

OPTIMIZATION OF SOLDER JOINT FATIGUE LIFE USING PRODUCT MODEL-BASED ANALYSIS MODELS

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ABSTRACT

Product Model-Based Analysis Models (PBAMs) have been presented as highly automated analysis modules for designer usage. Previous examples such as solder joint fatigue PBAMs have shown how explicit design-analysis associativity linkages enable seamless interfaces to solution tools (e.g., finite element analysis systems). These examples focused on using PBAMs for design verification, where a criteria such as fatigue life was checked given one design state as an input.

This paper presents a technique which utilizes PBAMs for design optimization. An example is given which maximizes solder joint fatigue life by iteratively changing PBAM inputs (the design variables) based on PBAM outputs (the analysis results). Benefits of the technique include the modular and flexible addition of an optimization agent to existing analysis modules.

L length
 h height
 E Young's modulus
 ν Poisson's ratio
 α coefficient of thermal expansion (CTE)
 σ_Y yield stress

Subscripts

pwa printed wiring assembly (PWA)
 pwb (bare) printed wiring board (PWB)
 c, s, sj component, substrate/PWB, solder joint
 (e.g., E_c, E_s, E_{sj})

NOMENCLATURE

\bar{N}_f average cycles to failure
 $\Delta \epsilon^p$ plastic cyclic strain range
 c fatigue ductility exponent
 \mathcal{E}_f fatigue ductility coefficient
 \bar{T} mean cyclic temperature, (°C)
 f load frequency, (cycles/day, $1 \leq f \leq 1000$)
 \bar{T}_{sj} mean cyclic solder joint temperature (°C)
 $\Delta \gamma_{sj}$ solder joint shear strain range
 F adjustment factor
 $\Delta(\alpha \Delta T)$ steady state thermal expansion mismatch
 T_o reference temperature
 T_c component temperature
 T_s substrate/PWB temperature

1. INTRODUCTION

Electronic Packaging Design and Analysis are very broad and complex areas. As products become more complex, tools that automatically search for optimum designs among a myriad of alternatives become increasingly necessary.

1.1 Design-Analysis Integration Background

This paper addresses this need by building on the multi-representation architecture (MRA) design-analysis integration strategy [Peak, et al., 1995]. In the MRA, product model-based analysis model (PBAMs) are analysis modules that enable highly automated analysis by linking detailed design models with analysis models of varying complexity, application, and solution technique.

Peak, et al. [1996] describe a methodology for creating such analysis modules and highlight applications to PWB warpage and plated through hole deformation. Tamburini, et al. [1996] present a STEP-based technique for creating product models used in the MRA for analysis.

1.2 Application to Design Optimization

The above work has concentrated on PBAM-based design verification where the user inputs one design state at a time to check criteria like solder joint fatigue. If the result is not acceptable, the user can adjust one or more inputs and ask the PBAM for a new result, and so on - a kind of “ manual optimization technique” (which is still advantageous in that the PBAM automates the bulk of the work).

However, it would be typically be more ideal if the user did not have to judge the results each time and adjust inputs but could still take advantage of PBAM automation. Thus, this paper introduces a technique for PBAM-based optimization. The next sections describe this technique and illustrate it using a solder joint fatigue test case.

2. PBAM-BASED OPTIMIZATION TECHNIQUE

This section describes a modular optimization agent which supports flexibility and automation by using PBAMs to achieve better designs. It is possible to achieve improved designs by using modular optimization agents that support flexible automation tools.

A Modular Optimization agent gets the analysis results and model parameters necessary to build an optimization model from a PBAM, and then processes them in the optimization model to further improve the objective function.

It is possible to create different optimization models based on input (design variables) to an optimization tool or altering design criteria and constraints imposed on the model which is being optimized. Thus, a designer can answer what-if questions and more easily explore a larger set of alternatives. Towards this purpose, the strategy taken is to establish a series of optimization models based on different design variables related to the analysis model and optimization tools. Furthermore, a set of optimization models based on modified objectives and constraints imposed on the analysis model can be constructed to enable flexibility.

The integration of PBAMs and optimization agents in this technique is described next.

