Latent Damage Assessment and Prognostication of Residual Life in Airborne Lead-free Electronics Under Thermo-Mechanical Loads

Pradeep Lall, Senior Member IEEE, Chandan Bhat, Madhura Hande, Vikrant More, Rahul Vaidya, Ranjit Pandher, Jeff Suhling, Kai Goebel

Abstract— Aerospace-electronic systems usually face a very harsh environment, requiring them to survive the high strain rates, e.g. during launch and re-entry and thermal environments including extreme low and high temperatures. Traditional health monitoring methodologies have relied on reactive methods of failure detection often providing little or no insight into the remaining useful life of the system. In this paper, a mathematical approach for interrogation of system state under cyclic thermo-mechanical stresses has been developed for 6-different leadfree solder alloy systems. Data has been collected for leading indicators of failure for alloy systems including, Sn3Ag0.5Cu, Sn3Ag0.7Cu, Sn1Ag0.5Cu, Sn0.3Ag0.5Cu0.1Bi, Sn0.2Ag0.5Cu0.1Bi0.1Ni, 96.5Sn3.5Ag second-level interconnects under the application of cyclic thermo-mechanical loads. Methodology presented resides in the pre-failure space of the system in which no macro-indicators such as cracks or delamination exist. Systems subjected to thermo-mechanical damage have been interrogated for system state and the computed damage state correlated with known imposed damage. The approach involves the use of condition monitoring devices which can be interrogated for damage proxies at finite time-intervals. Interrogation techniques are based on derivation of damage proxies, and system prior damage based non-linear least-squares methods including the Levenberg-Marquardt Algorithm. The system’s residual life is computed based on residual-life computation algorithms.

Index Terms—Prognostics, health monitoring, solder joint reliability, leading indicators of failure.

I. INTRODUCTION

Aerospace-electronic systems usually face a very harsh environment, requiring them to survive the high strain rates, e.g. during launch and re-entry and thermal environments including extreme low and high temperatures. Traditional health monitoring methodologies have relied on reactive methods of failure detection often providing little or no insight into the remaining useful life of the system. In this paper, a mathematical approach for interrogation of system state under cyclic thermo-mechanical stresses has been developed for 6-different leadfree solder alloy systems. Data has been collected for leading indicators of failure for alloy systems including, Sn3Ag0.5Cu, Sn3Ag0.7Cu, Sn1Ag0.5Cu, Sn0.3Ag0.5Cu0.1Bi, Sn0.2Ag0.5Cu0.1Bi0.1Ni, 96.5Sn3.5Ag second-level interconnects under the application of cyclic thermo-mechanical loads. Methodology presented resides in the pre-failure space of the system in which no macro-indicators such as cracks or delamination exist. Systems subjected to thermo-mechanical damage have been interrogated for system state and the computed damage state correlated with known imposed damage. The approach involves the use of condition monitoring devices which can be interrogated for damage proxies at finite time-intervals. Interrogation techniques are based on derivation of damage proxies, and system prior damage based non-linear least-squares methods including the Levenberg-Marquardt Algorithm. The system’s residual life is computed based on residual-life computation algorithms.

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In electronics assemblies, the built-in-self test (BIST) circuit involving error detection and correction circuits are used to give electronic assemblies the ability to test and diagnose themselves with minimal interaction from external test equipment. Chandramouli 1996, Drees 2004, Hassan 1992, Williams 1983, Zorian 1994. The results obtained from BIST functions can generate diagnostic information which in turn provides additional confidence in the measurement result and confirms the device availability. BIST helps in minimizing the interaction with external automated test equipment (ATE) as well as provides the advantage of a more robust “at-speed” test of the circuitry, however, the current form of BIST gives little insight about the system level reliability or the remaining useful life of the system. Several studies conducted [Allen 2003, Drees 2004, Gao 2002, Rosenthal 1990] have shown that BIST can be prone to false alarms and can result in unnecessary costly replacement, re-qualification, delayed shipping, and loss of system availability. Fuses and Canaries may be mounted on a part to provide advance warning of failure due to specific wear out failure mechanism. Advanced warning is used to provide a maintenance-window for correction action, after an initial failure or malfunction, to prevent additional or secondary failures [Mishra 2002, Anderson 2004]. However, past efforts have provided limited insight into methods for estimation of remaining useful life.

