Using statistical inverse methods for detecting defects in electronic components

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Abstract. The thermal modeling of electronic components is mandatory to optimize the cooling design versus reliability. Indeed most of failures are due to thermal phenomena [1]. Some of them are neglected or omitted by lack of data: ageing, manufacturing issues like voids in glue or solder joints, or material properties variability. Transient measurements of the junction-to-board temperature supply real thermal behavior of the component and PCB assembly to complete these missing data[2]. To complement and supplement the numerical model, inverse methods identification based on a statistical deconvolution approach, such as Bayesian one, is applied on these measurements to extract a Foster RC thermal network. The identification algorithm performances have been demonstrated on numerical as well as experimental dataset. Furthermore defects or voids can be detected using the extracted Foster RC networks.

1. Introduction
The first part of this study focuses on the statistical inverse methods used to identify the Foster network of a component, and on its application on experimental and numerical setups. The second part highlights the capabilities of this method to detect defects or voids. The impact of such defects or material properties changes on the deconvolution results is discussed.

2. Thermal impedance model
The mathematical modelling of the thermal impedance of an electronic package is essential to accurately predict its thermal behavior. Assuming that the electronic package is mounted on an ideal heat sink and its other external surfaces are considered adiabatic, a one dimensional conduction heat path model can be use[3]. Such considerations lead to model the thermal impedance of such system using a Foster network. Figure 1 shows the schematic representation of this kind of network and (1) shows its mathematical expression.

\[ Z_{th}(t) = \sum_{i=1}^{n} R_i \cdot \left[ 1 - \exp\left( -t/\tau_i \right) \right], \quad \tau_i = R_i \cdot C_i \]  

Figure 1. Foster network
However, in a miniaturized Integrated Circuit (IC), the intrinsic heat transfers occur very fast so a logarithmic time scale is typically used to express the discrete thermal impedance as shown in (2).

$$Z_{th}(z_i) = \sum_j R(\xi_j) \cdot [1 - \exp(-\exp(z_i - \xi_j))], \quad z = \ln(t) \text{ and } \xi = \ln(\tau)$$

(2)

$$Z = W \ast R, \quad w_{ij} = 1 - \exp(-\exp(z_i - \xi_j))$$

(3)

This mathematical expression (2) is a convolution product which can be expressed into matrix format as shown in (3). In practice, the vector $Z$ and the matrix $W$ are known. The only one remaining unknown is the vector $R$ which is solved using Bayesian deconvolution.

3. Bayesian deconvolution approach

The Bayesian deconvolution process [4][5] is based on the Bayes’s theorem which describes the probability of an event, based on prior knowledge of conditions that are related to the event. Associated to the expression of the total probability, an iterative algorithm can be formulated from (3). The resulting expression of the Bayesian deconvolution algorithm is shown in (4) and known as Richardson-Lucy algorithm [6][7]. Nevertheless, the matrix $W$ is usually ill posed in our application so a Van Cittert regularization procedure is applied on the Richardson-Lucy algorithm which leads to the Gold algorithm (5) being used [6][7]. For more details, readers are invited to consult [4][5][6][7][8].

$$R_j^{n+1} = R_j^n \frac{1}{\sum_i W_{ij}} \sum_k W_{ik} \cdot Z_k \cdot R_k^n$$

(4)

$$R_j^{n+1} = R_j^n \cdot \frac{(W^T \ast Z)_j}{\sum_k (W^T \ast W)_{jk} \cdot R_k^n}$$

(5)

Thus, the calculated vector $R^n$, after a very large number of iterations, allows entirely defining the Foster network of the system. However, this calculated Foster network from Bayesian deconvolution is a discrete one with many serial sets of parallel RC stages. In order to hasten the deconvolution process, a weighted average is used to calculate the time constant of each Gaussian-style area in the spectra and a concatenation of the magnitudes is used to evaluate the total resistance value of each stage. As a result, a Foster network with only few stages can be extracted from the Bayesian deconvolution process.

