A PRELIMINARY STUDY OF OPTIMIZATION TECHNIQUES FOR COMPACT THERMAL MODEL DEVELOPMENT OF MULTI-HEAT SOURCE COMPONENTS

Arun P. Raghupathy
Electronic Cooling Solutions Inc, Mountain View, CA 94043
University of Cincinnati, Cincinnati, OH 45221
arun@ecooling.com

Attila Aranyosi
Electronic Cooling Solutions Inc,
Mountain View, CA 94043

William Maltz
Electronic Cooling Solutions Inc,
Mountain View, CA 94043

Karman Ghia
Department of Aerospace Engineering
and Engineering Mechanics
University of Cincinnati
Cincinnati, OH, 45221

Urmila Ghia
Department of Mechanical, Industrial
and Nuclear Engineering
University of Cincinnati
Cincinnati, OH, 45221

ABSTRACT

The difficulty in modeling the wide range of scales in Computational Fluid Dynamics (CFD) simulations of system level cooling solutions can be addressed by employing Compact Thermal Models (CTM) of electronic components. Compact thermal models, in their true sense, are boundary condition independent network of resistors that are developed primarily to predict junction temperature and heat flux through the boundaries of a processor. One-resistor, two-resistor based star network models and multiple-resistor based star and shunt network models are currently being used for this purpose. CTMs have been successfully implemented for single-heat source IC chips. It can be conceived that even complex components, which have multiple power sources, can be replaced using CTMs in system level CFD simulations. There are many such components like the multi-chip modules, system in packages etc. The components of interest in the present study are the opto-electronic components such as X2, Xenpak, SFP, XFP etc.

The overall objective of the present study is to explore the possibility of CTM development for opto-electronic components using methodologies that employ either optimization or reduced order modeling approaches. The first route taken is to develop the methodology required in order apply DELPHI [6] (Development of Libraries and Physical Models for an Integrated Design Environment) based optimization approach for CTM generation of multi heat source components. The DELPHI based methodology employs optimization of the conduction and convection resistances in order to generate the final network of resistances. In essence, the optimization is the minimization of the error between the experimental and calculated values of the junction temperature and heat fluxes by varying the value of the resistances. Once the error is minimized, the resulting network of resistances can be used as a boundary condition independent CTM. Since optimization is the backbone of the DELPHI method, it is important to employ an optimization algorithm that can produce accurate results.

The DELPHI method also requires a network solver. The network solver solves for the compact model parameters (junction temperature and heat flux through the boundaries) based on the network topology. For this initial phase, the experimental results from the conduction-cooled application of a single chip as presented in Aranyosi et al. [11] are used for validation. This problem is chosen for validation purpose because the authors had used a Design of Experiments approach to reduce the number of boundary condition as opposed to a detailed boundary condition set employed by the DELPHI team. Such a reduced boundary condition set allows for faster execution of the optimization algorithm and for quick validations.

Unconstrained minimization using gradient-based Quasi-Newton method, constrained minimization using gradient-based Sequential Quadratic Method, Genetic Algorithm and hybrid Genetic Algorithm are the four different optimization algorithms that are tested for this purpose. MATLAB is used for implementation and testing of these algorithms. All the above-mentioned algorithms produced results with acceptable levels of accuracy. The hybrid Genetic Algorithm method performed the best for the chosen network topology.

1. INTRODUCTION

Computational Fluid Dynamics (CFD) plays an important role in the design and analysis of system level cooling solutions. Although many features in the some of the popular thermal analysis software allow for localized meshing, there often occur situations where multiple numbers of detailed components that need localized meshing thus increasing the computational load. One such component is the optical network component. Optical networking components are used in networking switches and routers. Due to their small form factor, many of them are ganged together for higher performance of the system. Due to the nature of arrangement of these components, their ability to transfer heat effectively is affected. Also, due to the sensitivity of the laser diode in these components to the heat transfer characteristics, it is critical to perform reliable thermal analysis during the design stages. Since having multiple components require a huge amount of computational resources, the problem can be addressed by employing Compact Thermal Models (CTM). An important outcome of using CTMs in CFD-based commercial software is the reduction in design/analysis time, while maintaining a certain required level of accuracy. This fact has gained the interest of many researchers to extend the capabilities of compact thermal models to those of reduced-order models.