2.1 PBAMs:

PBAMs represent engineering analysis models and include linkages to product model design information.[Peak and Fulton 1993]. They have been presented as highly automated analysis modules for designer usage. Via solder joint fatigue PBAMs, it has been shown how their explicit design-analysis associativity linkages enable seamless interfaces to solution tools (e.g., finite element analysis systems) [Peak et al. 1995]. PBAMs perform routine analysis by linking detailed design models with analysis models of varying complexity and application. Figure 1 highlights how a catalog of PBAMs can be used for design verification. The user selects a PBAM from the catalog. Then, required product and analysis entities are

connected to the selected PBAM. The creation, execution and interaction of submodels within the analysis are done automatically and results are presented.

In the new technique, the optimization agent becomes the “user” in the preceding scenario and employs the PBAM for design optimization. The optimization agent automatically determines PBAM inputs and judges PBAM results as described below.

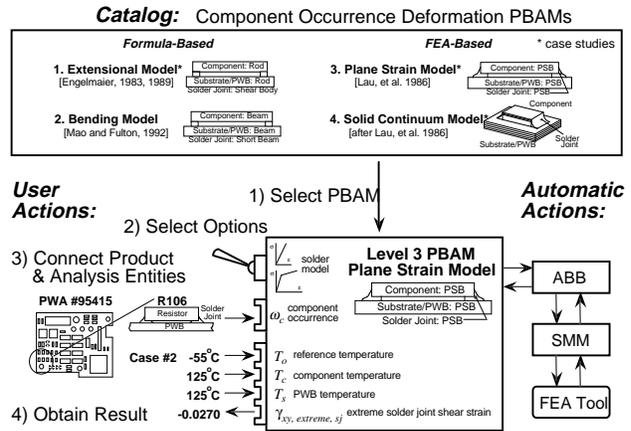


Figure 1 PBAMs for Design Verification Using Solder Joint Deformation

2.2 Optimization Agent

The Optimization Agent supports the integration of the analyzer (PBAM) and optimizer in such a way that compatibility between them is established. Just as PBAMs support modularized analysis routines depending on the stage of design and analysis needed, the optimization agent supports modularized optimization tools compatible with the analyzer.

Basically, the optimization agent is designed to support :

1) Feedback:

The optimization agent supplies feedback to the designer during every iteration of the optimizer and PBAM. Thus, a closed-loop process is performed that improves designs by meeting selected criteria and constraints.

2) Modular Optimization Approach:

One can determine the proper optimization tools necessary for a problem at hand depending on complexity of analysis relations, type of models and availability of tools. For example, a designer may have a limited optimization tool set or may want to use different tools depending on the stage of

the design. This capability offers the designer more freedom for analysis and optimization.

3) Flexible Models:

This feature enables changes in the optimization model, including changing, extending or contracting design variables. For example, two scenarios have been tested for calculating maximum fatigue life.

- a) In the first scenario, solder joint height is the only design variable.
- b) In the second scenario, height and PWB material are the design variables.

In both cases fatigue life maximization is the objective. Furthermore, the optimization agent is able to adapt to changes in objective and constraint functions. Figure 2 summarizes the different model alternatives supported by the optimization agent.

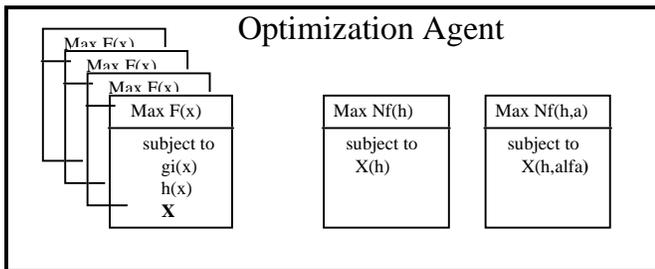


Figure 2 Optimization Agent

2.3 Integration Model

The approach taken in this integration process is shown in Figure 3.

The key components of this process are the analysis results from the PBAM and the optimization agent. Another important aspect is the coupling of the analysis program (PBAM) with the optimization program.

The PBAM supplies the analysis results such as Nf, stresses, displacements, frequencies etc. (depending on the problem at hand) for the given configuration. Those analysis results from the program (PBAM) can be used in the optimizer as objective and/or constraint functions. The optimizer returns with the new design variables, \mathbf{X} , needed to reduce the objective function. Optimizers work iteratively using the objective and constraint function values at each iteration. Gradient-based optimizers also require derivatives of the objective function and each constraint with respect to design variables.

