conditions are imposed, justified by the observation that the out-of-plane width is much larger than the thickness of the layers undergoing the failure process. This assumption, although fully valid for to the near crack tip zone where failure occurs, introduces differences with respect to the true problem in terms of the generation of the thermal strain components which is essentially equibiaxial. For instance, the actual out-of-plane width of the component body is much smaller than the PCB width. It brings in a small bias on absolute crack length values.

The FE mesh is presented in Fig. 9. A zoom on the region underneath the component is also provided. The interface between the nickel barrier and the solder joint is highlighted in red and corresponds to the region where the cohesive zone is inserted. A characteristic mesh length of 0.9% of the termination length has been set at this interface. It corresponds to 112 cohesive elements distributed from the initial crack tip to the end of the region underneath the component, i.e. up to the fillet of the joint. The element size of the cohesive zone as well as of the layers above and below is kept constant throughout this study.

The component assembly is subjected to the thermal cycle shown in Fig. 1. The temperature is imposed to be uniform within the model owing to the small size of the ceramic component. Note that the model is sensitive to time (see Eq. (1)) and thus to the heating rate.

3.2. Description of the materials

3.2.1. Material behaviour

All materials are considered thermally isotropic with a coefficient of thermal expansion $a$. Linear elastic isotropic behaviour is assumed for all materials with Young’s modulus $E$ and Poisson ratio $\nu$, via Hooke’s law.

Plastic deformation is allowed in both nickel and copper materials according to experimental data from Jenkins et al. [22] and modelled using $J_2$ flow theory. The temperature-dependent viscoplastic behaviour of the solder alloy is described using Anand’s model [23]. Other models have been studied in the literature, some of them considering grain size effects [24].

$$\dot{\varepsilon} = A \exp \left( \frac{-Q}{RT} \right) \sinh \left( \frac{\sigma \varepsilon^*}{s} \right)^{1/n},$$

where $\dot{\varepsilon}$ is the inelastic strain rate, $A$ is a material constant, $\varepsilon$ is the stress multiplier, $n$ is the strain rate sensitivity, $Q$ is the activation energy, $R$ is the ideal gas constant, $s$ is the deformation resistance which is computed via an evolution law:

$$\dot{s} = h_0 \left[ 1 - \frac{a}{s_0} \right]^{m} \left[ 1 - \frac{a}{s_0} \right] \text{sign}(1 - \frac{a}{s_0}) \dot{s},$$

where $h_0$ is the hardening constant, $a$ is the hardening strain rate sensitivity, $s_0$ is the saturation value of $s$, which writes:

$$s_0 = A \exp \left( \frac{Q}{RT} \right).$$

where $h_0$ is a coefficient of the saturation of the deformation resistance, $n$ is the strain rate sensitivity of the saturation of the deformation resistance.

The initial value of the deformation resistance, $s_{0}$, is also a material parameter.

3.2.2. Material parameters

Tables 1 and 2 list the values of the material parameters extracted from literature [3,6,16,25,26]. The Young’s modulus and reference stress values are normalized by the initial yield stress of the solder joint $\sigma_{0,y}$, equal to 28 MPa (at 20 °C) and at an inelastic strain rate of $5 \cdot 10^{-3}$ s$^{-1}$, calculated from Anand’s model parameters [6]. As suggested by Basaran and Jiang [27], the Young’s modulus of the solder alloy has been measured by nano-indentation on an actual manufactured sample, confirming the value of 42 GPa (at 25 °C) computed from the temperature-dependent equation in Table 1.

3.3. Cohesive zone model (CZM)

3.3.1. Model description

A layer of zero-thickness cohesive elements is inserted at the interface between the solder joint and the horizontal interface of the component, just below the nickel layer, see Fig. 9.