Research on the development of compact thermal models for electronic components has grown to a great extent since the pioneering work of Bar Cohen [1]. Extensive literature is available for work on compact modeling of IC packages [2]-[6]. Alternative approaches to generate CTM have been proposed by Bosch and Sabry [7] and Codecasa [8]. For complex multi-heat source components, reduced order modeling approaches and experimental system identification methods have been proposed by Shapiro [9]. Very little data has been published on compact modeling of optical components such as SFPs. Development of compact models for SFPs has been attempted by Murphy and Yi [10]. Their white paper from Agilent Technologies describes the experiments and subsequent validation of the detailed computational model against experimental data. They constructed their compact model by simplifying the geometry and using lumped thermal conductivities. They show that their simplified geometry provides accurate results for certain conditions, but they do not mention whether their model achieves boundary condition independence or not.

The present study focuses on the extension of the DELPHI based compact model development procedure to develop CTMs for multi-heat source geometry. One of the main difficulties in extending the DELPHI based methodology to development of CTM for multi-heat source components is the degree of freedom of the variables in the optimization procedure. Developing CTM for a reduced set of boundary condition can circumvent this issue. Extreme and unrealistic boundary conditions can be omitted. Another alternative is to employ a Design of Experiments approach as used in Aranyosi et al. [11] to reduce the degree of freedom of variables.

As a first step, the necessary tools for generating CTMs, namely a network solver and an optimizer are developed. Preliminary results obtained for validation of these tools are presented. The validation is done by comparing results to that of a single heat source IC chips. Since statistical optimization is an important component of the DELPHI methodology, the present study analyzes four different optimization algorithms. This is done to identify the most robust optimization algorithm. This algorithm can then be used for future work.

2. DATA FOR OPTIMIZATION

The present work is concerned with the development of the procedure and the analysis of different optimization algorithms. So, the geometry, experimental and network layout data are obtained from Aranyosi et al[11]. The authors have carried out detailed experiments for validation of PQFP type packages in conduction-cooled applications. Although benchmark geometries have been proposed for validation [12], the present work compares results of the data from optimization to that of Aranyosi et al.[11] because the authors have reduced the boundary condition set used in developing the CTM using a design of experiments approach. Such a reduced boundary condition set allows for faster execution of the optimization algorithm and allows for quick validation and fixes. The present work maintains the notation used in [11] so that the reader could refer to the paper for detailed description of experimental and CTM development procedure. The thermal network for which the resistances are optimized is shown in Fig.1. Details of the boundary conditions used for validation and verification of the CTM and the network layout are provided in [11].

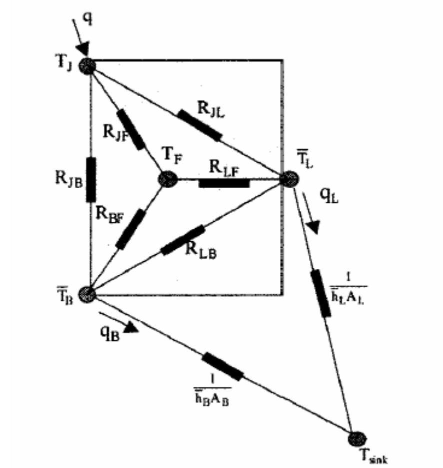

Fig.1 Thermal network used in the present optimization study [11]

