Comments on *"A Response to Prof. Sniedovich"* (Ben-Haim, April 10, 2007)

1. I am very pleased with your reponse. Your explanations and comments confirm the validity of my assessment of Info-Gap as a methodology for decision making under severe uncertainty.

2. Your comments do not support your claim that I am mistaken in the interpretation. To the contrary, they support my claim that Info-Gap's uncertainty model is fundamentally flawed. To wit:

   (a) We agree that the robustness deployed by Info-Gap is local in nature and is defined in terms of the immediate neighborhood of an estimate $\tilde{u}$ of the true value of u.

   (b) We agree that under severe uncertainty this estimate is a poor indicator of the true value of u and is likely to be substantially wrong.

   (c) We thus also agree that given this state of affairs there is no reason to believe that the solution generated by Info-Gap is likely to be robust in the neighborhood of the true value of u.

   (d) We agree then that graphically the picture is this:

   (e) The conclusion is therefore that Info-Gap's uncertainty model is fundamentally flawed: it does not deal with severe uncertainty, it simply ignores it[1]. The picture above speaks for itself.

3. Your assertion that Info-Gap theory does not claim that the solutions it generate are robust is, in the very least, strange. In Ben-Haim [2001] you bestow the impressive title "**robust-optimal**" on these solutions. For example, in Ben-Haim[2001, p. 41, below eq. (3.19)] you write:

   Let $\mathcal{Q}$ be the set of all available or feasible decision vectors q. A **robust-optimal decision** is one which maximizes the robustness on the set $\mathcal{Q}$ of the available q-vectors. We denote the **robust-optimal action** by $\hat{q}_c(r_c)$, noting that usually the **robust-optimal action** depends on the critical reward. $\hat{q}_c(r_c)$ is defined implicitly from the following optimization

   $$\hat{\alpha}(\hat{q}_c(r_c)) = \max_{q \in \mathcal{Q}} \hat{\alpha}(q, r_c) \tag{3.20}$$

   Similarly in Ben-Haim [2001, p. 75, below eq. (3.125)] we find:

   The **robust-optimal investment** for critical reward r_c is the vector q which maximizes $\hat{\alpha}(q, r_c)$, as in eq (3.20) on page 41.

   The situation is similar in Ben-Haim [2006] except that the term "robust-optimal" is replaced by "robust-satisficing".

   Similar statements are found in your lecture notes and presentations[2]. Not surprisingly, other users of Info-Gap also claim that the solutions they obtain are robust!

   In short, contrary to your claim, the fact is that Info-Gap goes out of its way to stress that the solutions it generates are robust. Perhaps this is due to a badly chosen terminology, but the fact remains ...

4. The question regarding the magnitude of the robustness – whether it is small or large – is another issue altogether. Note that since Info-Gap evaluates the robustness in the neighborhood of a poor estimate of u, we are still in the dark with regard to the unknown "true" robustness, namely the robustness in the neighborhood of the true value of u. Thus, the fact that the robustness generated by Info-Gap is large/small does not mean that the true robustness is large/small. So what is the point here?

[1] Indeed, Info-Gap's uncertainty model does not model uncertainty as such. It represents nested neighborhoods around a given value of the parameter under consideration. You can conduct this analysis even if the exact (true) value of u is known with certainty.

[2] Eg. one of your workshops was entitled "*Info-gap analysis of engineering systems: robust decisions under severe uncertainty*".

5. I am not suggesting that conducting robustness analysis around a poor estimate of the true value of the parameter of interest is totally useless. I merely indicate the obvious: (i) all that Info-Gap does is exactly this and (ii) this is a far cry from providing a methodology for dealing with decision making problems under severe uncertainty, which is what Info-Gap claims to do.

6. That is, Info-Gap is fundamentally flawed because it ranks decisions based on robustness and performance analysis conducted only in the immediate neighborhood of a poor estimate that is likely to be substantially wrong.

7. Your interpretation of the term "point estimate" is mistaken, hence your conclusion is not valid. In the context of this phrase the word "*point*" means "*an element of the topological space under consideration*". This is a standard interpretation.

   The issue that I raised in my analysis is valid: the generic Info-Gap model deals exclusively with a single point estimate of the parameter of interest and its immediate neighborhood (see Appendix).

8. Your comments regarding "optimizing vs satisficing" are based on misconceptions concerning the modeling aspects of optimization problems. It is well known that any satisficing problem can be stated as an **equivalent** optimization problem (Sniedovich [2006]). Thus, the Info-Gap *Satisficing is better than optimizing* campaign is pointless: it is a matter of style rather than substance. What is important is what you try to optimize and what you try to satisfice and this must be in line with the decision maker's goals, objectives and constraints (see Appendix).

   In any case, Info-Gap attempts to maximize robustness, and this is optimization par excellence.

9. Your comment on Ben-Tal and Nemirovski's work, and Robust Optimization in general, is long overdue. Indeed, it is very odd that the Info-Gap literature is completely oblivious to this well established and very relevant area of optimization theory. As I indicate in my paper:

   > It is unfortunate that Info-Gap seems to be unaware of the extensive body of knowledge available in this area of optimization, which is very relevant to what Info- Gap is attempting to do.

