SAE 03ICES-004

Automated Determination of Worst-case Design Scenarios

B. Cullimore
C&R Technologies, Inc.

ABSTRACT

This paper describes readily available techniques for automating the search for worst-case (e.g., "hot case", "cold case") design scenarios using only modest computational resources. These methods not only streamline a repetitive yet crucial task, they usually produce better results.

The problems with prior approaches are summarized, then the improvements are demonstrated via a simplified example that is analyzed using various approaches. Finally, areas for further automation are outlined, including attacking the entire design problem at a higher-level.

BACKGROUND

This paper is the final installment of a series on the automation of engineering analysis tasks, with an emphasis on thermal engineering. Reference 1 introduced the importance of parametric modeling, Reference 2 describes the application of optimization technologies to design problems, Reference 3 describes their application to automated calibration ("correlation") of models to test data, Reference 4 introduces means of handling uncertainties and variations statistically, and References 5 and 6 concern the extension of these advanced techniques to multidisciplinary design problems.*

This paper describes the application of statistical sampling and optimization techniques to the automatic searching for worst-case design scenarios. It builds upon a foundation provided in the earlier papers, and concludes with a discussion of revolutionary design methodologies that are possible via the simultaneous inclusion of all such technologies: the elimination of the need to define worse-case scenarios in the first place. Nevertheless, an attempt has been made to make the basic points of this paper accessible without having read the prior papers.

PROBLEM STATEMENT

To produce a design, scenarios are first developed against which candidate designs can be evaluated. For a thermal engineer, this often involves stacking up worst-case environments, performance degradations, property and mission uncertainties, etc. into *at least* two sets: a hot case and a cold case. Often, it is not clear which situation generates the most extreme responses. This lack of a clear-cut scenario is especially common in spacecraft thermal control, where orbital variations, articulating components, and the importance of transient responses confound simplistic approaches. It is also common that simplifying assumptions (e.g., steady-state at subsolar point) result in excessive margin and hence inefficient designs. Furthermore, the worst case for one component is rarely the same as that for another.

In producing a hot case, for example, the engineer sometimes applies conflicting but conservative assumptions such as estimated end-of-life (degraded) optical properties combined with estimated beginning-of-life (undegraded) power generation and dissipation. For orbital environments, it isn't always clear which beta angles (β, the angle between the orbital plane and the sun-planet vector) result in the worst case. Small beta angles maximize planetary heat sources and battery dissipations, while large angles maximize time spent in the sun. In cases where transient effects can be neglected without excessive conservatism, the worst-case position within the orbit (e.g., subsolar, shadow entry, shadow exit, orbital average) must be found for any particular beta angle. Solar panels, antennae, and other payloads sometimes articulate to track celestial or terrestrial targets. Some dissipative components turn on or off at different times in the orbit for different durations, or otherwise exhibit complex duty cycles.

In any reasonably complex design, the determination of an adequately (but not excessively) conservative design scenario is far from trivial. There exist standards for design margin, but no standards or guidelines for determining the cases against which such margins will be applied. The sheer number of cases that must be evaluated overwhelms the computational resources available to the thermal engineer. Worse, almost any change to the design or its mission requires a re-evaluation of the worst case scenarios that were previously chosen.

CURRENT STATE-OF-THE-ART

Because of the difficulty in performing a thorough search for the absolute worst case possible, compromises are often made. For example, worst-case *environments* are often sought instead of the more appropriate criteria: conditions that result in the highest and lowest operating *temperatures*. Such a limited search of heat rates instead of temperatures is still in need of automation, and the methods described in this paper are applicable to that criterion

* Similarly, the approaches outlined in this paper can be easily extended to multidisciplinary worst-case searches (e.g., greatest thermoelastic distortion) by combining them with the techniques described in Reference 6.

as well even though the examples below focus on the more appropriate criterion of peak temperature.

Another common compromise is to use orbital average environments or stationary points in determining the worst case scenario. This greatly reduces the computational burden, such that more points can be searched. Without such an approach, each transient evaluation of a single case not only begins with a steady state, but must execute *at least* two transient orbits in order to “wash out” initial conditions: to arrive at a cyclically converged profile.