3. OPTIMIZATION ALGORITHMS

An important part of the Compact Thermal Model development procedure is the optimization of resistances over many different boundary conditions. Optimization is the minimization of the error between the experimentally measured data to the calculated CTM parameters such as junction temperature and heat flowing through the sides. The objective function that has to be minimized is shown in Eq. 1.

$$Obj\,Fn = \sum_{n=1}^{nBCs}\left(\left(\frac{T_{j,c}-T_{j,d}}{T_{j,d}}\right)^2 + W\sum_{i=1}^{nSides}\left(\frac{q_{i,c}-q_{i,d}}{q_{total}}\right)^2\right) \quad (1)$$

The nature of the objective function is very important in the analysis of the optimization procedure, as it is unique to each physical problem. The resistance values of the network are changed in order to calculate the CTM parameters, which in turn are used in the objective function. The weighting function, W controls for optimization targeted towards junction temperature or heat flow. This weighting function is either allowed to be a variable that needs to be optimized, or is kept fixed.

The objective function in Eq.1 can have multiple maxima and minima. The best algorithm will be able to find the global minimum and avoid all local minimums. Gradient based optimization methods and stochastic optimization methods are studied in the present work.

i. Quasi-Newton (QN) Method

This unconstrained non-linear optimization [13] is a popular gradient-based optimization method. For implementation of this algorithm for optimization of the objective function in Eq.1, the weighting function has to be fixed at a specific constant value. The decision variables, i.e., the resistances are also left to be unconstrained. They are not bound and are allowed to float. Under these conditions, the Quasi-Newton method can be used for optimization of the given objective function. The method requires an initial guess for the resistance values.

ii. Sequential Quadratic Programming (SQP) Method

This constrained non-linear optimization method is a direct approach optimization method where equality and inequality constraints are handled without any transformation into an unconstrained problem. This method [13] allows for setting lower and upper bounds for the resistance values. Here, the weight variable can also be allowed to float between an upper and lower bound. This method also requires an initial guess for the resistance values.

iii. Genetic Algorithm (GA)

Genetic Algorithm is a stochastic method which works in a totally different way when compared to the above two gradient-based methods. It works on the principal of evolution of the fittest variables that minimize the objective function. The implementation of method is done by integrating the open source code developed by Houck et al [15]. The code has been validated in great detail as shown in their work. This method searches for the entire solution space and has more probability of finding a global minimum than a local one. The biggest advantage of this method is that it does not require an initial guess.

iv. Hybrid Genetic Algorithm (Hybrid GA)

It is observed in the literature [14, 15] that when stochastic methods are used along with gradient-based methods, the resulting performance is better than either of the methods used individually. Although, Genetic Algorithms are good at finding a global minimum, sometimes they end up locating the region of the global minimum but take a long time to converge to the actual global minimum. In these cases, when a gradient-based method is used, it can accelerate the convergence. In the present study, the result from the GA, which is the best population of variables, is passed on as an initial guess to the Sequential Quadratic Methods. Since gradient-based methods are very good at finding a local minimum, this combination is expected to work better than either of the methods used alone. Past successes of hybrid Genetic Algorithms have been discussed in [15].

4. RESULTS AND DISCUSSION

The different algorithms described in the previous section are used for optimization of the objective function in Eq.1. The first four boundary conditions shown in Table 1 are used for generating the CTM parameters. The next four boundary conditions are not part of the CTM generation boundary condition set, and are used for verification of the predicted resistances.

Table 1. Boundary conditions used for validation and verification of CTM parameters [11]

Boundary Condition #	h_l (W/m^2K)	h_b (W/m^2K)
1	764	30
2	415	209
3	37304	84
4	35221	10157
5	509	58
6	697	67
7	55521	81
8	45286	3062

Tables 2, 3, 4 and 5 each show the generated CTM parameters; junction temperature (T_j) and heat flow on each side (q_l and q_b) for QN method, SQP method, GA method and Hybrid GA method respectively. Tables 2a, 3a, 4a and 5a show the CTM parameters predicted by the respective optimization method. In this table, the data is compared to the experimental values obtained by Aranyosi et al [11]. Tables 2b, 3b, 4b and 5b show the resistance values predicted for the network topology shown in Fig.1. Tables 2c, 3c, 4c and 5c show the results from the application of the resistance values for the boundary condition that are not part of the CTM generation set. This table allows for verification of the predicted resistance values.

