

# Satisficing in Computational Electromagnetics

Hugh Sasse and Alistair Duffy  
De Montfort University, Leicester  
[hgs@dmu.ac.uk](mailto:hgs@dmu.ac.uk), [apd@dmu.ac.uk](mailto:apd@dmu.ac.uk)

## Introduction

Nevil Shute said “An engineer is someone who can do for ten shillings what any fool can do for a pound” [1]. This doesn't only imply ingenuity, it implies being able to perform trade-offs. Where these trade-offs are not adequately performed leading to a product with a better specification than needed, we often refer to the system as “Over-engineered”. Engineering can be said to boil down to solving practical problems within the constraints specified by the problem itself, including factors such as time constraints and limitations on costs. Of course, in Nevil Shute's time, finite element analysis and computational fluid dynamics were still some years away. However, they are commonplace in mechanical systems design these days. Most engineering calculations were done with slide rules, with the inherent approximations and inaccuracies, because the costs in time in doing precision arithmetic were prohibitive. Yet, this was generally good enough.

Considering another example which suggests that the optimum engineering solution is not the most appropriate systems solution: ‘ “We work to a spreadsheet where there is a bottom line on what we had to meet,” says Brooks, whose iRobot company worked with Hasbro on the interactive doll My Real Baby. The goal was to make the doll as lifelike as possible, but if a component cost a penny too much the bean-counters vetoed it-even if it would have made a big difference to performance. “This almost made some of the engineers cry,” Brooks says.’[2]

What we do, pretty much every day, is to set up models or measurements that are good enough, trying to resist the urge to over-engineer. This is captured by the concept of “satisficing” which starts to give a framework for rigor in deciding on these trade-offs.

So, what is satisficing? When searching for a solution to a problem there is an expectation that the solution will be the optimum solution. Sometimes this is not practical, and we must be satisfied with “good enough”: something that meets the minimum requirements but perhaps not much more. Satisficing embodies this idea, and carries with it the implication that it is no bad thing to meet the minimum need and not necessarily the optimum solution to all requirements. Optimality is not always mandated. A concept which is familiar to most people is that cost increases with search space: if you have a short time to shop you may well be satisfied with a purchase quality that could be improved on if more time was available. Satisficing behavior would be to stop at the first "good enough" product, where as optimizing behavior would be to shop until all the time was expended, except that needed to go back and purchase the best product. One hears of people "going beyond the call of duty". The ‘call of duty’ would have been good enough but this person went beyond that? Clearly one's duty in this case is less than the optimal behavior [3].

An optimizing strategy can, ironically, be suboptimal: improving the performance of a product may delay its roll-out. However, time to market may well make the difference between your product getting market share and someone else's getting market share, i.e. missing first mover advantage. Whereas a satisficing (good enough) strategy would produce much better returns overall.

In chapter 15 of [4], in which the term "satisficing" was coined, it is argued that a complex algorithm need not exist to achieve satisficing behavior. This article aims to look at satisficing from the standpoint of CEM and suggest a relatively simple strategy for realizing a satisficing approach to simulations, which encourages all parties involved in the modeling to understand the assumptions, constraints and limitations involved in getting it "good enough"

### **In EMC Veritas.**

How can satisficing be used in EMC work? Firstly, there are a number of areas where time/cost tradeoffs occur, and we must decide how to meet those constraints. For example, when considering product design we must understand how the product, whatever it may be, will behave in susceptibility and emissions terms, and we must therefore have a good enough understanding of this to allow our design to meet the various national or international directives. We could optimize our simulations for best attainable accuracy, or we could just make them sufficiently accurate for the task in hand. Here we run into semantics: what do we mean by sufficiently accurate? "Truth? What is that?" is a question that goes back at least two millennia!

Stirling [5] describes how searching for an optimum value is a global search, requiring knowledge of the whole space of possibilities. This is described as "substantive rationality", and given a tractable mathematical model of the system being explored, the optimum is provably the best. He goes on to say that this is not the only way to decide what is acceptable. In "procedural rationality" an algorithmic approach to finding a solution is used. Thus, rather than analysis, search is used. For example, one may use hill climbing, the simplex method, simulated annealing, genetic algorithms, or particle swarm optimization to obtain an acceptable solution. Given that all these methods involve exploration of the solution space to find an acceptable solution, rather than direct derivation of the solution, it is possible, and for complex systems even likely, that a better solution can be found. However, since the search process justifies the choice in terms of meeting the criteria, the resulting solution is still acceptable.

There are systems where it is not possible to derive a tractable equation for the system to be analyzed, but a solution can be recognized relatively easily. This is the case where simulations or experiments are used to determine the acceptability of a system's configuration. Usually there is some high dimensionality (many degrees of freedom) in the problem domain that would make derivation impossible. Given the number of wires in the wiring loom of a vehicle, for example, the number of possible layouts is enormous. Even in something as apparently simple as modeling twisted pair cabling, performing an analytical assessment of the costs of materials and technical performance for something with an elliptical cross section is nontrivial.

Simulation is standard practice in many fields of engineering. In electromagnetics it is clearly cheaper to compute results than to actually cut metal and try things out and can provide a better insight than possible with measurements alone. But accepting this state of affairs begs the question: are the simulations themselves satisfactory? How good do they need to be, and how much can we reduce the computational time and thus the cost in order to get a satisfactory answer?