Finally, a few organizations have employed a “full factorial” (FF) search: the identification of all significant sources of variation (e.g., beta angle, properties, usage scenarios), and a complete and systematic evaluation of all possible combinations (subject to finite discretization). Such searches are automated by scripting repetitive runs of geometric math models (GMM) and thermal math models (TMM). Using older software that is nonparametric and/or not designed for repetitive analyses, such searches take weeks of computer time and often require specialized equipment such as arrays of parallel processors.

Parametric software (Ref 7) tremendously speeds up this heavy-handed search by avoiding unnecessary preprocessing, recompiling, and even recomputation of previously stored results. Nonetheless, a full factorial search remains an expensive proposition, especially when it must be repeated many times as the design or mission evolves.

Herrera et al (Ref 8) proposed using a Monte Carlo sampling technique to locate the worst-case design scenario. In their sample case, 250 evaluations (sample cases) were tested, each performed using older stand-alone nonparametric software. Therefore, a custom set-up was required: parallel arrays of processors. Even if more modern software had been applied to this case, many more evaluations are usually required for Monte Carlo techniques than 250: usually on the order of 1000. Therefore, such an approach is not significantly different from a full factorial search. Also, both techniques rely on finite sampling and therefore tend to locate a *poor* scenario, but not necessarily the *worst* possible case.

EXAMPLE MISSION DESCRIPTION

As a mechanism for illustrating various points, a sample space vehicle, mission, and thermal model will be employed. This vehicle and its mission were chosen to be generic. They are greatly simplified not only to avoid any issues with classified or proprietary information, but also to be both easy to describe and fast to solve such that comparisons with the current computationally inefficient methods can be made. In fact, *only data relevant to the hot case is provided* to further simplify the presentation. The problems encountered and their solution, however, are common to many spacecraft and indeed many other terrestrial thermal engineering problems.

The following description is therefore relatively terse. The full model can be obtained electronically upon request.
.

The example vehicle consists of a nadir-facing (3 axis stabilized) box in low Earth orbit (300km). The box is an aluminum shell 0.5m x 0.75m x 1m. In the velocity vector (+X axis) is a 0.75m wide by 3m long solar panel that tracks the sun on two axes. Opposite the solar panel (on the trailing side) is a 1m diameter parabolic radar dish that nominally faces the Earth (+Z axis), but that scans +/-30 degrees in the YZ plane. The vehicle can operate at any beta angle (0 to 90). Figure 1 depicts the thermal model of the vehicle in orbit just after it leaves the shadow, with β=30°.

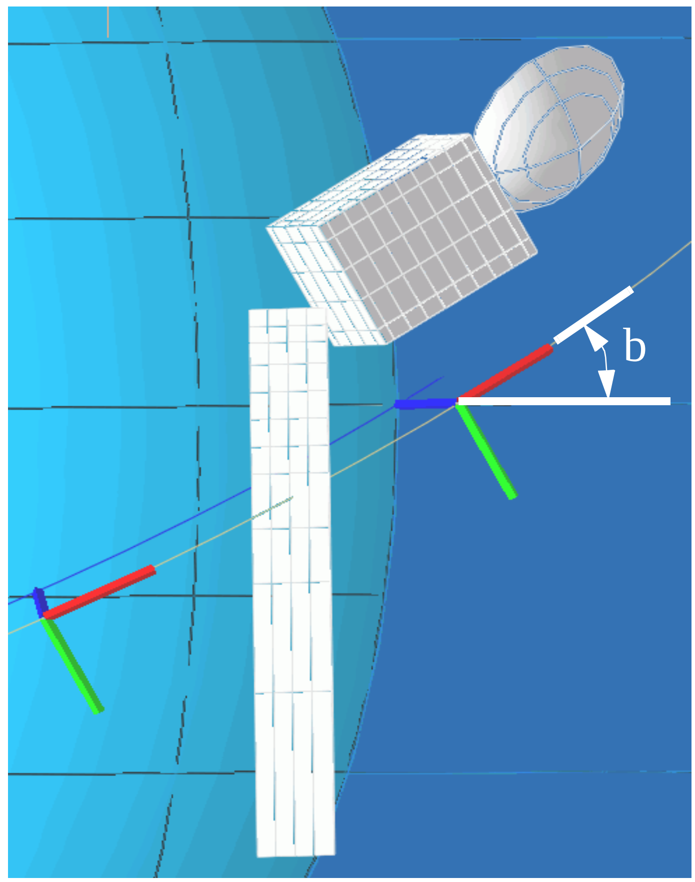

Figure 1: Example Vehicle
for Demonstration of Hot Case Search

The +Y and -Y faces of the box are available (and are fully utilized) as radiators. The remainder is insulated with MLI. The insides of the box (and all components) are painted black.

