WHEN THE OBVIOUS IS NOT OBVIOUS: USING MULTIRESOLUTION MODELING TO DISCOVER HIDDEN FACTORS IN DECISION MAKING

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Abstract
This paper addresses a method for multiresolution modeling that uses flexible and scalable variable-fidelity models to provide insight into highly dimensional multi-objective problems. The authors advocate the use of Quick Understanding, Evaluation, and Synthesis Tools (QUESTs) to visually interrogate a complex decision space, understand sensitivities to assumptions, and discover the hidden factors that are often critical to the decision making process. These QUESTs are an integral component within the continuum of modeling tools that integrates subjective estimates with back-of-the-envelope estimators, first-order physics-based simulations, and higher-fidelity simulation tools encapsulated within surrogate models that are used to fully explore the design and decision space. This paper will demonstrate how these hidden factors, elucidated through the proposed approach, often have a far greater impact on the design of complex systems than the physics-based parameters that are "obvious" through engineering intuition. Several case studies are reviewed and used to demonstrate the proposed methodology.

1 Introduction

Decision making is a part of politics, engineering, intelligence analysis, and everyday life. The confluence of increasing computer power and the maturation of analytic design tools drives many organizations to seek increasing quantitative, physics-based modeling to support a sound decision making process. A number of increasingly complex modeling techniques including scenario analysis, constructive simulation, agent-based modeling, system dynamics, and discrete event simulation have been used in recent years to solve a number of increasingly complex problems. Unfortunately, large-scale high-fidelity simulations are not a universal solution. Developing a simulation to provide decision support to major defense acquisitions, military operations, or technology investment is often too cumbersome, expensive, and time consuming for practical applications.

On the other hand, qualitative assessments that include back-of-the-envelope calculations, rules-of-thumb, the Delphi method, the Analytic Hierarchy Process (AHP), and dozens of other expert-driven decision making techniques offer a less rigorous but more practical decision aid. Unfortunately, these approaches are often inappropriate for "real" problems because they oversimplify non-linear behavior and are driven by a number of tacit assumptions that are never stated or discussed by the expert group. Considerable effort is often spent debating between these classes of modeling approaches, choosing the "right" model, building models, executing simulations, and analyzing results; however, little attention is given to *clearly stating the problem in a standard, well-defined form.*

This deficiency can often be traced to "hidden factors" – that is, the set of key factors influencing a decision process that are initially overlooked but become obvious only after significant consternation and considerable investigative and deliberative effort. The purpose of this paper is to highlight common mistakes in decision making and propose a multiresolution modeling approach to uncover these "hidden" factors early in the design process. Before applying modeling approaches to *solve the problem right*, a structured approach is needed to ensure that you are *solving the right problem*.

2 What are "Hidden Factors"?

In the design of most new military vehicles, it seems that speed, endurance, and payload capacity are frequently assumed to be the standard set of requirements. The new concept is deemed to provide enhanced performance if it can travel faster, farther, and/or carry more cargo than existing systems. Yet, there are oftentimes hidden factors or effects that have a greater impact on the system than the "obvious" set of stated performance requirements. Hidden factors are those metrics that have a profound impact on the success of the design, but that are not inherently obvious in the problem definition phase of the design process.
Hidden factors are:

1. Often initially seen as insignificant
2. Confounded with other factors
3. Inputs wrongly assumed to be outputs
4. Desirements stated as requirements
5. Easily calculable from first principles
6. Encapsulated within opaque subroutines
7. Assumptions experts do not agree on

These hidden factors usually emerge at some point during the design and decision process – usually when the designers are painstakingly trying to figure out why their models or prototypes are not delivering the expected results. Sometimes these hidden factors remain hidden until after the solution has been manufactured and deployed. It is only when the solution is fully operational that it becomes embarrassingly apparent that a significant driving factor has been overlooked.

As a famous example, the design decision to limit date fields to only two digits to conserve computer memory in the 1960s and 1970s led to the Y2k problem. Programmers of the era never considered the impact – they assumed their programs would not be around decades later. The global cost of this design decision is estimated at somewhere between $300 and $600 billion dollars [1].