All the optimization algorithms predicted junction temperatures within 5% of the experimental measured value for all boundary conditions. The only discrepancy can be seen in the SQP method where the maximum error was 11%. The maximum error of approximately 53% occurs in the prediction of the heat flow for certain boundary conditions.

Table 2. Comparison of predicted CTM parameters obtained from Quasi-Newton Method

(a)

Boundary Condition #	**Experimental Data**			**Compact Model Data**			**Error %**		
	Tj (deg C)	**ql (W)**	**qb (W)**	**Tj (deg C)**	**ql (W)**	**qb (W)**	**Tj**	**ql**	**qb**
1	129.68	0.1766	0.0734	124.1406	0.177	0.073	4.3	-0.2	0.5
2	71.21	0.0468	0.2032	71.3027	0.0482	0.2018	-0.1	-3.0	0.7
3	42.28	0.2206	0.0294	39.9721	0.2185	0.0315	5.5	1.0	-7.1
4	29.59	0.0992	0.1508	30.9928	0.0984	0.1516	-4.7	0.8	-0.5

(b)

Resistances					
Rjb	Rlb	Rjl	Rjf	Rbf	Rlf
399.1	214.6	383.6	252.9	84.1	250.3

(c)

Boundary Condition #	**Experimental Data**			**Compact Model Data**			**Error %**		
	Tj (deg C)	**ql (W)**	**qb (W)**	**Tj (deg C)**	**ql (W)**	**qb (W)**	**Tj**	**ql**	**qb**
5	124.92	0.1169	0.1331	119.4202	0.1171	0.1329	4.4	-0.2	0.2
6	103.49	0.1271	0.123	101.2916	0.1258	0.1242	2.1	1.0	-1.0
7	41.63	0.2227	0.0274	42.1013	0.208	0.042	-1.1	6.6	-53.3
8	30.49	0.1126	0.1374	30.5236	0.1051	0.1449	-0.1	6.7	-5.5

Table 3. Comparison of predicted CTM parameters obtained from SQP Method

(a)

Boundary Condition #	**Experimental Data**			**Compact Model Data**			**Error %**		
	Tj (deg C)	**ql (W)**	**qb (W)**	**Tj (deg C)**	**ql (W)**	**qb (W)**	**Tj**	**ql**	**qb**
1	129.68	0.1766	0.0734	123.8505	0.1794	0.0706	4.5	-1.6	3.8
2	71.21	0.0468	0.2032	72.1925	0.0463	0.2037	-1.4	1.1	-0.2
3	42.28	0.2206	0.0294	37.5512	0.2307	0.0193	11.2	-4.6	34.4
4	29.59	0.0992	0.1508	32.2679	0.1036	0.1464	-9.1	-4.4	2.9

(b)

Resistances					
Rjb	Rlb	Rjl	Rjf	Rbf	Rlf
463.2	97.9	526.2	215.9	72.9	94.0

(c)

Boundary Condition #	**Experimental Data**			**Compact Model Data**			**Error %**		
	Tj (deg C)	**ql (W)**	**qb (W)**	**Tj (deg C)**	**ql (W)**	**qb (W)**	**Tj**	**ql**	**qb**
5	124.92	0.1169	0.1331	121.5904	0.1191	0.1309	2.7	-1.9	1.7
6	103.49	0.1271	0.123	103.1925	0.1291	0.1209	0.3	-1.6	1.7
7	41.63	0.2227	0.0274	36.8485	0.2327	0.0173	11.5	-4.5	36.9
8	30.49	0.1126	0.1374	32.819	0.1236	0.1264	-7.6	-9.8	8.0