A “payload component” is located inside the box and is attached to the nadir (+Z) face via a contact conductance of 1000 W/m^2-K. This component dissipates a constant 60W.

A “battery” roughly representative of a single or common pressure vessel (SPV, CPV) nickel-hydrogen cell is mounted on the opposite (-Z) face with the same contact conductance. The battery dissipates 100W while discharging, -20W (endothermic) while charging (the first 1000 seconds after shadow exit), and 10W during a trickle charge (the remainder of the time in the sun).

Figure 2 depicts the vehicle in two different orientations, with different sides of the box removed in each case to show the internal components.

For 10 minutes during each orbit, a 600W dissipation occurs within the box as the vehicle downloads data to a ground location. From an thermal/orbital perspective, the point at which this “download pulse” commences is uncertain: it can start at any time during the orbit.

EXAMPLE VEHICLE THERMAL MODEL

A thermal model was constructed in Thermal Desktop (Ref 7, 9), with SINDA/FLUINT (Ref 10) as the underlying thermal/fluid solution engine (including statistical analysis and optimization drivers).

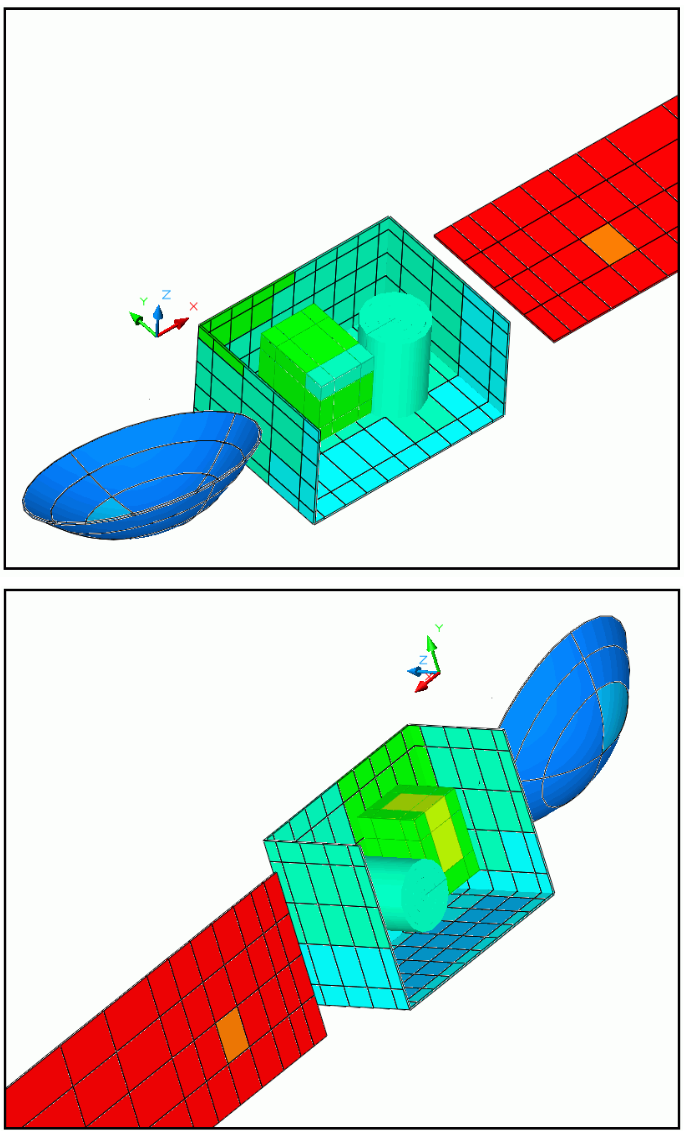

Figure 2: Example Vehicle
(Shown postprocessed, near sides removed to show inside details.)

The resolution of the model is coarse: about 250 nodes. No attempts were made to fine-tune the accuracy and convergence parameters: the defaults were used. Although mixed finite-difference (FDM) and finite-element (FEM) models are possible in Thermal Desktop, the example model used only finite differences because of the simplicity of the surfaces and solids involved.