Lall, et al. [2004b, 2005, 2006a, 2007b] have previously developed leading indicators of failure. Proxies like the phase growth rate of solder interconnects have been experimentally identified as leading indicators to failure. In this paper, the PHM approach presented is different from state-of-art diagnostics and resides in the pre-failure-space of the electronic-system, in which no macro-indicators such as cracks or delamination exist. The presented PHM methodologies enable the estimation of prior damage in deployed electronics by interrogation of the system state. This methodology eliminates the need to capture the prior stress history and helps in accurate prediction of remaining useful life. In this paper a mathematical approach has been presented to calculate the prior damage in electronics subjected to cyclic and isothermal thermo-mechanical loads. Mathematical relationships have been developed for computation of residual life. This health monitoring framework will facilitate quick assessment of system state and potential for failure of critical electronic systems.
### Table 1: Test Vehicle

<table>
<thead>
<tr>
<th>Body Size</th>
<th>Solder</th>
<th>Package Type</th>
<th>I/O Ball Pitch (mm)</th>
<th>Die Thick (mm)</th>
<th>Die Size (mm)</th>
<th>BT Thick (mm)</th>
<th>BT Pad Type</th>
<th>Ball Diameter (mm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>10 mm</td>
<td>Sn4Ag0.5Cu, (SAC405)</td>
<td>TABGA</td>
<td>144</td>
<td>0.8</td>
<td>0.36</td>
<td>7.0</td>
<td>0.36</td>
<td>NSMD 0.48</td>
</tr>
<tr>
<td>10 mm</td>
<td>Sn3Ag0.5Cu, (SAC305)</td>
<td>CABGA</td>
<td>100</td>
<td>0.8</td>
<td>0.26</td>
<td>6.4</td>
<td>0.26</td>
<td>NSMD 0.50</td>
</tr>
<tr>
<td>10 mm</td>
<td>Sn1Ag0.5Cu, (SAC105)</td>
<td>CABGA</td>
<td>100</td>
<td>0.8</td>
<td>0.26</td>
<td>6.4</td>
<td>0.26</td>
<td>NSMD 0.50</td>
</tr>
<tr>
<td>10 mm</td>
<td>Sn0.3Ag0.7Cu, (SAC0307)</td>
<td>CABGA</td>
<td>100</td>
<td>0.8</td>
<td>0.26</td>
<td>6.4</td>
<td>0.26</td>
<td>NSMD 0.50</td>
</tr>
<tr>
<td>10 mm</td>
<td>Sn0.3Ag0.7Cu0.1Bi, (SACX)</td>
<td>CABGA</td>
<td>100</td>
<td>0.8</td>
<td>0.26</td>
<td>6.4</td>
<td>0.26</td>
<td>NSMD 0.50</td>
</tr>
<tr>
<td>10 mm</td>
<td>Sn0.2Ag0.7Cu0.1Bi0.1Ni, (SACX+)</td>
<td>CABGA</td>
<td>100</td>
<td>0.8</td>
<td>0.26</td>
<td>6.4</td>
<td>0.26</td>
<td>NSMD 0.50</td>
</tr>
<tr>
<td>10 mm</td>
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<td>100</td>
<td>0.8</td>
<td>0.26</td>
<td>6.4</td>
<td>0.26</td>
<td>NSMD 0.50</td>
</tr>
</tbody>
</table>

In addition, separate set of board assemblies have been subjected to isothermal aging at 125°C. All the assemblies were daisy-chained and continuously monitored for failure detection during cycling.

### III. MICRO-STRUCTURAL EVOLUTION WITH DAMAGE PROGRESSION

Temperature excursions during operation of a circuit are due to both power-cycling and variations in ambient conditions resulting in thermo-mechanical cyclic stresses and strains induced primarily by thermal expansion mismatch between the package and the board assembly. Previous researchers have studied the micro structural evolution of ternary SnAgCu alloys at elevated temperatures using bulk real solder joints with different designs, geometry and process conditions. The SnAgCu microstructure comprises Ag₃Sn and Cu₆Sn₅ dispersed within the tin matrix. The relatively low percentage of alloying elements, 1-4% for Ag and 0.5% for Cu results in phases which comprise a small percentage of the total volume within the solder joint. The microstructural evolution of SnAgCu alloys over time has been found to effect the thermo-mechanical properties and damage behavior [Ye 2000, Allen 2004a,b, Kang 2004, Xiao 2004, Henderson 2004, Kang 2005, Korhonen 2007, Jung 2001].