10. It is even more unfortunate that Info-Gap is unaware of the fact that its generic model is a simple instance of Wald's [1945] famous Maximin model (see more on this in Sniedovich [2006]).

In summary then,

A. Info-Gap does not deal with severe uncertainty, it simply ignores it. Conceptually, this involves two ingredients:

   – Replacing severe uncertainty by a poor estimate of the true value of the parameter of interest.
   – Conducting a vanilla Maximin-type worst-case analysis in the neighborhood of the estimate.

B. Info-Gap's preference model ranks decisions on the basis of robustness evaluated on the immediate neighborhood of a poor estimate that is likely to be substantially wrong.

C. This amounts to practicing voodoo decision making under severe uncertainty in broad daylight.

D. Hence, Info-Gap's uncertainty model is fundamentally flawed in the framework of decision making under severe uncertainty.

E. There is no ground to Info-Gap's assertion that the solutions it generates are robust.

F. Info-Gap's "satisficing is better than optimizing" campaign is counter-productive.

G. More details on discrepancies between what Info-Gap claims it is and does and what it actually is and does can be found in the paper *What's wrong with Info-Gap? An operations Research perspective.* A copy of this paper is available on my website at

`www.ms.unimelb.edu.au/~moshe/frame_maximin.html`

Moshe Sniedovich
April 22, 2007

Appendix

1. Point Estimate

In the context of Info-Gap, a point estimate of u is simply an element of the assumed uncertainty region, $\mathcal{U}$. Thus, even if $\tilde{u}$ is a function, say a pdf, it is still a **point estimate** of the true value of u. The fact that in some applications this estimate is actually a function or a set, does not change fact that Info-Gap's uncertainty model is based on a single point estimate and its immediate neighborhood.

This is in sharp contrast to how things are done in say, Robust Optimization, where it is recognized that it is important to base the analysis on a relatively large number of point estimates (scenarios), properly spread over the entire region of uncertainty.

And given that Info-Gap is just a simple instance of Wald's Maximin model, the following tip (quoted in Sniedovich [2006]) is relevant here:

> If the forecaster tries to specify too many discrete forecasts, in an attempt to cover most possibilities, discrete minimax may yield too pessimistic strategies or even run into numerical, or computational, problems due to the resulting numerous scenarios. Similarly, as the upper and lower bounds on a range of forecasts get wider, to provide coverage to a wider set of possibilities, the minimax strategy may become pessimistic. Thus, scenarios have to be chosen with care, among genuinely likely values. The minimax strategy will then answer the legitimate question of what the best strategy should be, in view of the worst case.
>
> Rustem and Howe [2002, p. xiii]

So how should we judge a methodology for decision making under SEVERE UNCERTAINTY that is based on a SINGLE POINT ESTIMATE that is likely to be SUBSTANTIALLY WRONG? I argue the obvious: we should note that the methodology in question does not deal with severe uncertainty – it simply ignores it.

2. Satisfice vs optimize

Info-Gap's *Satisficing is Better than Optimizing Campaign* is counter-productive. The same problem can be formulated in various (equivalent) ways and the choice is a matter of style rather than substance.

Take for example the very simple game defined by a pair $(\mathcal{Q}, s)$ where $\mathcal{Q}$ represents the set of available decisions and s is a real-valued function on $\mathcal{Q}$ stipulating the score associated with decision $q \in \mathcal{Q}$. Assume that you win the game if and only if the decision $q \in \mathcal{Q}$ you select is such that $17 \leq s(q) \leq 21$.

In this case the problem associated with winning the game can be described by the following simple satisficing problem:

$$\textit{Satisficing Problem:} \quad \textit{Find a } q \in \mathcal{Q} \textit{ such that } 17 \leq s(q) \leq 21 \,.$$

Obviously, in general, a winning decision is not necessarily one that optimizes the score $s(q)$ over $\mathcal{Q}$. That is, to win the game you do not have to optimize (minimize or maximize) your score. In fact, if you do this you may lose the game.

But this does not mean that you cannot formulate the very same game as an optimization problem. To show how easily this can be done, let

$$w(q) := \begin{cases} 1 & , \quad 17 \leq s(q) \leq 21 \\ 0 & , \quad \textit{otherwise} \end{cases} \quad , \; q \in \mathcal{Q}$$

and consider

$$\textit{Optimization Problem:} \qquad w^* := \max_{q \in \mathcal{Q}} w(q)$$

Clearly, a decision $q \in \mathcal{Q}$ is a solution to the satisficing problem if and only if it is an optimal solution to the optimization problem. Thus, the two problems are equivalent.

This is not an accident. It is well known that for any satisficing problem there is an equivalent optimization problem. And the good news is that the construction of such an equivalent optimization problem is a straight forward exercise (see Sniedovich [2006]).

There are many advantages – and some disadvantages – to formulating a decision problem as an optimization problem rather than as a satisficing problem. Be it as it may, the claim that satisficing is better than optimizing is ridiculous.