Because of the mass of the components, a full transient simulation of the orbit was performed and maximum temperatures of each component were tracked. Therefore, each evaluation point consisted of a steady-state using orbital-averages as initial conditions, plus a two-orbit transient. (The use of two orbits was verified to be adequate to extinguish the effects of initial conditions and achieve cyclic convergence.) Only predictions from the final orbit were used in the search for the hottest temperatures experienced by any component.

The average total run time for the evaluation of a single case was about 45 seconds on a 1.8Ghz Intel Pentium® 4. This includes the calculation of radiation factors and orbital environments[*] at 15 orbit positions, recalculation of the conduction/capacitance network including contact conduction, automatic transfer of recalculated data from Thermal Desktop to SINDA/FLUINT, and the execution of the steady state and two-orbit transient integration.

Part of this speed results from the use of parametric tools designed specifically for such repetitions (Ref 5) since such parametric variations are needed for a variety of tasks (sizing, correlation to test data, sensitivity and reliability assessments, etc.). This speed allows almost 100 cases to be tested per hour on a modest single-processor PC. While this model was not honed for speed, a more realistic vehicle model would be much larger. Therefore, the need remains to keep the number of tested cases to an absolute minimum, which is the focus of the remainder of this paper.

PARAMETERS FOR HOT CASE SEARCH

In this simplified example, there are two components of concern: the “battery” and “payload.” Only the hot case will be considered since only one example is needed to illustrate the methodologies available. Obviously, in a real vehicle design many more components and cases would need to be considered, again reinforcing the need for improved methodology and not just faster software or bigger computers.

Similarly, only three parameters will be used to explore the “design space” of the vehicle and mission:

1. the beta angle (β), which is allowed to vary from 0 (largest shadow) to 90 degrees (full sun, no shadow);
2. the scan angle of the radar dish, which can be located up to 30 degrees off nadir (-30 to 30) at any

* using oct-cell accelerated Monte Carlo Ray Tracing to handle specularity

point in the orbit, and is slow enough to be considered stationary in any design case evaluation;

3. the start time of the download pulse, which can occur at any time (between 0 and the orbit period, about 5400 seconds).

The selection of these parameters, the designation of their potential range of variation, and simplifying conservative assumptions (such as not considering the scan angle to change during an orbit) are critical to the success of the subsequent search, and cannot be readily automated: an experienced and careful engineer is still an important ingredient. Removal of other uncertainties from consideration as parameters, such as using fixed end-of-life (degraded) optical properties and maximum possible component dissipations and/or minimum possible efficiencies, keeps the problem from becoming intractable.

FULL FACTORIAL SCAN

As noted above, a "full factorial" (FF) scan means a search made of all parameters, each evaluated at several discrete levels in combination with all other variations. In the example provided, four beta angles of 0, 30, 60, and 90 degrees are evaluated, as are three scan angles of -30, 0, and 30 degrees, and four pulse start times (0, 1600, 3200, and 4800 seconds from the subsolar point). The number of cases to be evaluated at this coarse resolution is 4*3*4 = 48.

Using the dynamic mode in Thermal Desktop and the DSCANFF design space scanner in SINDA/FLUINT, the results listed in Table 1 were produced.

Table 1: Results of Full Factorial Scan

Component	beta angle (deg)	scan angle (deg)	pulse start time (sec)	Peak Temp (K)	Time of Peak (sec)
Battery	60	-30	0	291.7	3525
Payload	90	-30	0	301.8	760

The drawbacks of this simplistic method quickly become clear: the number of cases that must be evaluated grows rapidly for any reasonable resolution of any one parameter or with the addition of any new parameter. For example, to test more beta angles (say 10 values: 0, 10, ... 90) and then to add another parameter with 3 levels raises the number of cases that must evaluated from 48 to 360. Without higher resolution, the engineer risks missing a point of maximum temperature: the true worst case. Therefore, a full factorial search typically requires on the order of 1000 (meaning from 300 to 3000) evaluations for a realistically complex mission.

If a Monte Carlo approach were used, the values of parameters are picked randomly from within their range (usually using a simple uniform probability distribution function--all values are equally likely). A similar order of magnitude of evaluations is required. Therefore, the Monte Carlo approach does not represent any improvement, and has the disadvantage of not checking the boundaries of the problem (i.e., upper and lower limits of all parameters), where the true maxima or minima often exist.