Table 4. Comparison of predicted CTM parameters obtained from GA Method

(a)

Boundary Condition #	Experimental Data			Compact Model Data			Error %		
	Tj (deg C)	ql (W)	qb (W)	Tj (deg C)	ql (W)	qb (W)	Tj	ql	qb
1	129.68	0.1766	0.0734	124.9882	0.1745	0.0755	3.6	1.2	-2.9
2	71.21	0.0468	0.2032	70.2074	0.049	0.201	1.4	-4.7	1.1
3	42.28	0.2206	0.0294	42.5265	0.2078	0.0422	-0.6	5.8	-43.5
4	29.59	0.0992	0.1508	29.9056	0.091	0.159	-1.1	8.3	-5.4

(b)

Resistances					
Rjb	Rlb	Rjl	Rjf	Rbf	Rlf
205.6	451.2	865.3	317.1	578.9	76.8

(c)

Boundary Condition #	Experimental Data			Compact Model Data			Error %		
	Tj (deg C)	ql (W)	qb (W)	Tj (deg C)	ql (W)	qb (W)	Tj	ql	qb
5	124.92	0.1169	0.1331	119.6641	0.1168	0.1332	4.2	0.1	-0.1
6	103.49	0.1271	0.123	101.5696	0.1255	0.1245	1.9	1.3	-1.2
7	41.63	0.2227	0.0274	42.0549	0.21	0.04	-1.0	5.7	-46.0
8	30.49	0.1126	0.1374	30.6849	0.1004	0.1496	-0.6	10.8	-8.9

Table 5. Comparison of predicted CTM parameters obtained from Hybrid GA Method

(a)

Boundary Condition #	Experimental Data			Compact Model Data			Error %		
	Tj (deg C)	ql (W)	qb (W)	Tj (deg C)	ql (W)	qb (W)	Tj	ql	qb
1	129.68	0.1766	0.0734	124.7524	0.1742	0.0758	3.8	1.4	-3.3
2	71.21	0.0468	0.2032	70.6623	0.0506	0.1994	0.8	-8.1	1.9
3	42.28	0.2206	0.0294	42.5476	0.2058	0.0442	-0.6	6.7	-50.3
4	29.59	0.0992	0.1508	29.8099	0.097	0.153	-0.7	2.2	-1.5

(b)

Resistances					
Rjb	Rlb	Rjl	Rjf	Rbf	Rlf
310.7	635.6	983.8	147.7	179.6	146.7

(c)

Boundary Condition #	Experimental Data			Compact Model Data			Error %		
	Tj (deg C)	ql (W)	qb (W)	Tj (deg C)	ql (W)	qb (W)	Tj	ql	qb
5	124.92	0.1169	0.1331	119.4158	0.1171	0.1329	4.4	-0.2	0.2
6	103.49	0.1271	0.123	101.2867	0.1258	0.1242	2.1	1.0	-1.0
7	41.63	0.2227	0.0274	42.0998	0.2079	0.0421	-1.1	6.6	-53.6
8	30.49	0.1126	0.1374	30.5201	0.1051	0.1449	-0.1	6.7	-5.5

For the gradient-based methods studied, the weighting function, W has to be defined. This has to be done in a trial and error fashion. This does not allow for complete automation of solving the problem. Once a suitable value is found, then the objective function produces a global minimum value. For the Genetic and hybrid Genetic Algorithms, this is not a problem. Since the algorithm searches the entire solution space, an optimum value of W is found corresponding to the global minimum. Also, in this study no markedly different results were found when comparing Genetic Algorithms with hybrid Genetic algorithms. During certain runs, GA produced minimum values that were not the absolute minimum. The hybrid GA consistently produced global minimum values.