4. Experimental results

A vehicle test composed of three Dual Flat No-lead (DFN) packages with 10 leads was used to perform experimental measurements. These packages are mounted on a Printed Circuit Board (PCB) which is itself on a cold plate considered as an ideal heat sink. The copper stack-up of the PCB is composed of two external signal layers and two buried ground ones which are sandwiched between FR4 layers. The reader are invited to refer to [8] for more details on the experimental setup. Diodes are used to access the junction temperature of the components. The thermal impedances are then deduced from these temperature changes divided by the power step.

The presented Bayesian deconvolution process is now applied on the three experimental impedances. The resulting spectra of the resistance magnitudes according to time constant ($\tau_i$) are displayed in figure 2 and the related extracted parameters $\tau$ and $R$ are enlisted in table 1.

As highlighted in figure 2, the three resulting spectra present the same shape. For each Device Under Test (DUT), six significant time constants are identified by the algorithm after a large number of iterations. However, these spectra still reveal disparities which could be explained by their different positions and/or soldering joints on the PCB. On another hand, the extracted Foster networks reconstructed very well the thermal behavior of each DUT as shown by the great regression coefficient.
(\(r^2\)) between the original experimental thermal impedance and the one reconstructed with the extracted parameters \(R\) and \(\tau\).

\[
\begin{array}{cccccc}
\text{DFN10} - 0 & \text{DFN10} - 27 & \text{DFN10} - 45 \\
\hline
i & \tau_i \ [\text{s}] & R_i \ [\text{°C.W}^{-1}] & \tau_i \ [\text{s}] & R_i \ [\text{°C.W}^{-1}] & \tau_i \ [\text{s}] & R_i \ [\text{°C.W}^{-1}] \\
1 & 0.00344 & 1.47 & 0.00343 & 1.87 & 0.00591 & 1.25 \\
2 & 0.108 & 9.97 & 0.119 & 10.4 & 0.0987 & 7.11 \\
3 & 0.325 & 11.0 & 0.344 & 10.5 & 0.242 & 10.9 \\
4 & 1.06 & 20.3 & 1.08 & 19.6 & 0.918 & 19.0 \\
5 & 3.94 & 6.99 & 4.33 & 7.52 & 2.84 & 11.0 \\
6 & 11.8 & 1.49 & 19.7 & 1.37 & 10.3 & 2.83 \\
\end{array}
\]

\[
\begin{array}{cccc}
I & \tau_i \ [\text{s}] & R_i \ [\text{°C.W}^{-1}] & \tau_i \ [\text{s}] & R_i \ [\text{°C.W}^{-1}] \\
3D - 1 & 0.0113 & 5.36 & 0.00356 & 2.40 \\
3D - 2 & 0.112 & 8.67 & 0.0137 & 2.25 \\
MF & 0.361 & 13.8 & 0.0565 & 3.23 \\
4 & 1.32 & 17.9 & 0.141 & 5.81 \\
5 & 3.52 & 6.32 & 0.321 & 12.6 \\
6 & 8.28 & 0.895 & 1.17 & 17.2 \\
7 & - & - & 2.94 & 7.94 \\
8 & - & - & 7.36 & 1.46 \\
\end{array}
\]

The presented study focuses on understanding the origin of the disparities between these experimental spectra. For this purpose, a numerical model of the test vehicle is constructed to simulate the behavior of the components under various physical changes in the model. The study is conducted on the three components but only the results of the component named DFN10 – 0 are presented to lighten the discussion.

5. Numerical simulations

Considering manufacturing data and technological analyses allowed the creation of a relevant three-dimensional model for the complete test vehicle. Its geometry is modeled on ANSYS SpaceClaim® and ANSYS Icepak® (version 19.2 and 19.3) is used to perform the numerical simulations. Meshing independence of the model is obviously verified. Numerical model ambient conditions setting is related to the ones observed during the experiments. Thermal radiation is taken into account and natural convection phenomena are considered. The PCB is modelled in two different ways: either the detailed model of all its geometry or an approximation of the copper coverage subdivision referred as “Metal Fraction” (MF) approach [9]. The latter permits to omit a lot of meshing elements so simulation time is saved.
Thus, three deconvolutions are conducted on the numerical model. Two are done on the full detailed model and one with MF approach for the PCB. The only difference between the two simulations on the full detailed model is the number of points for the input thermal impedance. Indeed, for the simulation termed as “3D – 2”, twenty points are added in the very first instants of the simulation, namely the decades between $10^{-4}$ and $10^{-2}$. Figure 3 displays the resulting spectra and table 2 enlisted their extracted Foster network’s parameters.