Micro-structural coarsening during thermo-mechanical deformation is attributed to the generation of excess vacancies caused by the combined effect of local hydrostatic state of stress, and the instantaneous inelastic strain rate [Dutta 2003a, 2003b, 2004; Jung 2001]. Evolution of solder microstructure in 63Sn37Pb and lead-free chip resistor solder joints due to thermal fatigue have been studied previously by previous researchers [Sayama, et al. 1999, 2003] and thermal fatigue correlated with occurrence of microstructural coarsening in the fatigue damaged region in of 63Sn37Pb solder interconnects [Frear 1990, Morris 1991]. Correlation of grain coarsening with thermal fatigue has also been established for high-lead solders [Bangs 1978, Wolkowitz 1987, Tribula 1989]. Previously the authors have investigated the grain-size evolution and derivatives of phase growth rate as prognostics parameters on a wide range of leaded and Sn4Ag0.5Cu devices in underhood applications [Lall 2004b, 2005, 2006a,b, 2007].

In this paper, prognostics health management methodology has been presented to assess the prior damage based on solder grain coarsening model. Phase growth under thermal cycling and thermal aging has been identified as the damage precursor to compute the residual life. The relation between phase growth parameter and time for polycrystalline material is given by [Callister 1985]

\[
g^n - g_0^n = Kt
\]

Where \( g \) is the average grain size at time \( t \), \( g_0 \) is the average grain size of solder after reflow, \( K \) and \( n \) (varies from 2 to 5) are time independent constants. Senkov and Myshlev [1986] applied the theory of phase growth process in a super plastic alloy and validated the theory for Zn/Al eutectic alloy. They expressed the phase growth parameter \( S \) as:

\[
S = g^4 - g_0^4 = Kt
\]

In this study, changes in solder microstructure and its derivatives have been investigated for use as the leading indicators of failure and interrogation of system state for assessment of damage from prior stress histories. Quantitative metrics of changes in microstructure have been identified and relationships developed to represent damage progression. Data presented covers a wide range of solder alloys including various lead-free area-array packaging architectures in extreme temperature cycling and steady-state temperature environments. The phase growth parameter has been defined as the relative change from phase-state after reflow, instead of the absolute value of phase state. Figure 1 shows Ag₃Sn phases in solder microstructure.

![Gray Scale Image](image1)

![Mapped Image](image2)

Figure 1: 96.5Sn3.0Ag0.5Cu Solder Microstructure showing Ag₃Sn, and Cu₆Sn₅ lighter-color phases, and Sn darker-color phases.

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In this section, a methodology for determining prior damage by interrogating the damage proxies of test structures has been presented. Two sets of electronic assemblies have been subjected to thermal cycling (-40°C to 125°C and -55°C to 125°C). The thermal environments are intended to simulate a field application environment. The parts are withdrawn from the application environment for redeployment in a new field environment. The damage proxies have been interrogated to determine the extent of damage inflicted and also remaining useful life of that assembly if it is to be re-deployed. Following sections will explain the prediction of stress history using phase growth and IMC growth in thermal cycling and thermal aging environments respectively.

Levenberg-Marquardt Algorithm:
The relationship between the phase growth parameter and time is nonlinear because it contains terms with fourth power. Inverse solution for interrogation of system-state is challenging for damage evolution in such systems. Levenberg-Marquardt (LM) algorithm is an iterative technique that computes the minimum of a non-linear function in multi-dimensional variable space [Madsen 2004, Lourakis 2005, Nielsen 1999]. It has been used successfully for computation of nonlinear least-square solutions. The Levenberg-Marquardt method with a combination of steepest descent using line-search and the Gauss-Newton method has been used for solution of the problem.