Hidden factors that remain hidden are often a consequence of bad assumptions, poorly defined need statements, a failure to imagine alternative scenarios, and an inability to eliminate insignificant degrees of freedom from the problem. The next section introduces a philosophy to uncover hidden factors early in the design process to avoid suboptimal solutions and allocate modeling resources to the most critical aspects of the problem.

3 Using Multiresolution Models to Uncover Hidden Factors

One-size-fits-all monolithic simulation tools often obfuscate complexity by performing calculations inside opaque subroutines carelessly linked in thousands of ways to other opaque subroutines and executed *ad nauseam* on distributed computing environments. On the other hand, expert-driven methods circumvent complexity by oversimplifying the problem to general rules of thumb that do not universally apply across unusual or unforeseen scenarios.

Multiresolution models, are families of models used "both to describe the same phenomena at different levels of resolution, *and* to allow users to input parameters at those different levels depending on their needs" [2]. In this paper, we focus primarily on a wide array of techniques ranging from facilitated workshops, back-of-the-envelope estimates, and first-order spreadsheet models.

These Quick Understanding, Evaluation and Synthesis Tools (QUESTs) are suitable for exploratory analysis and sensitivity studies to understand design parameters. They are also useful to elicit tacit assumptions and identify parameters encapsulated within opaque subroutines. These tools are ideally employed very early in the design and decision process – before any high fidelity modeling or optimization has taken place.

The primary objective of a QUEST is to provide enhanced insight into the problem, and a level of understanding for a relatively small time and monetary investment. Figure 1 depicts different types of QUESTS in comparison with more traditional Design and Simulation approaches [3]. The position of each

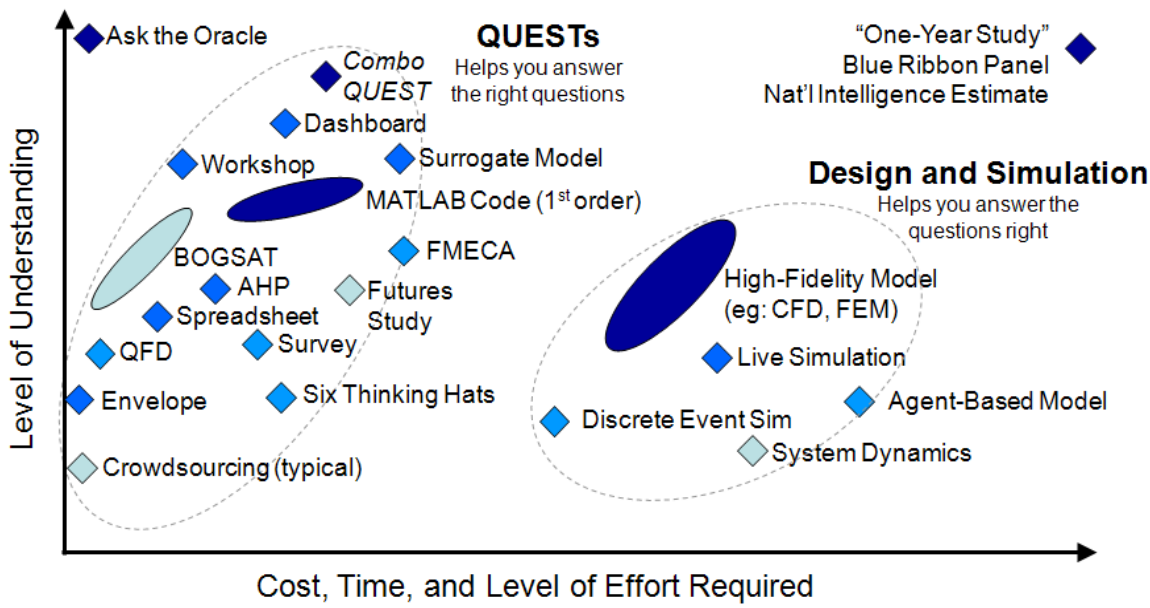

Figure 1. Comparison of Modeling Techniques by Complexity and Understanding Gained.

shape indicates the resultant "problem understanding" gained for a given level of effort. The depth of color indicates the relative confidence in each method. For example, "Ask the Oracle" yields perfect understanding with high confidence and no expenditure of effort – but assumes that a wise, all-knowing engineer with expertise in the problem is available. High-fidelity models may be very confident but produce a level of understanding that is extremely dependent on the level of effort expended.