In this process, first, the design variables are initialized. These initial parameters are selected preferably in the feasible region of the design space (i.e. the region in which all the constraints

are satisfied). Then the PBAM is run to obtain values that are used in the calculation of constraints and objective functions. For example, for this paper the PBAM supplies a fatigue life value for the objective function. In the next step, the optimizer uses objective and constraint function values to decide what changes should be made in the design variables to reduce the objective function and remain in the feasible region. For the fatigue problem, the objective function is an explicit function of solder joint height and PWB material. In the analysis stage, derivatives of all the functions are also calculated (known as sensitivities). Gradient-based optimizers use these derivatives to decide on the direction to change design variables to reach the optimum. Then, the PBAM executes again with the updated design variables and outputs a new value for the objective function. This cycle continues until the objective function value converges.

3. SOLDER FATIGUE CASE STUDY

This section describes how the technique has been applied to solder joint fatigue cases based on Engelmaier's model [Engelmaier, 1983,1989]. PBAMs representing this model, including finite element-based variations, are explained in [Peak 1993; Peak and Fulton, 1993]

3.1 Physical Description

Figure 4 shows a surface mount resistor soldered on a PWB.

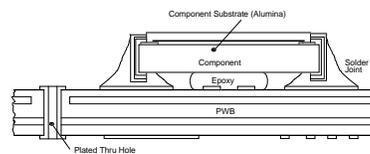


Figure 4 Soldered Component on a PWB

The above physical realization can be modeled using various approaches and degrees of complexity.

3.2 Analysis Model (PBAM)

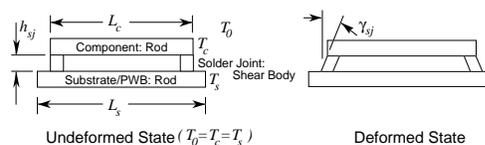


Figure 5 Engelmaier Model for Solder Joint Deformation

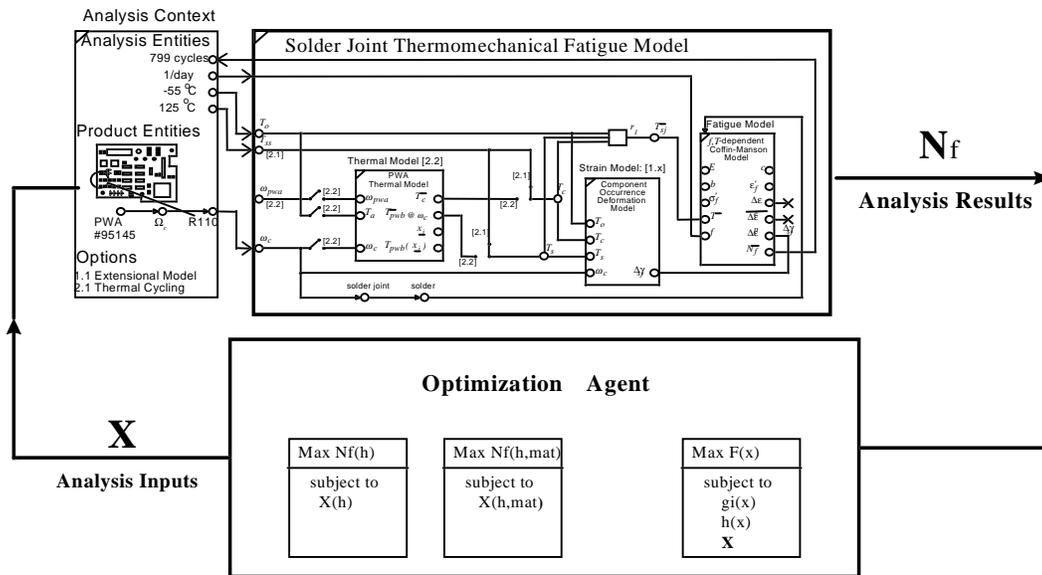


Figure 3 Integration of a PBAM and an optimization agent

The major steps to calculate the fatigue life of solder joints are presented in an N^2 diagram [Rogers, 1990] in Figure 6. Every box in this diagram shows a module which is a major calculation step towards prediction of fatigue life. Feed forward information is represented by connections above the diagonal of the N^2 diagram. For example, information from module 1 is used in modules 2, 3 and 4. There is no feedback for this case as indicated by the lack of connections below the diagonal. In the MRA, these calculation steps are represented by a modular nesting of PBAMs and analysis building blocks (ABBs) [Peak, 1993].