Let \( f \) be a assumed functional relation between a measurement vector referred to as prior-damage and the damage parameter vector, \( p \), referred to as predictor variables. Mathematically, the function, \( f \), which maps a parameter vector to a response-vector “\( x \)” are provided and it is desired to find the parameter vector \( p \), that best satisfies the functional relation \( x=f(p) \), while minimizing the squared distance \( \varepsilon \). The steepest gradient descent method has been used to impose the descending condition, i.e., \( F(p_{k+1})<F(p_k) \). Depending on the starting guess \( p_0 \), a given function may have numerous minimizers, not necessarily the global minima. It therefore becomes necessary to explore the whole bounded space to converge to the global minima. Iteration involves finding a descent direction “\( h \)” and a step length giving a good decrease in the F-value. The variation of an F-value starting at “\( p \)” and with direction “\( h \)” is expressed as a Taylor expansion, as follows:

\[
F(p + \alpha h) = F(p) + \alpha h^T F'(p) + O(\alpha^2)
\]

where \( \alpha \) is the step-length from point “\( p \)” in the descent direction, “\( h \)”.

For a sufficiently small \( \alpha \), \( F(p + \alpha h) \approx F(p) + \alpha h^T F'(p) \). If \( F(p + \alpha h) \) is a decreasing function of \( \alpha \) at \( \alpha = 0 \), then \( h \) is the descent direction. Mathematically, “\( h \)” is the descent direction of \( F(p) \) if \( h^T F'(p) < 0 \). If no such “\( h \)” exists, then \( F'(p)=0 \), showing that in this case the function is stationary. Since the condition for the stationary value of the objective function is that the gradient is zero, i.e. \( F'(p+h) = L'(h) = 0 \). The descent direction can be computed from the equation,

\[
( J^T J) h_{gn} = -J^T g
\]

In each step, Newton method uses \( \alpha = 1 \), and \( p = p + \alpha h_{gn} \), where subscript ‘\( gn \)’ indicates gauss-newton. The value of \( \alpha \) is found by line search principle described above. Levenberg-Marquardt algorithm is a hybrid method which utilizes both steepest descent principle as well as the Gauss-Newton method. When the current solution is far from the correct one, the algorithm behaves like a steepest descent method: slow, but guaranteed to converge. When the current solution is close to the correct solution, it becomes a Gauss-Newton method. The LM method actually solves a slight variation of Equation (11), known as the augmented normal equations.

\[
( J^T J + \mu I) h = -J^T g
\]

The term \( \mu \) is called as the damping parameter, \( \mu > 0 \) ensures that coefficient matrix is positive definite, and this ensures that \( h \) is a descent direction. When the value of \( \mu \) is very small, then the step size for LM and Gauss-Newton are identical. Algorithm has been modified to take the equations of phase growth and inter-metallic growth under both iso-thermal aging and cycling loads to calculate the unknowns.
V. PROGNOSTICATION OF LEADING-INDICATORS

Since the equations governing the phase growth and IMC compound are non-linear in nature, the Levenberg-Marquardt Algorithm has been used to interrogate the system state in terms of damage proxies. The LM algorithm has been modified to incorporate the equations for leading indicators of failure (e.g. phase growth and inter-metallic growth) under cycling loads and iso-thermal aging loads. The methodology is as follows:

**Micro-structural Evolution**

The following phase growth equation has been used for the development of the prior stress history is as follows:

\[ g_4 - g_0^4 = a(N)^b \]  

From the population devices subjected to thermal cycling, four condition monitoring devices have been withdrawn and sectioned for four different thermal cycle durations. The phase size has been measured for all samples. Each of the following equations represents an interval of withdrawal, leading to the following equations.

\[ g_1^4 = g_0^4 + a(N + \Delta N_1)^b \]  
\[ g_2^4 = g_0^4 + a(N + \Delta N_2)^b \]  
\[ g_3^4 = g_0^4 + a(N + \Delta N_3)^b \]  
\[ g_4^4 = g_0^4 + a(N + \Delta N_4)^b \]  

In equations (11) – (14), we can see that there are four unknowns \( g_0, a, N, b \). In order to compute the damage (no. of thermal cycles), it is necessary to solve this set of non-linear equations using a non-linear least squares methodology. In the present case, we have used the Levenberg Marquardt Algorithm (LMA) to obtain the solution. Variable solutions differ widely in their magnitudes. In order to find the global minima of the error, it is necessary to solve the equations for a bounded solution space. Based on the accelerated test experimental data, acceptable range for each variable, for each alloy system was developed. The variable range, for each variable was divided uniformly to form numerous initial guess values to be given as input guesses to the LM algorithm. Table 2 shows the range for each variable for each alloy system.