A bi-linear (triangular) traction-separation law represents the near interface behaviour under traction and shear forces, see Fig. 10, with a
Fig. 6. Prediction assessment of the regression submodel with (a) a comparison between experimentally observed true crack lengths and model predictions (misclassified samples are shown in red, see Fig. 5) and (b) the distribution of the predictions errors. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Fig. 7. Impact of the joint thickness normalized by the PCB thickness on the predicted crack lengths for several resistor sizes. The component nomenclature used in the legend is as follows: the first two figures indicate the component length and the last two, the component width, both expressed in hundredths of inches.

Fig. 8. Model geometry with a magnified view of the crack initiation region underneath the component.

Table 1

<table>
<thead>
<tr>
<th>Material</th>
<th>$E$ [GPa]</th>
<th>$E/\sigma_y$</th>
<th>$\nu$ [-]</th>
<th>$\alpha \times 10^{-6}$ C$^{-1}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Alumina ceramic</td>
<td>410</td>
<td>14.640</td>
<td>0.25</td>
<td>5.5</td>
</tr>
<tr>
<td>Nickel</td>
<td>180</td>
<td>6430</td>
<td>0.31</td>
<td>13</td>
</tr>
<tr>
<td>Solder</td>
<td>62−0.067T</td>
<td>2214−2.39T</td>
<td>0.35</td>
<td>27</td>
</tr>
<tr>
<td>Copper</td>
<td>120</td>
<td>4280</td>
<td>0.35</td>
<td>17</td>
</tr>
<tr>
<td>Polyimide PCB</td>
<td>27</td>
<td>964</td>
<td>0.3</td>
<td>15.5</td>
</tr>
</tbody>
</table>

Table 2

<table>
<thead>
<tr>
<th>Material parameter</th>
<th>Value</th>
<th>Dimensionless value [-]</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Lambda$</td>
<td>$4 \times 10^6$ [m$^{-1}$]</td>
<td>–</td>
</tr>
<tr>
<td>$Q/R$</td>
<td>9400 [K]</td>
<td>–</td>
</tr>
<tr>
<td>$\zeta$</td>
<td>1.5 [-]</td>
<td>–</td>
</tr>
<tr>
<td>$m$</td>
<td>0.303 [-]</td>
<td>–</td>
</tr>
<tr>
<td>$h_0$</td>
<td>1379 [MPa]</td>
<td>49.25</td>
</tr>
<tr>
<td>$a$</td>
<td>1.3 [-]</td>
<td>–</td>
</tr>
<tr>
<td>$f$</td>
<td>13.79 [MPa]</td>
<td>0.4925</td>
</tr>
<tr>
<td>$n$</td>
<td>0.07 [-]</td>
<td>–</td>
</tr>
<tr>
<td>$s_0$</td>
<td>12.41 [MPa]</td>
<td>0.4432</td>
</tr>
</tbody>
</table>
peak stress $\sigma$ and a fracture energy $\Gamma_0$. The separation is normalized by the thickness of a selected thick joint of 200 $\mu$m. The unload/reloading behaviour is also displayed in Fig. 10. The initial stiffness of the traction–separation law is chosen sufficiently high to avoid adding non-physical compliance to the system; it is raised to 1000 times the elastic modulus of the solder at 20 °C.

The peak stress value directly controls plastic dissipation throughout the joint. Most simulations are performed with a constant normalized peak stress ($\sigma_0/\rho_0$) of 2 (at 20 °C), see Fig. 10. Numerous convergence issues have been encountered with lower values, e.g. $\sigma_0/\rho_0 = 1$ (at 20 °C). Such a low value leads to the emergence of a second failure process zone at the other end of the joint (see right-hand side of the cohesive zone in Fig. 9). This is usually not observed during experimental tests, justifying the use of a normalized peak stress larger than 1.

4. Model validation and parametric study

A dimensional analysis is first performed to identify the relevant non-dimensional parameters to guide the parametric survey. The numerical model parameters are then identified and validated by comparison with the machine learning processed experimental data. An additional parametric study is finally proposed outside of the available data set.

4.1. Dimensional analysis

The main focus of the parametric study is on the role of geometric dimensions on the predicted failure response. The dimensions of interest were shown in Fig. 8, including the component length $L_{comp}$, thickness $t_{comp}$, termination length $L_{termin}$, solder joint thickness $t_{solder}$, and copper footprint thickness $t_{Cu}$. The PCB thickness ($t_{PCB}$) is selected as a reference length.