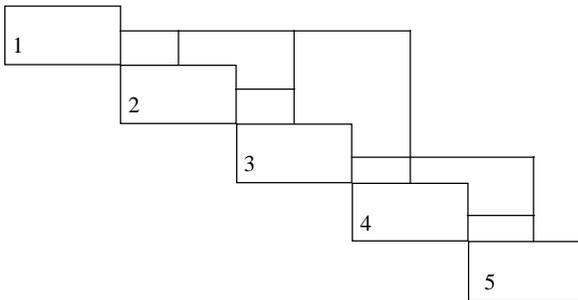


Figure 6 N^2 Diagram - Prediction of fatigue Life

1. Global PWA Thermal State

a) Power Cycling Case (Operating temperatures)

Turning on/off an electronic product is the most common example of such a case. Temperature differences between

components and PWB will occur during operation, causing strain in the solder joints due to CTE mismatches. In this study, we assume a thermal analysis has already been done, where $T_0 = 20^\circ\text{C}$, yielding $T_c = 89^\circ\text{C}$ and $T_s = 88^\circ\text{C}$.

2. Global PWA Thermomechanical state

Global warpage effects are not considered in this case study. Boundary conditions for the model are assumed to be zero.

3. Local Solder Joint Thermomechanical State

Engelmaier[1983,1989] developed the following relations by assuming uniform shear strain in the solder joint. (Figure 5)

$$\Delta(\alpha\Delta T) = \alpha_s (T_s - T_0) - \alpha_c (T_c - T_0)$$

$$\gamma_{sj} = \frac{L_c \Delta(\alpha\Delta T)}{2h_{sj}}$$

4. Solder Properties

The following relations are developed by Engelmaier and are used to calculate fatigue life in Step 5.

$$c = -0.442 - 0.0006\bar{T} + 0.0174 \ln(1 + f)$$

$$\bar{T} = \bar{T}_{sj} = \frac{1}{4}(2T_0 + T_c + T_s)$$

5. Solder Joint Fatigue Life

Strain range is calculated using the below two relations assuming plastic deformation dominates. F is an correction factor based on type of solder joint and experimental results.

$$\Delta\gamma_{sj} = F \left| \gamma_{sj} \right|$$

$$\Delta\varepsilon^P = \Delta\gamma_{sj}$$

Fatigue life model is based on a low yield stress and creep under small loads. A modified Coffin-Manson relation for low cycle fatigue is used by Engelmaier. The exponent c is frequency and temperature dependent and comes from Step 4.

$$\bar{N}_f = \frac{1}{2} \left(\frac{\Delta\varepsilon^P}{2\varepsilon_f} \right)^{1/c}$$

Given the above, one can see that the case study analysis model, though formula-based, is non-trivial as it involves several nonlinear relations and numerous variables.

3.3 Optimization Model

The case study optimization models are summarized by the following format.

Find

Design variable Notation

solder joint height (h)
PWB material type (α_s) *Scenario 2 & 3*

Maximize

Solder Fatigue life:

(Objective Function)

$$\bar{N}_f = \frac{1}{2} \left(\frac{\Delta\varepsilon^P}{2\varepsilon_f} \right)^{1/c}$$

Bounds on variables

$$0.0001 \leq h(in) \leq 0.1$$

$$\alpha_s \times 10^{-6} / ^\circ C \in \{10,15,7,21\} \quad \text{Scenario 2}$$

$$\alpha_s \times 10^{-6} / ^\circ C \in \{1,2,3,4,5,6,8,9,10,15,7,21\} \quad \text{Scenario 3}$$

Three scenarios have been investigated. In the first scenario, solder joint fatigue life is maximized with respect to solder joint height, with all other parameters held constant. Solder joint height can range from 0.001 to 0.5 inch. This design variable is considered a continuous variable. In this scenario

the PWB material has a coefficient of thermal expansion of $\alpha_s = 15.7 \times 10^{-6} / ^\circ C$.

In the second scenario, the primary pwb material is added as another design variable which determines α_s in the analysis inputs. This problem is mixed in nature. PWB material is a discrete variable, while solder joint height is continuous a variable. This requires using different optimization tools to handle this case. Three pwb materials are investigated with the following properties:

| | |
|------------|----------------------------------|
| Material 1 | $\alpha_s = 10 \times 10^{-6}$ |
| Material 2 | $\alpha_s = 15.7 \times 10^{-6}$ |
| Material 3 | $\alpha_s = 21 \times 10^{-6}$ |

The third scenario is the same as the second, except maximized Nf values are calculated based on a larger set of materials..