LATIN HYPERCUBE SCAN

Superior alternatives to both the full factorial and Monte Carlo scans exist: descriptive sampling methods such as the latin hypercube method.

The basics of the latin hypercube (LH) method are demonstrated visually in Figure 3. Instead of selecting values of parameters randomly as is done in a Monte Carlo approach, values are selected "descriptively." The resolution of all sampled parameters is the same as the total number of cases evaluated. In Figure 3, a problem with two parameters (A and B) has been sampled with a resolution of 5: five values of each parameter are sampled, but the same value of any one parameter is never tested twice. The cells within the hypercube are themselves chosen randomly,* and nonuniform probability distributions may be used if available.

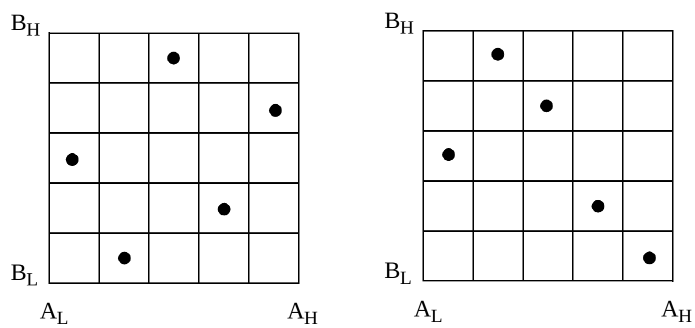

Figure 3: Two Possible Latin Hypercube Samplings of a Two Dimensional Design Space with a Discretization Level of Five

When used for gathering statistical information, LH descriptive sampling is approximately 5 to 10 times more efficient than Monte Carlo sampling (as can be verified using the DSAMPLE vs. SAMPLE reliability evaluation routines in SINDA/FLUINT). In other words, the same level of accuracy can be gained in only 10% to 20% of the evaluations needed by the Monte Carlo (and presumably the FF) search methods. This means use of the LH method cuts the order of magnitude of evaluations needed for realistic worst-case searches from 1000 to about 100.

To illustrate this point, an LH scan of the example problem was made to determine the hot case, using a resolution of 20 in the SINDA/FLUINT DSCANLH utility: twenty total evaluations were made, with each parameter tested once

* Variations of the LH method exist in which cells are chosen deterministically. For example, in a "space filling" LH method, cells are chosen such that distances between cells are maximized.

at 20 different values. For example, tested beta angles were 2.25, 6.75, 11.25, ... 87.75). The results are presented in Table 2: better answers are obtained using a fraction of the cost of the FF scan.

Table 2: Results of Latin Hypercube Scan

Component	beta angle (deg)	scan angle (deg)	pulse start time (sec)	Peak Temp (K)	Time of Peak (sec)
Battery	47.25	-1.5	1088	291.8	3683
Payload	78.75	13.5	122	303.0	880

Some important general conclusions are now possible. First, the scan angle is really not a relevant parameter: changes in the position of the dish have only a small effect on the temperatures of components within the spacecraft box because insulation exists on the side of the box facing the dish. Beta angle is the most important parameter, and the pulse start time is intermediate in importance.

The main advantage of the LH method over the FF method is that important parameters are sampled at maximum resolution, while the inclusion of unimportant parameters does not significantly increase the cost of the search. In other words, the inclusion of the unimportant scan angle didn't prevent the LH method from out-sampling the FF method on more important parameters such as beta angle, and therefore it found a better answer in a shorter time.

This advantage is reduced, however, if there are many important and independent parameters. Nonetheless, in such cases LH methods can be used to help identify which parameters to include or exclude from more narrowly focussed FF or Monte Carlo scans.

OPTIMIZATION APPROACH

A drawback to any sampling method is that it cannot obtain the absolute maximum or minimum temperature of any component: its accuracy is subject to the resolution chosen. This means that there is a relationship between the cost of the solution and its accuracy. This conclusion is so common in engineering analysis problems that it might at first seem strange that an alternative exists whose cost is not strongly related to its accuracy: optimization technology.

As the name implies, optimization algorithms can be applied to automating the search for more efficient or less costly designs, as discussed in Reference 2. However, many other problems can be cast as optimization problems. For example, "find the values of uncertainties that minimize the difference between test data and model predictions" represents the application of optimization technology to the automation of test data calibration or "correlation" (Ref 3).