The lifetime of the assembly is assessed through a failure criterion $F$, it is expressed as a function of the most relevant parameters (see Fig. 8):

$$ F = f\left(\frac{E_{solder}G_s}{3\pi(1-\nu_s^2)v_s^2t_{solder}G_s}, \frac{t_{solder}}{t_{PCB}}, \frac{t_{Cu}}{t_{PCB}}, \frac{L_{comp}}{t_{PCB}}, \frac{L_{termin}}{t_{PCB}}, \frac{E_{PCB}}{E_{solder}}\right). $$
In this study, after several preliminary investigations, failure is defined based on the crack length after 100 thermal cycles; this will be explained in more detail later in this section. The relative crack length is expressed in percent of the interface length between the component termination and the solder joint; in other words, the crack length \( a \) is normalized by \( L_{\text{term}} \) (see Fig. 8). Fig. 11 illustrates an example of a simulated crack length.

Fig. 12 shows the variation of the relative crack length as a function of the number of cycles for several preliminary simulations, for several component length and thickness configurations. The crack growth rates are not constant during crack propagation. Thick and large configurations exhibit accelerated crack growth before complete failure whereas saturation is observed for the shortest component. The crack growth rate can initially be high to decrease to moderate levels at increased number of cycles, see e.g. \( L_{\text{comp}}/L_{\text{PCB}} = 1.2 \) in Fig. 12a. This behaviour motivates the use of the proposed crack length indicator after 100 cycles instead of a crack growth rate indicator such as \( \frac{da}{dn} \text{|init} \). Full failure can also be attained before 100 cycles. Sometimes, numerical instabilities do not allow simulations to run until complete failure.

A systematic analysis of the complete failure of the joint (100% of the termination length) was not attempted to reduce the computational

---

**Fig. 12.** Determination of an appropriate failure criterion based on a series of preliminary simulations showing the variation of crack length with the number of cycles for several component (a) lengths \( L_{\text{comp}}/L_{\text{PCB}} \) and (b) thicknesses \( t_{\text{comp}}/t_{\text{PCB}} \).

**Fig. 13.** Effect of \( L_{\text{comp}}/L_{\text{PCB}} \) and \( t_{\text{comp}}/t_{\text{PCB}} \) on crack lengths for FE simulations with (a) \( \Gamma_0 = 1 \text{ J/m}^2 \), (b) \( \Gamma_0 = 2 \text{ J/m}^2 \) and (c) \( \Gamma_0 = 4 \text{ J/m}^2 \) (at 20°C) and machine learning processed experimental data. A ’+’ sign indicates a simulation performed under a small strain framework (Appendix).
burden in addition to convergence issues. The number of cycles could have been increased up to 500 as well to allow one-to-one comparisons with experimental data but, again, it would have significantly increased computational costs. A trade-off was thus selected at 100 cycles.

Most simulations are carried out in a finite strain setting. However, in order to overcome possible convergence difficulties already mentioned above, some simulations were conducted within a small strain framework. A comparison between finite strain and small strain simulations is included in Appendix.

4.2. Identification of \( \Gamma_0 \)

The identification of the fracture energy value is performed through the analysis of the effect of both component length \( L_{\text{comp}} \) and thickness \( t_{\text{comp}} \). Fig. 13 shows the variation of the crack lengths after 100 cycles as a function of the component length for different thicknesses and for three values of \( \Gamma_0 \): (a) 1, (b) 2 and (c) 4 J/m\(^2\) (at 20°C). The machine learning processed experimental data (dotted lines) are compared to numerical results (solid lines). Due to convergence issues, it has not been possible to obtain the simulated crack length for \( \Gamma_0 = 2 \) J/m\(^2\) (Fig. 13b) at \( L_{\text{comp}}/t_{\text{PCB}} = 2 \) for the thinnest component and to overcome the missing value, another simulation with a shorter component has been conducted.