One can note that the number of thermal impedance points is a critical parameter. Indeed, it is essential to simulate enough temperature points per decade and especially in the first decades. Figure 3 also highlights the importance of taking into account every geometry detail in order to identify all time constants in the thermal impedance. Only four peaks are identified using the MF approach against eight when using the full detailed model to simulate the thermal impedance of the component.

However, the three extracted Foster networks accurately reconstruct the transient thermal behavior of the component as showed by the good regression coefficients.

Physical defects in the numerical model are now added. Their impacts on the Bayesian deconvolution are discussed in the following development. The component’s wire bonding are deleted and a numerical simulation is conducted (3D – WB). The soldering joint’s thermal properties (thermal conductivity and capacity) are modified to simulate a brazing layer defect (3D – BL). Figure 4 presents the deconvolution results for these simulations and table 3 enlists the extracted parameters for the Foster network.

As highlighted in figure 4, the deconvolution algorithm well identifies eight peaks for each dataset. Indeed, as shown by the regression coefficient, the extracted networks still reconstructed very well the thermal behavior of the component. However the disparities are detected between each spectrum. It appears that an added defect, wire bonding or brazing layer void, in the numeric model can be identified by comparing the extracted Foster network. So the perfect numeric model can be updated to take into account real manufacturing imperfections to study the model sensitivity or to study unknown electronic package applications. Although these defects are easily detected, their impacts are not concentrated on one Gaussian-style area but several ones. Indeed, it appears that one peak is not related to one physical element or one part of the electronic package. This is the main problematic of the process, the quantification of defects, in terms of thermal properties, is not trivial.

### Table 3. Foster network’s parameters derived from numerical transient data for different changes in the 3D-model (DFN10 – 0)

|     | 3D  | 3D – WB | 3D – BL |
|-----|-----|---------|---------|
| $\tau_i$ | $R_i$ [°C.W$^{-1}$] | $\tau_i$ | $R_i$ [°C.W$^{-1}$] | $\tau_i$ | $R_i$ [°C.W$^{-1}$] |
| 1   | 0.00356 | 2.40  | 0.00419 | 3.01  | 0.00402 | 2.89  |
| 2   | 0.0137  | 2.25  | 0.0198  | 2.22  | 0.0188  | 2.21  |
| 3   | 0.0565  | 3.23  | 0.0576  | 1.91  | 0.0598  | 2.31  |
| 4   | 0.141   | 5.81  | 0.123   | 6.11  | 0.125   | 5.55  |
| 5   | 0.321   | 12.6  | 0.312   | 14.3  | 0.313   | 12.8  |
| 6   | 1.17    | 17.2  | 1.20    | 18.2  | 1.16    | 16.3  |
| 7   | 2.94    | 7.94  | 3.11    | 7.92  | 2.93    | 7.85  |
| 8   | 7.36    | 1.46  | 8.11    | 1.13  | 7.36    | 1.45  |

$R^2$ = 0.9999998

**Figure 4.** Resistances spectra derived from numerical data for different changes in the 3D-model for millions of iterations

### 6. Conclusion

The performances of the identification process based on the Bayesian deconvolution methods have been validated on numerical and experimental results. The deduced Foster network matches well the transient thermal behavior of the tested components. Moreover this study demonstrates that the
method permits to identify the voids inside solder joint or the wire bonding delamination. Although the conversion of Foster echelon to thermal properties is complex, this identified network allows the study of the impact of manufacturing effects on Printed Wiring Board assembly.

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