Analogously, optimization technology can be directly applied to automate the search for the worst-case design scenarios: "find the values of beta angle, scan angle, and pulse start time that maximize the peak temperature experienced by the battery."

The SINDA/FLUINT Solver module (Ref 10) and other off-the-shelf commercial packages (including the Solver module in Microsoft Excel®) are therefore directly applicable.

As applied to the example problem, the user chooses the beta angle, scan angle, and pulse start time as *design variables* and chooses either the battery or payload peak temperature as the *objective* to be maximized (or minimized for the cold case). Starting from a user-selected point, the Solver takes about 20 to 100 evaluations to find the maximum or minimum.

There are three main drawbacks of using only optimization methods. First and foremost, the optimization has to be repeated for every component of interest. For this example problem in this paper, this means only two Solver calls are needed, but in a more realistic vehicle and mission, the number of optimization runs might increase intractably. By way of comparison, recall that a single statistical run (whether LH, FF, or Monte Carlo) can return worst-cases for all equipment simultaneously.

The second and third drawbacks have the same root cause (and the same solution, as will be presented later). It is difficult to predict ahead of time how many evaluations will be needed, in part because the user may not have specified a good starting point. The third and more worrisome drawback is that local minima or maxima may exist. The Solver, like most optimization algorithms, may stop and declare success at a point that doesn't represent the worst possible case, simply the first one it found: results are sensitive to the starting point.

It should be noted that most engineers new to optimization are overly concerned with this issue (i.e., local minima/maxima) for most other applications. The traditional application to design optimization, for example, rarely encounters this problem because such design problems (e.g., sizing, locating, etc.) are highly constrained and start from reasonable points. The "local minima" concern *is* relevant, however, for both worst-case searching and calibration to test data since they are both usually unconstrained. In fact, the problem is most acute for worst-case searching since there is no good starting point: the whole purpose of automating a search is that the topology of the design space is poorly known ahead of time.

HYBRID METHOD

The second and third drawbacks of the optimization approach are both related to the selection of a poor starting point, and this problem can be readily addressed by a simple hybrid method: using a low-resolution latin hypercube scan to pre-search the design space for a good starting point for the optimization engine. In SINDA/FLUINT parlance, simply call DSCANLH (once) immediately before calling SOLVER (one or more times per component).

To demonstrate, when the results of Table 2 are used as the starting point for an optimization-directed search, the best-yet worst cases are found, as reported in Table 3. To achieve these results took 25 evaluations for the battery, and 62 for the payload (more were required for that component because of the nature of that maximum, which is discussed later). Note that a much more coarse LH search could have preceded such an optimization: a resolution of 10 would have sufficed as well, although a trade-off clearly exists between better starting points (greater LH resolution) versus more time spent in the optimization search.

Table 3: Results of Hybrid LH/Optimization Method

Component	**beta angle (deg)**	**scan angle (deg)**	**pulse start time (sec)**	**Peak Temp (K)**	**Time of Peak (sec)**
Battery	47.9	0.8	1276	292.1	3678
Payload	73.5	17.3	7.1	303.7	774

RESULTS DISCUSSION

Given that the hybrid method produced the best answers at an efficient cost (and is hence the recommended general-purpose strategy), the results in Table 3 will be treated as conclusive. Therefore, a brief review of those results will be made for the example problem before returning to the topic of search methods.

As was noted before, the importance of the scan angle is minimal: it could effectively be removed as a search parameter without causing much difference in the results. The beta angle is more critical, which is usually true in orbital spacecraft design.

The peak temperature for the payload (Figure 4) occurs in almost full sun (meaning β=90°), except that radiative cross-communication with the battery means that the payload temperature is maximized when the battery is also at least a little active: high β, but less than 90°. In full sun, the battery dissipation reduces to a small trickle charge of 10W, versus an orbital average of about 40W when shadow is encountered and the solar panels shut down, requiring battery assist. This “just a modest shadow” result is what caused the Solver to take more evaluations for the payload than for the battery. The worst-case time for the download pulse to occur is near the subsolar point from the perspective of the payload, since that coincides with its highest temperature already.