5. CONCLUSION

The tools necessary for generating compact thermal models are developed in the present study. CTM development procedure and experimental data from Aranyosi et al [11] are used as a basis for validation of the developed code. Also, four different popular optimization algorithms are compared in order to select the most robust one for future CTM development purposes. Two gradient based methods; the Quasi-Newton Method and the Sequential Quadratic method are studied along with a stochastic method; Genetic Algorithm. The fourth type of algorithm that is analyzed is the Hybrid Genetic Algorithm that incorporates both the GA and the SQP methods. Although all the algorithms provided reasonably accurate results, the hybrid GA method proved to be the most robust and flexible for CTM development purposes.

6. REFERENCES

1. Bar-Cohen, A and Krueger, W.B., "Determination of the weighted-average case temperature for a single chip package", in Cooling of Electronic Systems, S. Kakac and H. Yuncu, Eds. Kluwer, 1994, pp. 789-810.
2. Lasance, C. J.M., "Special Section on Compact Thermal Modeling", IEEE Transactions on Components and Packaging Technologies, Vol. 26, No. 1, March 2003
3. Lasance, C.J.M., "Thermal characterization of electronic parts with compact models: Interpretation, Application and the need for a paradigm shift", in Proc. SEMITHERM-XIII, Austin, TX, 1997, pp. 40-48.
4. Bar-Cohen, A. and Krueger, W.B., "Thermal characterization of chip packages-Evolutionary development of compact models", IEEE Transactions on Components, Packaging and Manufacturing Technology, Part A, vol. 20, no.4, pp. 399-410, December 1997
5. Lasance, C. J. M., Vinke, H, and Rosten H, "Thermal Characterization of Electronic Devices with Boundary Condition Independent Compact Models", IEEE Transactions on Components, Packaging and Manufacturing Technology – Part A, Vol. 18, No.4, December 1995
6. Rosten, H. I., "DELPHI - a status report on the European Union Funded Project for the Creation and Validation of Thermal Models of Electronic Parts", Thermal Management of Electronic Systems, Proc. of Eurotherm Seminar 29, September 1995, Leuven, Belgium
7. E. Bosch and M. N. Sabry, "Thermal compact models for electronic systems," in Proc. SEMITHERM XVIII, 2002, pp. 21–29.
8. L. Codecasa, D. D'Amore, and P. Maffezzoni, "Compact thermal networks for modeling packages," IEEE Trans. Comp. Packag. Technol., vol. 27, no. 1, pp. 96–103, Mar. 2004.
9. Shapiro, B., Creating Compact Models of Complex Electronic Systems: An Overview and Suggested Use of Existing Model Reduction and Experimental System Identification Tools", IEEE Trans. Comp. Packag. Technol., vol. 26, no. 1, pp. 165-172, Mar. 2003.
10. Murphy and Yi, "Thermal Analysis Design and Validation of an SFP Transceiver CFD Model", ONIDS 2002, White Paper HFBR-5710L.
11. Aranyosi, A., Ortega, A., Evans, J., Tarter, T., Pursel, J., Radhakrishnan, J, " Development of Compact Thermal Models for Advanced Electronic Packaging: Methodology and Experimental Validation for a Single-Chip CPGA Package", IEEE Inter Society Conference on Thermal Phenomena, 2000
12. Lasance, C. J.M., "Two Benchmarks to Facilitate the Study of Compact Thermal Modeling Phenomena", IEEE Transactions on Components and Packaging Technologies, Vol. 24, No. 4, December 2001
13. Optimization Toolbox, MATLAB
14. Saqlain, Akhtar S. and Linshu, H. " Simulation based Optimization Strategy for Liquid Fueled Multi-Stage Space Launch Vehicle", Proceedings of the Sixth International Conference on Parallel and Distributed Computing, Applications and Technologies, IEEE, 2005.
15. Houck, C., Joines, J and Kay, M, "A Genetic Algorithm for Function Optimization: A Matlab Implementation", NCSU-IE TR 95-09, 1995.