Table 2: Variable Range for phase growth in thermal cycling for various alloys (based on experimental data)

<table>
<thead>
<tr>
<th>Alloy System</th>
<th>Constant 'a'</th>
<th>Constant 'b'</th>
<th>Initial Grain size 'g0'</th>
</tr>
</thead>
<tbody>
<tr>
<td>SAC105</td>
<td>0.0004 – 0.0013</td>
<td>1.10 – 1.20</td>
<td>0.92 – 1.02</td>
</tr>
<tr>
<td>SAC305</td>
<td>0.0005 – 0.0015</td>
<td>1.12 – 1.22</td>
<td>0.97 – 1.07</td>
</tr>
<tr>
<td>SAC405</td>
<td>0.0001 – 0.001</td>
<td>1.15 – 1.25</td>
<td>0.80 – 0.90</td>
</tr>
<tr>
<td>SAC307</td>
<td>0.00005 - 0.003</td>
<td>1.00 -1.25</td>
<td>0.95 -1.15</td>
</tr>
<tr>
<td>SnAgCuBi</td>
<td>0.0001 - 0.002</td>
<td>1.15 - 1.40</td>
<td>1.40 – 1.60</td>
</tr>
<tr>
<td>SnAgCuBiNi</td>
<td>0.0001 - 0.002</td>
<td>1.50 - 1.70</td>
<td>1.00 – 1.20</td>
</tr>
<tr>
<td>Sn3.5 Ag</td>
<td>0.002 - 0.02</td>
<td>1.00 - 1.20</td>
<td>1.35 – 1.55</td>
</tr>
</tbody>
</table>

The form of equation used in LMA for phase growth is

\[ g = \sqrt[3/4]{g_0^4 + a(N + \Delta N)^b} \]  

Since the method does a linear approximation to the specified function in the neighborhood of the parameter to be found using Taylor series expansion for next approximation, it is necessary to give Jacobian with respect to each unknown.

\[ \frac{\partial g}{\partial g_0} = \frac{g_0^3}{(g_0^4 + a(N + \Delta N)^b)^{3/4}} \]  
\[ \frac{\partial g}{\partial a} = \frac{(N + \Delta N)^b}{4(g_0^4 + a(N + \Delta N)^b)^{3/4}} \]  
\[ \frac{\partial g}{\partial N} = \frac{ab(N + \Delta N)^b}{4(N + \Delta N)(g_0^4 + a(N + \Delta N)^b)^{3/4}} \]  
\[ \frac{\partial g}{\partial b} = \frac{ag(N + \Delta N)(N + N + \Delta N)^b}{4(g_0^4 + a(N + \Delta N)^b)^{3/4}} \]  

The row corresponding to the least minimization error was isolated, and the variables in that row were selected as the
final values for \( g_0, a, N, b \). Schematic illustration of the operation is shown in Figure 2.

**Intermetallic Compound Growth**

The following IC growth equation has been used for the development of the prior stress history is as follows:

\[ y(t) = y_0 + k(t + \Delta t)^{0.5} \]  \( \quad (20) \)

In order to interrogate the system state using IMC as a damage proxy, three condition monitoring devices have been withdrawn at discrete time intervals, leading to the following equations for the evolution of IMC thickness.

\[ y_1(t) = y_0 + k(t + \Delta t_1)^{0.5} \]  \( \quad (21) \)

\[ y_2(t) = y_0 + k(t + \Delta t_2)^{0.5} \]  \( \quad (22) \)

\[ y_3(t) = y_0 + k(t + \Delta t_3)^{0.5} \]  \( \quad (23) \)

The unknowns in this case being \( y_0, k, t \). Similar to the methodology used for microstructural coarsening (explained above), LMA was used to get the solution. In order to explore the whole design space, acceptable range for each variable, for each alloy was developed. Table 3 shows the range for each variable for each alloy system. The Jacobian with respect to each unknown was also provided as follows:

\[ \frac{\partial y}{\partial y_0} = 1 \]  \( \quad (24) \)

\[ \frac{\partial y}{\partial k} = \left( t + \Delta t \right)^{1/2} \]  \( \quad (25) \)

\[ \frac{\partial y}{\partial t} = \frac{1}{2} \frac{k}{\left( t + \Delta t \right)^{1/2}} \]  \( \quad (26) \)