First, the FE model adequately captures the experimental trend predicted by the machine learning analysis of Section 2.2. These results show that both the length and the thickness of components have a first-order effect on the crack lengths. Longer and thicker joints are more prone to cracking than short and thin configurations. With \( \Gamma_0 = 1 \) J/m\(^2\), the predicted crack lengths are in line with the machine learning processed experimental data for the two thickest components. However, the trend for the thinnest component diverges from the micro-section observations, significantly overestimating the crack length. For \( \Gamma_0 = 4 \) J/m\(^2\), the behaviour of the thinnest component is well captured but for both normalized thicknesses \( t_{\text{comp}}/t_{\text{PCB}} = 0.2 \) and 0.3, the numerical results underestimate the crack length. The intermediate work of separation value \( \Gamma_0 = 2 \) J/m\(^2\) provides the best predictions and will be selected in what follows unless explicitly mentioned otherwise. Both machine learning and numerical trends are close, from a qualitative point of view but also quantitatively. This is a major result of this work made possible by the use of the machine learning approach to extract the trends needed for model comparison and validation.

4.3. Validation

4.3.1. Effect of solder joint thickness \( t_{\text{solder}} \)

The magnitude of the solder thickness significantly impacts the failure resistance according to observations and experience, see Fig. 7. In general, the thicker the joint, the longer the lifetime. Simulations have been conducted for the three works of separation values \( \Gamma_0 = 1 \), 2 and 4 J/m\(^2\). The comparison between the numerical and machine learning predicted crack lengths is shown in Fig. 14. For \( \Gamma_0 = 2 \) and 4 J/m\(^2\), a minimum crack length is obtained at an intermediate solder joint thickness (around a thickness ratio of \( 40 \)·\(10^{-3}\) for \( \Gamma_0 = 2 \) J/m\(^2\) and between 10 and \( 40 \)·\(10^{-3}\) for \( \Gamma_0 = 4 \) J/m\(^2\)). Experimentally, this is not observed on micro-sections but, generally, the solder joint thickness rarely exceeds \( t_{\text{solder}}/t_{\text{PCB}} = 40 \)·\(10^{-3}\) and no data was available above \( t_{\text{solder}}/t_{\text{PCB}} = 100 \)·\(10^{-3}\) to confirm this trend. Note that these results confirm, similarly to Fig. 13, that \( \Gamma_0 = 2 \) J/m\(^2\) provides the best crack length predictions and reasonably well describes the experimental observations. The model correctly captures the crack resistance up to a normalized thickness of \( 40 \)·\(10^{-3}\) while overestimating the crack growth rate.

4.3.2. Effect of component termination length \( L_{\text{term}} \)

The termination length of the component is also the contact length between the solder joint and the bottom of the component and hence, the length of the cohesive zone. Numerical results presented from this section are simulated with the previously selected work of separation \( \Gamma_0 = 2 \) J/m\(^2\). Fig. 15 indicates that the termination length is also a first-order parameter affecting fatigue failure resistance. Within the simulated length range, the crack length varies from around 100% down to 0%, for short and long terminations, respectively. The impact
4.4. Additional parametric study

The role of two additional parameters on joint failure, i.e. the copper pad thickness and the PCB stiffness, that were not part of the experimental database and hence not part of the machine learning approach, is now explored in this section.

4.4.1. Effect of copper pad thickness $t_{Cu}$

The copper pad thickness $t_{Cu}$ (see Fig. 8) is another parameter that can vary in actual printed circuit boards. Several configurations are simulated for a range of $t_{Cu}/t_{PCB}$ varying between $4 \times 10^{-3}$ and $63 \times 10^{-3}$. This range of normalized copper pad thickness is wider than in practice, where $t_{Cu}/t_{PCB}$ is often close to $30 \times 10^{-3}$. Fig. 16a shows that an increase in the copper pad thickness significantly delays crack propagation.