The worst case for the battery (Figure 5) occurred at a lower beta angle: an angle where the battery was more active but still a little more sun reached the radiators than would occur at β=0°. (At β=0°, the radiators see no sun and only planet shine.) Also, the worst time for the download pulse to occur from the point of view of the battery was near shadow entry.

Are these results obvious in retrospect? And if so, does this render an automated search useless?

The author believes the answer to the second question is “no.” Even if the results were obvious *in advance*: “obvious” to one engineer may not be so obvious to another (perhaps a customer!), so having a numerical study to support strong intuition is usually welcome. Indeed, it is mandatory to apply scepticism and intuition to the results of a numerical study before they can be trusted. In other words, *each method is not trustworthy if used alone*: both are needed to confirm each other. More pragmatically and less philosophically, being able to trivially rerun an automated search each time conditions or designs change has definite value.

ADVANCED TECHNIQUES

Further refinements of the search algorithms are possible, but have not yet been explored nor implemented.

A near-term enhancement would be to interject a Response Surface Model (RSM, Ref 11) after the LH scan. An RSM is a simplified representation of the design space,

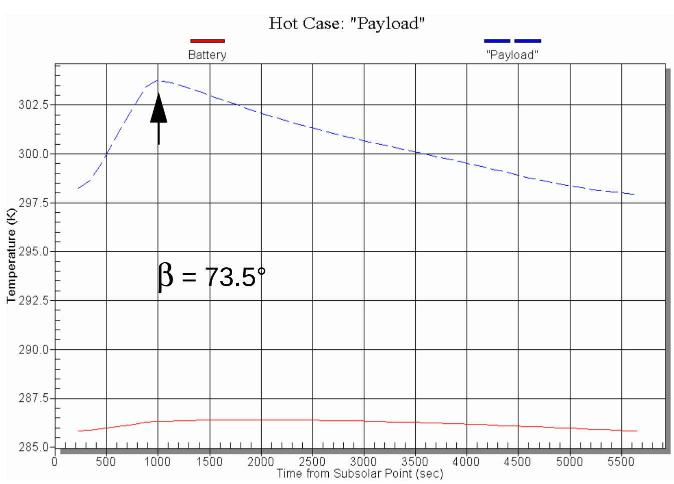

Figure 4: Hot Case Orbital Temperatures of “Payload”

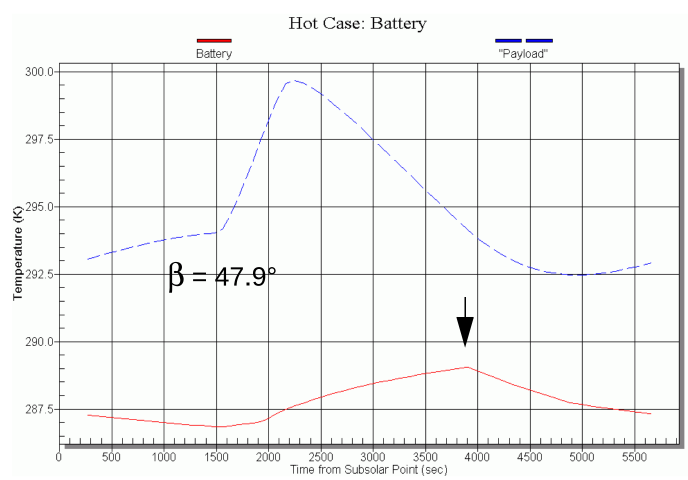

Figure 5: Hot Case Orbital Temperatures of Battery

often in the form of a polynomial "curve fit," that can be used to rapidly search for an optimum solution without further costly thermal simulations. In other words, data from the LH scan can be used to arrive at an approximation of the problem, which can be used to find an optimum, which can in turn either be used as a final product or as an even better starting point for a full optimization search.

Other enhancements are more revolutionary. For example, instead of using uniform probability distributions, each parameter can be sampled based on an underlying probability. For example, if the radar dish in the example problem were to execute a slow sinusoidal sweep, it would spend very little time pointing directly at the Earth and more time at the extremes: the likelihood of the scan angle assuming any one value is not the same as another value. Such an enhancement is relatively easy to accommodate, providing such statistical information is available or can be easily produced.