### **How to Satisfice**

The need for satisficing behavior has been argued, but the above discussion does not suggest how to apply this. In contrast there is much information about how to apply optimization strategies. So, the following is presented in order to partially redress this imbalance.

**1. Consider what the goals of the activity (experiment, simulation) are.** A reverberation chamber problem may be to "determine the working volume and stirring ratios within a given chamber for a specified stirrer".

**2. Determine the range of parameters and associated collection of values that must be met for those goals to be satisfied.** This is akin to determining the region in which solutions lie when doing linear programming. An example might be:

- What simulation method is going to be used, or what range of techniques are available to use (e.g. a member of the set {TLM, BEM, MOM, FDTD})?
- How many computers are there on which we may simultaneously, or in parallel, run simulations?
- What is the available memory?
- What time is available to undertake the simulations? This is, of course a function of other aspects of the model – in the reverberation chamber example this may be a function of modeled time, stirrer positions and frequency resolution
- What accuracy is required of the model? For example how coarse can we accept stepped angular surfaces, what details can be excluded, how accurately is the modeling of material properties required.
- Are there a number of different geometries required for the system? For example, how many stirrer positions are required in the simulations and experiments?

Applying a satisficing approach to the reverberation chamber modeling problem, the criteria above lead us to decide that we will use TLM (we have the software), on one computer (we only have a commercial license for the one machine), that machine has only 1GB of memory, we can only really afford one day for each geometry because we have several to do, and these constraints are the dominant parameters which determine the other parameters. This gives a rational basis for how we proceeded, but other researchers, with different facilities, would proceed differently. In such a case they would be able to supply critique (validation) of our results (how things perform with more or less memory, whether other simulation techniques support this, etc.) We also decided that the level of agreement we were prepared to accept was "fair" because of the simplifications imposed by the above constraints. This term was made numeric using the Feature Selective Validation (FSV) method. Thus, we also established what we meant by satisfactory agreement, in a form which is reproducible and can be communicated to all parties involved.

**3. Use “Five Whys” to explore these reasons in depth.** “Five Whys” is the practice of mining into actual reasons for a decision by iterating "Why?" about 5 times.

**4. Iteratively create models and dry-run them to see if they meet the constraints, on a "Go"/"No Go" basis before proceeding with the actual simulation.** Effectively asking whether the constraints have been met or whether the solution is ‘over engineered’.

Where is the satisficing activity in this? It is actually in the setting of the criteria and in the "Go"/"No Go" decision. This is the simple system used by Simon [4] in his organism model. An organism requiring food (and possibly water, and other necessities) explores an otherwise featureless landscape, using energy from the food to traverse the space. The food is randomly distributed through the space in random sized heaps, and it finds these visually provided they are near enough to the organism. It sleeps if sated. Simon is able to show that without optimization, the visual range of the organism and its ability to store the energy are the main constraints on its survival, that it has a high probability of survival for reasonable values of these constraints, and that with low energy storage the resource must be plentiful. He gives the example of the abundance of oxygen and the continual need to breathe. Perhaps this accept/reject non-optimizing strategy seems too simple to work. However, Simon shows that meeting the criteria satisfices the need of a simple organism to survive, which is the acid test. In chapter 14 of the same work, Simon explains how this "Go"/"No Go" may be a dynamic function, dependent on information gathered during exploration. For example, if solutions seem to be rare, it may be pragmatic to accept what is available. However, if there are many solutions evident, one may be more discerning.

## **Discussion**

Trading off variables to achieve a workable solution has been a mainstay of engineering practice, so in that sense "satisficing" is nothing new. Also, in the sense that the term has been around since about 1957, it is not itself new. However, with the emphasis in the recent past being on optimization, satisficing is worth considering more closely, principally because of its inherent contribution to cost savings whilst meeting the real constraints. This would seem to tie in with Lean Engineering practice, and thinking tools from the Theory of Constraints [6]. Having a word for this activity aids in its formalization. Formalization, in turn, enables people to discuss this implicit part of engineering practice, making assumptions and decisions explicit, and available to be challenged, re-evaluated, and shared more freely and objectively. An optimum solution may be the result of the search for a satisficing solution, but the search for an optimum solution would probably reject one that is actually 'good enough'.

## **References**

[1] Nevil Shute, "Slide Rule: The Autobiography of an Engineer" William Heinemann, London. 1954

[2] Duncan Graham-Rowe, Ben Crystall, Graham Lawton, "Jobs for the bots", New Scientist, 10 February 2001, pp26-35

[3] Michael Byron "Satisficing and Maximizing: Moral Theorists on Practical Reason" Cambridge University Press 2004

[4] Herbert A. Simon, "Models of man : social and rational : mathematical essays on rational human behavior in a social setting" Chapman & Hall, 1957

[5] Wynn C Stirling "Satisficing Games and Decision Making (with applications to Engineering and Computer Science)" Cambridge University Press 2003

[6] Eliyahu M. Goldratt, Jeff Cox, "The Goal", North River Press; 3rd edition (July 2004)