4.4.2. Effect of PCB elastic modulus $E_{PCB}$

The PCB copper content influences the apparent elastic modulus as copper is much stiffer than glass fibre reinforced polyimide. Fabric and resin volume fractions are also important parameters and can significantly impact the material properties [38]. The elastic modulus is varied from glass fibre reinforced epoxy PCB material without copper, i.e. 17 GPa [39], polyimide also without copper, i.e. 25 GPa [21] (the two lowest values) to pure copper, the highest modulus with 120 GPa [40]. In this very broad range of $E_{PCB}/E_{sold},$ a significant impact on crack resistance is predicted, see Fig. 16b. Increasing the PCB stiffness results in joints being more susceptible to fatigue cracking. This may be explained by the increase of the overall stiffness of the assembly, the joint being more constrained during thermal cycles.

is also more pronounced between the two shortest lengths than for the others. The trend captured by the finite element model qualitatively and quantitatively agrees with the experimental micro-section characterizations.
5. Discussion

5.1. Origin of the parameter effects

To supplement and further discuss the crack propagation behaviour, it is insightful to address a more simple static analysis (without CZM) in order to unravel the fundamental origin of the different effects discussed up to now by looking at the field quantities. In particular, emphasis will be placed on the role of equivalent inelastic strain per cycle (equivalent strain per cycle) at the crack tip (left-hand side of the magnification presented in Fig. 9), which is also the location where the inelastic strains are the largest. Fig. 17 shows this maximum inelastic strain for (a) several component lengths and (b) several solder joint thicknesses. The amount of inelastic strain accumulated is higher when the component length increases, leading to premature damage of the joint. This is in line with the longer cracks predicted by the crack propagation simulations, see Fig. 13b. The accumulated inelastic strain decreases with solder joint thickness (Fig. 17b) until a normalized joint thickness of around 40 $\cdot 10^{-3}$, from which it starts to increase. Again, this behaviour is similar to the crack propagation analysis presented in Fig. 14.

This comparison is now extended to configurations previously simulated in Section 4. Fig. 18 presents both static (with the accumulated inelastic strain per cycle at the crack tip as a failure criterion) and propagation (with crack lengths after 100 thermal cycles) approaches. The trend of Fig. 17 is confirmed. However, a static analysis does not have the level of richness of the crack propagation studies on thermal ageing behaviour. The crack growth behaviour can, indeed, reveal self-stabilizing effects (see $t_{\text{solder}}/t_{\text{PCB}} = 85 \cdot 10^{-3}$ in Fig. 20) or unstable crack growth (see $t_{\text{solder}}/t_{\text{PCB}} = 4 \cdot 10^{-3}$), leading to an accelerated failure. This will be discussed in Section 5.2.

5.2. Relative importance of shear and tensile stress components

The FE model also allows the identification of the distribution between shear and normal stress components. The evolution of the ratio of shear and tensile stress ranges during the hundredth cycle can be investigated for several conditions. Fig. 19 shows the variation of this stress ratio in a static analysis for the simulated range of normalized copper footprint thickness and PCB stiffness. An increase of $t_{\text{Cu}}/t_{\text{PCB}}$ causes an increase in shear stresses relative to tensile stresses. It also highlights, as expected, that shear is the prevailing component responsible for solder joint failure. Increasing PCB stiffness leads to a decrease in the shear to traction ratio up to a point where the normal stress slightly dominates the shear component.