**Figure 3**: SEM Back-scattered Images of Phase Growth versus Thermal cycling (-55°C to 125°C, for various leadfree solders, 100 I/O Chip Array BGA, Magnification 750x)

**Figure 4**: Phase Growth parameter, at various levels of cycles for 100 I/O Chip Array BGA, for various solder alloys.

<table>
<thead>
<tr>
<th>Table 3: Variable Range for IMC growth for various alloys</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Alloy System</strong></td>
</tr>
<tr>
<td>SAC 105</td>
</tr>
<tr>
<td>SAC 305</td>
</tr>
<tr>
<td>SAC 0307</td>
</tr>
<tr>
<td>SACX</td>
</tr>
</tbody>
</table>

Initial guess values for variables \( y_0, k, t \) were varied one at a time, while keeping the other three variable constant and were provided as input to the Levenberg-Marquardt algorithm. The output from the algorithm, \( y_0, k, t \) and minimization error
was computed for each iteration. The row corresponding to the least minimization error was isolated, and the variables in that row were selected as the final values for $y_0$, $k$, $t$.

VI. CHARACTERIZATION OF DAMAGE PROGRESSION

Two identical sets of test-samples have been subjected to thermal cycling. In this section, the first data-set has been discussed. The first data-set has been used to characterize the progression of leading indicators of failure with the initiation and progression of thermo-mechanical damage. Figure 3 shows the microstructural evolution versus thermal cycling measured from SEM back-scattered images of 100 I/O Chip Array BGA Package at different levels of thermal cycle for the various leadfree alloys.

Since Ag atoms have a higher diffusion rate in the molten solder, they can diffuse out of the way and thus allow the Sn dendrites to grow. Particles of Ag$_3$Sn grow either to spheres or to needles shape. The average phase growth parameter $S$ measured under thermal cycling and thermal aging for each individual component has been plotted versus cycles in Figure 4. The phase growth data in this study indicates that phase growth rate stays fairly uniform during the thermal cycle tests. The phase growth also follows a linear pattern under isothermal aging. Since, an electronic system may have variety of material sets and packaging architectures, the linearity of micro-structural evolution depicts the validity of phase growth as a proxy for damage progression. The damage progression can thus be tracked in various devices based on damage proxies.

In addition to the phase growth progression, the progression of IMC growth has also been studied. The aged components have been cross sectioned at various interval of thermal aging. The IMC thickness has been measured in SEM using 1000x magnification using commercial image processing software. An energy dispersive X-ray (EDX) has been used to examine the morphology and the composition of the intermetallic compound layer at the copper/solder interface. Colloidal silica solution has been applied for the detailed intermetallic compound composition observation and detection. Figure 5 shows SEM backscattered images exhibiting examples of IMC growth with aging time for 100 I/O, BGA solder ball for all the seven-alloys. Trend analysis of intermetallic thickness growth on SEM using image processing software, indicates a square root dependence of IMC thickness versus aging time.
\[ y = y_0 + kt^n \]  
(27)

Where \( y(t) \) is IMC growth thickness during aging, \( y_0 \) is the initial thickness of intermetallic compounds, \( k \) is the coefficient standing for the square root of the diffusivity at aging temperature, and \( t \) is test time. The exponent value, \( n = \frac{1}{2} \) has been used in the above equation, which reveals a diffusion-controlled mechanism during aging. The average IMC growth measured at each level of test time has been plotted versus time (Figure 6).

### VII. Model Validation

**Case Study-1: Thermal Cycling:**

In case of thermal cycling, values of \( g_0, a, N, b \) were computed. Figure 7 shows the minimum error is in the neighborhood of 200 cycles for the SAC105 in the 100 I/O CABGA. This correlates well with the actual value of 250 cycles from experimental data. Similar process has been used to interrogate the system state for various solder alloys and the solution in each case are indicated by the minima of the error in the graphs in Figure 7. Table 4 to Table 5 show the comparison between values from experiment and algorithm.