3.4 Results

The results obtained for design variables and objective functions for each scenario is given tabulated in Table 1.

| | <u>Scenario1</u> | <u>Scenario2</u> | <u>Scenario3</u> |
|-----------------|--------------------|--------------------------------|-------------------------------|
| h(in) | 0.1 | 0.1 | 0.1 |
| Material | - | $\alpha_s = 10 \times 10^{-6}$ | $\alpha_s = 6 \times 10^{-6}$ |
| Nf | 30.5×10^6 | 278×10^6 | 5.604×10^9 |

Table 1 Design Variable and N_f Final Results

Figure 7 gives the design variable value in Scenario 1 at every iteration of the optimizer and show how this value converges rapidly.

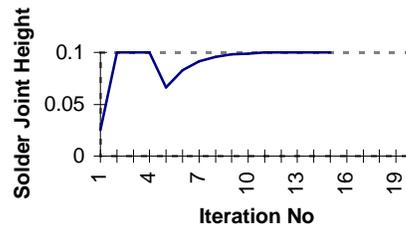


Figure 7 Iteration History of Design Variables for Scenario 1

The results for the third scenario are tabulated in Table 2. Figure 8 also shows Maximized Nf values for various material with different CTE based on Table 2.

| $\alpha \times 10^{-6}$ | $N_f \times 10^5$ |
|-------------------------|-------------------|
| 1 | 77 |
| 2 | 116 |
| 3 | 192 |
| 4 | 372 |
| 5 | 968 |
| 6 | 5604 |
| 8 | 2316 |
| 9 | 625 |
| 10 | 278 |
| 15.7 | 30.5 |
| 21 | 11 |

Table 2 Max N_f values for different material

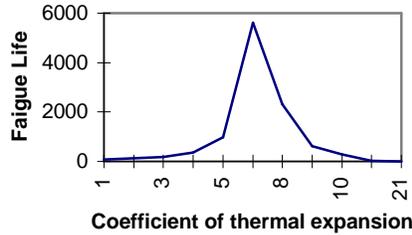


Figure 8 Maximized N_f values for Different Solder Material

4. DISCUSSION

The PBAM is written in the object oriented language (Small Talk). Optimizer is Broyden-Fletcher-Goldfarb-Shanno algorithm based on variable metric method and written in Fortran.[Press et al.]. The integration requires an interface that enables automated iteration during the process.

After integration and runs for various cases, results are obtained as seen in the tables. The initial design point is the same for all scenarios. Design variable “h” converges smoothly after an initial peak value (Figure 7).

The strategy to ensure that the global optimum has been achieved is to search from different initial points in the design space and verify that the results are converging to the same optimum value. For that reason, different starting design variables have been tried, and they all converged to the same values shown in the result tables. The optimum solder joint height is found to be the upper limit value of the design variable (as would be expected from examining the relations in Section 3.2). Solder joint fatigue life increases as solder joint height increases.

Two design variables, one discrete and the other continuous, are used to achieve maximum fatigue life in the second scenario. For this and the third scenario, one would expect the

optimum α_s to be the value that yields zero thermal mismatch, $\Delta(\alpha\Delta T)$: $\alpha_{s,optimum}=6.7 \times 10^{-6}$ in this case. This is confirmed in Table 1 where the PWB material with CTE closest to $\alpha_{s,optimum}$ gives the maximum fatigue life. Meanwhile, solder again height reached the maximum allowable limit.

Materials with different CTEs have been optimized in the third scenario. The reason is to demonstrate that the technique correctly predicts fatigue life is maximum when α_s , and $\alpha_{s,optimum}$ are closest to each other, even with α_s candidates on either side. One can conclude that fatigue life increases as CTE of PWB material approaches to 6.7×10^{-6} value and decreases when the CTE diverges from that value as seen in Figure 8 and Table 2.

5. SUMMARY

The coupling of PBAMs with an optimizer has been performed using the following approach:

- 1) Initialize optimizer parameters.
- 2) Call the optimizer.
- 3) Supply design variables from optimizer to the PBAM, and then get the objective function value from the PBAM and send it to the optimizer.
- 4) Continue until the objective function value converges to the optimum.

This new PBAM-based optimization technique is illustrated by maximizing solder joint fatigue life given solder joint height and PWB material as design variables. This technique aids the design of products like PWA’s by supplying feedback and by supporting modular optimization capabilities and flexible analysis models.

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¹Some references are available at www.eislab.gatech.edu