5.3. Limits and perspectives of the selected failure criterion

As already discussed in Section 4.1, the selection of a failure criterion is a trade-off between computational cost, possible convergence issues and representativeness. Fig. 20 presents the variation of the crack length as a function of the number of thermal cycles for four normalized joint thicknesses ranging from 4 to 85 $\cdot 10^{-3}$. For a thin joint, i.e. $t_{\text{solder}}/t_{\text{PCB}} = 4 \cdot 10^{-3}$, the crack growth rate is relatively constant up to 40 to 50 cycles, where it starts to increase. The propagation then accelerates until complete failure. For thicker joints, after a first propagation stage, the crack growth rate decreases significantly (for $t_{\text{solder}}/t_{\text{PCB}} = 15 \cdot 10^{-3}$ and 42 $\cdot 10^{-3}$), up to a plateau (for $t_{\text{solder}}/t_{\text{PCB}} = 85 \cdot 10^{-3}$). This first propagation stage is amplified for thicker joints, see especially $t_{\text{solder}}/t_{\text{PCB}} = 42 \cdot 10^{-3}$ and $t_{\text{solder}}/t_{\text{PCB}} = 85 \cdot 10^{-3}$. After the low crack growth rate stage, it increases again, see $t_{\text{solder}}/t_{\text{PCB}} = 15 \cdot 10^{-3}$. These highly non-uniform and non-linear behaviours highlight the limitation of the selected failure criterion at 100 cycles. Still, the cohesive zone model has been validated and showed its ability to predict crack lengths in accordance with the machine learning processed experimental data. As a perspective, more sophisticated failure criteria related to the crack propagation behaviour, such as the crack growth rate, could therefore provide additional insight to this analysis. Grain size effects on solder material behaviour could also be investigated to better link with material characteristics and probably enhance even more the predictive capabilities of the model.
6. Conclusions

An advanced finite element model predicts the fatigue crack propagation in electronic component solder joints subjected to cyclic thermal loading, accounting for the viscoplastic behaviour of the joint and the failure process for a wide range of assembly configurations. Comparisons between FE simulations and machine learning processed experimental data were conducted and showed the ability of the selected cohesive zone model to adequately capture the experimentally observed trends. The main findings of this study are:

- Machine learning techniques facilitate data analysis of microsection damage observations and provide rationalization of the effect of individual assembly parameters on solder joint failure. This innovative data treatment improves the relevance of the validation of the numerical model and leads to more exploitable results.
- A finite element model is constructed accounting for (i) the temperature-dependent viscoplastic constitutive behaviour of the solder material and (ii) the fatigue crack nucleation and growth via a traction–separation law. The fatigue crack growth predictions are in agreement with the machine learning processed experimental observations.
- Geometric properties such as component length, thickness, termination length, copper pad and solder joint thickness, as well as PCB stiffness, considerably influence the crack growth rate and therefore assembly reliability.
- Predictions based on the accumulated inelastic strain per cycle as a failure criterion (obtained via simplified static finite element calculations without crack nucleation and growth) are in line with those obtained with more sophisticated crack growth simulations but do not provide insight on the role of assembly parameters on crack growth.
  - An increase of the shear stress component driving the growth of the fatigue crack is found when increasing the copper pad thickness and decreasing the PCB stiffness.

The present study provides design guidelines for new or optimized assemblies with respect to thermomechanical reliability. These considerations can also help to predict damage accumulation on existing component assemblies. In summary, based on the explored parameter space in this study, the following configurations lead to an increased resistance to joint failure: (i) a short and thin component, (ii) a sufficiently thick joint, (iii) a long component termination, (iv) a thick PCB copper pad, and (v) a low PCB elastic modulus.

Code availability

The code will be made available to reader upon reasonable request.

Data availability

Data will be made available on request.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.
Appendix. Small strain and finite strain frameworks

Due to convergence issues, several simulations were conducted with a small strain instead of a finite strain setting. Fig. A.21 shows two comparisons between these two frameworks. It only slightly impacts crack lengths and allows more calculations to run, such as illustrated in Fig. A.22.

References

[9] Chaillot A, Grieu M, Munier C, Lombaert-Valot I, Bousquet S, Chastanet C, Scheider for his precious help to obtain converging and reliable numerical simulations and Dr. Marc Bekemans and Dr. Benoît Dompierre for inspiring discussions. Computational resources have been provided by the supercomputing facilities of the Université catholique de Louvain (CISM/UCL) and the Consortium des Équipements de Calcul Intensif en Fédération Wallonie Bruxelles (CECI) funded by the Fond de la Recherche Scientifique de Belgique (F.R.S.-FNRS), Belgium under convention 2.5020.11 and by the Walloon Region.