#### Table 4: Comparison of computed values of N, \( g_0 \) from prognostication model versus experimental result.

<table>
<thead>
<tr>
<th>Cycles ‘N’</th>
<th>Grain Size ‘( g_0 )’ (in ( \mu \text{m} ))</th>
<th>Expt</th>
<th>LM</th>
<th>Error (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>SAC 105</td>
<td>250</td>
<td>200</td>
<td>20</td>
<td>0.97</td>
</tr>
<tr>
<td>SAC 305</td>
<td>250</td>
<td>200</td>
<td>20</td>
<td>1.04</td>
</tr>
<tr>
<td>SAC 405</td>
<td>250</td>
<td>225</td>
<td>10</td>
<td>0.84</td>
</tr>
<tr>
<td>SAC 0307</td>
<td>250</td>
<td>225</td>
<td>10</td>
<td>0.90</td>
</tr>
<tr>
<td>SACX</td>
<td>250</td>
<td>177</td>
<td>29.2</td>
<td>1.55</td>
</tr>
<tr>
<td>SACX-Plus</td>
<td>250</td>
<td>175</td>
<td>30</td>
<td>1.11</td>
</tr>
<tr>
<td>96.5Sn3.5Ag</td>
<td>250</td>
<td>175</td>
<td>30</td>
<td>1.43</td>
</tr>
</tbody>
</table>

#### Table 5: Comparison of computed values of \( a \) and \( b \) from Prognostication model versus experimental result.

<table>
<thead>
<tr>
<th>Constant ‘a’</th>
<th>Constant ‘b’</th>
</tr>
</thead>
<tbody>
<tr>
<td>Expt (x 10^-4)</td>
<td>LM (x 10^-4)</td>
</tr>
<tr>
<td>SAC 105</td>
<td>8</td>
</tr>
<tr>
<td>SAC 305</td>
<td>10</td>
</tr>
<tr>
<td>SAC 405</td>
<td>3</td>
</tr>
<tr>
<td>SAC 0307</td>
<td>7</td>
</tr>
<tr>
<td>SACX</td>
<td>15</td>
</tr>
<tr>
<td>SACX-Plus</td>
<td>13</td>
</tr>
<tr>
<td>96.5Sn3.5Ag</td>
<td>8.1</td>
</tr>
</tbody>
</table>

Figure 7: Plot of Error vs. No. of Thermal cycles (N) for 100 I/O CABGA solder interconnects for various alloys.

In addition, the interrogation algorithms have also been used to determine the initial state of the system including the initial gain size and the damage evolution under operational stresses of the system. The damage progression under prior stresses is indicated by the constants “a” and “b” in Table 5. Based on the interrogation of system state at 250 cycles, the microstructural evolution of the solder has been predicted for the various solder alloys.

Figure 8: Prognostication of grain size from algorithm (based on \( g_0, a \) and \( b \)) vs. grain size from experimental values for various solder alloys.
Figure 8 shows the comparison between the predicted versus the experimental values of phase size. The experimental data and model show good correlation. The micro-structural evolution of solder has been previously correlated with the damage progression under the intended use environment. The models can thus interrogate prior damage and predict the damage progression under cyclic thermo-mechanical stresses.

Case-2: Isothermal Aging:
In case of thermal aging, values of $y_0$, $k$, $t$ have been computed. Figure 9 shows that the error is minimum in the neighborhood of 621 hrs for SAC105 in the 100 I/O CABGA. This correlates well with the actual value of 667 hrs from experimental data. Similar process has been used to interrogate the system state for various solder alloys and the solution in each case are indicated by the minima of the error in the graphs in Figure 9. The values of interrogated prior life have been tabulated in Table 6. System damage state from interrogation algorithms show good correlation with the experimentally measurements of prior damage. The correlation holds true for various leadfree alloys.

Based on the interrogation of system state at 667 hours, the micro-structural evolution of the solder-pad intermetallic has been predicted for the various solder alloys. Figure 10 shows the comparison between the predicted versus the experimental values of intermetallic thickness. The experimental data and model show good correlation. The micro-structural evolution of the IMC has been previously correlated with the damage progression under the intended use environment. The models can this interrogate prior damage and predict the damage progression under steady-state thermo-mechanical stresses.