An even more revolutionary approach is to dispense with a separate, distinct, worst-case search: to fold the uncertainties and variations in environment and usage into the production of the design itself. In other words, dispense with the traditional approach of margin stack-up and worst-case development in favor of optimizing a design based on overall reliability. Refer to Chapter 5 of Ref 10 for more details. Such an approach eliminates both over and under design: it avoids, for example, designing for a condition that is nearly impossible to encounter and focuses instead on more realistic (and therefore probable) scenarios.

Unfortunately, reliability-based design synthesis is still computationally intractable for realistically complex problems. Its implementation also requires a change in infrastructure, mindset, and perhaps even military and commercial standards. Although it is being applied more and more in limited situations (Taguchi Robust Design and Six Sigma, for example: Ref 12, 13), it remains a technology for the future. Nonetheless, it is important to maintain ideals and to work steadily and patiently toward them.

CONCLUSIONS

Methods and algorithms for automating the search for worst-case design scenarios have been presented using a simplified sample case. A relatively simple and efficient hybrid method has been recommended that greatly reduces the required number of design point evaluations.

This approach is already available in prepackaged form in commercial off-the-shelf software. However, it could also be scripted relatively easily in order to be applicable to other thermal analysis software, even if computational efficiency were sacrificed by iteratively re-executing such software.

Alternatively, one could employ high-resolution latin hypercube scans alone (versus hybrid methods requiring an optimization engine). This approach makes automated search technology accessible to a wider audience. Even though it represents a compromise, it is certainly preferable to the prior state-of-the-art.

REFERENCES

1 B. Cullimore, "Optimization, Data Correlation, and Parametric Analysis Features in SINDA/FLUINT Version 4.0," SAE 981574, ICES, July 1998.

2 B. Cullimore, "Nonlinear Programming Applied to Thermal and Fluid Design Optimization," ECTC/ITHERM, May 2002.

3 J. Baumann et al, "Nonlinear Programming Applied to Calibrating Thermal and Fluid Models to Test Data," SEMI-THERM, March 2002.

4 B. Cullimore, "Dealing with Uncertainties and Variations in Thermal Design", IPACK2001-15516, InterPack '01 Proceedings, July 2001.

5 B. Cullimore et al, "Integrated Analysis of Thermal/Structural/Optical Systems," SAE 2002-01-2444, July 2002.

6 B. Cullimore et al, "Automated Multidisciplinary Optimization of a Space-based Telescope," SAE 2002-01-2445, July 2002.

7 T. Panczak et al, "A CAD-based Tool for FDM and FEM Radiation and Conductor Modeling," SAE 981577, International Conference on Environmental Systems (ICES), July 1998.

8 F. Herrera and A. Sepúlveda, "Stochastic Approach to Spacecraft Thermal Control Subsystem," SAE 2000-01-2484, July 2000.

9 T. Panczak et al, "Integrating Thermal and Structural Analysis with Thermal Desktop," SAE 1999-01-2126, ICES, July 1999.

10 SINDA/FLUINT User's Manual, available in PDF at www.crtech.com

11 R. Myers and D. Montgomery, Response Surface Methodology, Second Edition (2002), John Wiley & Sons, Inc.

12 G. Taguchi et al, Robust Engineering, First Edition (1999), McGraw-Hill Professional.

13 D. H. Stamatis, Six Sigma and Beyond: Design of Experiments, Volume V, First Edition (2002), Saint Lucie Press.

DEFINITIONS, ACRONYMS, ABBREVIATIONS

CAD.................. Computer Aided Design
CPV.................. Common Pressure Vessel
FDM .... Finite Difference Modeling
FEM.................. Finite Element Modeling
FF..................... Full Factorial
GMM .... Geometric Math Modeler (e.g., RadCAD®)
LH..................... Latin Hypercube
MLI .... Multilayer Insulation
PC .... Personal computer (e.g., Intel Pentium® class)
RadCAD........... Radiation analyzer in Thermal Desktop
RADK .... Radiation conductor (network element)
RSM .... Response Surface Model

SINDA/FLUINT Thermal/fluid analyzer from C&R Technologies

SINDA.............. Thermal side of SINDA/FLUINT

SPV .... Single Pressure Vessel

Thermal Desktop®......... CAD-based FDM/FEM thermal modeling environment from C&R Technologies

TMM .... Thermal Math Modeler (e.g., SINDA)

CONTACT INFORMATION

C&R Technologies, Inc.
URL: .... www.crtech.com
Voice:............... 303 971 0292
Fax:.................. 303 971 0035