Table 6: Comparison of computed values of $t$, $y_0$ from prognostication model and experimental result

<table>
<thead>
<tr>
<th>Aging Time 't' (hrs)</th>
<th>IMC Size 'y0' (μm)</th>
<th>Expt LM Error (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>SAC 105</td>
<td>667</td>
<td>621</td>
</tr>
<tr>
<td>SAC 305</td>
<td>667</td>
<td>625</td>
</tr>
<tr>
<td>SAC 405</td>
<td>22</td>
<td>28</td>
</tr>
<tr>
<td>SAC0307</td>
<td>667</td>
<td>690</td>
</tr>
<tr>
<td>SACX</td>
<td>667</td>
<td>830</td>
</tr>
<tr>
<td>SACX-Plus</td>
<td>667</td>
<td>829</td>
</tr>
<tr>
<td>96.5Sn3.5Ag</td>
<td>667</td>
<td>915</td>
</tr>
</tbody>
</table>

VIII. IMPLEMENTATION OF PHM TECHNIQUE

The PHM technique presented in the paper may be implemented using condition monitoring devices, which can be cross-sectioned to interrogate the system state and determine the failure progression of the assembly. Consider an electronic assembly which has been deployed in the field application. The assembly needs to be redeployed in the same environment.

The condition monitoring devices in the system will then, be withdrawn at periodic intervals in the deployed environment. The condition monitoring devices will be cross-sectioned and their grain size data will be extracted. This data
will be analyzed using Levenberg’s-Marquardt Algorithm and methodologies discussed earlier, to find out the initial grain size ($g_0$) and the prior time of deployment (N, or t) for which the component has been deployed. The rate of change of phase growth parameter, ($dS/dN$), will be computed using the computed values of damage proxies or leading indicators-of-failure. The rate of change of phase growth parameter ($dS/dN$) can be correlated to time-to-1%-failure [Lall 2004, 2005, 2006]. Residual Life (RL) can be calculated using the equation, $RL = N_{f}^{\varepsilon} - N$.

IX. SUMMARY AND CONCLUSIONS

A methodology has been presented to calculate the prior damage in electronics subjected to cyclic and isothermal thermo-mechanical loads. The time duration for which the component has been deployed and initial grain size is been estimated using Levenberg-Marquardt Algorithm with Trust Regions. Methodology has been demonstrated using various leading-indicators of failure including, phase growth and intermetallic thickness. The presented approach uses non-linear least-squares based method of estimating prior stress history, and residual life, by interrogating system-state prior to redeployment. The prior stress histories have been calculated for both cyclic thermo-mechanical loads and isothermal loads. Computed results have been correlated with the experimental data for various aging times and thermal cycles for several packaging architectures. Model predictions of interrogated prior system damage correlate well with experimental data. The correlations indicate that the leading indicators based PHM technique can be used to interrogate the system state and thus estimate the Residual-Life of a component. The presented approach of computing residual life can be implemented prior to appearance of any macro-indicators of damage like crack. Methodology presented using condition monitoring components to find out the residual life is promising because these components experience the same environment as actual component.

**NOMENCLATURE**

- $a$: Cyclic Phase Growth Coefficient
- $b$: Cyclic Phase-Growth Exponent
- $f$: Function Relationship
- $g$: Grain Size, $\mu m$
- $g_0$: Initial Grain Size, $\mu m$
- $g(p)$: $\varepsilon^T \varepsilon$, the squared error
- $h$: Descent Direction
- $h_m$: Descent Direction for Gauss-Newton Method
- $HM$: Health Management
- $IMC$: Intermetallic Compound
- $J$: Jacobian, $\partial f(p)/\partial p$
- $k$: Intermetallic Growth Coefficient
- $N$: Number of Thermal Cycles, (dimensionless)
- $p$: Predictor Variable
- PHM: Prognostic Health Management
- $RL$: Remaining Useful-Life
- $S$: Phase Size, $\mu m^4 - \mu m_0^4$
- $t$: Time (hours)
- $y$: Intermetallic Thickness ($\mu m$)
- $y_0$: Initial Intermetallic Thickness ($\mu m$)

**Greek symbols**

- $\alpha$: multiplier for descent direction
- $\Delta N$: Prognostication Neighborhood in cycles (cycles)
- $\Delta t$: Prognostication Neighborhood in time (hours)
- $\mu$: damping parameter
- $\delta p$: perturbation of predictor variable
- $\varepsilon$: Error, $x - Jf(p)$

**REFERENCES**


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