QUESTs require significantly less effort and cost to create when compared to traditional, monolithic simulation-intensive approaches. They identify those metrics that truly drive the design so that higher fidelity (more expensive and more time consuming) modeling efforts can be used to answer the right questions. QUESTs provide inexpensive, quick-turnaround tools that help identify and eliminate misguided assumptions and eliminate some of the degrees of freedom from the problem early on to focus modeling efforts on the factors that matter most.

QUESTs are <u>not</u> intended to produce *the answer* to the overarching problem, nor are they intended to be a replacement for high fidelity models or experienced Subject Matter Experts (SMEs). They do not help you *answer questions right* any more than traditional design tools ensure you are *answering the right question.*

QUESTs combine people, processes, and tools to facilitate collaborative decision making and provide a common, result-oriented framework for problem definition, understanding, and communication. Our research has shown that hidden factors are nearly always "obvious" to all participants at the ***end*** of the study. In fact, presenting less-than-complete conclusions early stimulates discussion and elicits expert assumptions that were previously unknown or unstated.

Therefore, a key benefit of QUESTs is to showcase the problem and its sensitivities early, preferably using an interactive demonstration or Visual Analytics approaches to encourage these discussions.

Finally, the socialization of the decision space often results in redefinition of constraints or the early elimination of infeasible alternatives, greatly reducing subsequent analytical effort with high-fidelity tools. While simple, first-order QUESTs seldom have the fidelity to perform detailed design to validate requirements, their reliance on first-principles and straightforward analysis frequently trims the alternatives to a more manageable set. QUESTs can be used to identify what is *not* the answer.

4 Case Studies

Ignoring hidden factors typically results in one of three common mistakes in decision making:

1. Solutions that incorrectly estimate the impact of seemingly insignificant factors.
2. Solutions that are optimized for the wrong performance metrics.
3. Solutions that are optimized for the right metrics, but in the wrong direction.

The remainder of this paper presents case studies that demonstrate each of these mistakes, and demonstrates how QUESTs could be used to eliminate these common mistakes and uncover hidden factors.

4.1 Case Study: Real-Estate Tradeoffs

Hidden factors are not only the bane of complex technical problems; they plague everyday life decisions as well. One common example is the purchase of a new home. Anyone who has gone through this process knows that there are many factors at play in the decision, and the choice will have a great impact on the buyer's life for many years to come.

In shopping for new real estate, there are the "obvious" metrics on that play a role in the evaluation: price, number of bedrooms, number of bathrooms, the size of the garage, etc. There are also the "obvious" tradeoffs to be made – usually you can get more square footage for the money the further you're willing to live from the city's epicenter. While most people do account for these tradeoffs in their decision, they usually do a poor job of evaluating just how much the different metrics actually factor in to the decision or considering the impact of different scenarios.

Using housing data from a popular real estate, a simple tool can be created to show this tradeoff. Figure 2 shows the estimated annual cost of houses in four cities in Virginia based on a 20 year loan with a fixed interest rate of 5%. The estimates are based on recent cost averages per square footage.

Let's assume that the buyer's workplace is located in Arlington: a popular location for businesses and government jobs. Let's also assume that our buyer is comfortable paying no more than 28% of their $100,000 salary on housing. Figure 2 lists the cities on the horizontal axis in order of their distance from Arlington, with McLean being the closest (8 mi), followed by Reston (18 mi), and Leesburg (36 mi) being farthest away. This chart clearly depicts the decrease in average annual housing cost with increasing location.

This is the way that most people intuitively see and understand the tradeoff when they are house shopping (even though only engineers go through the trouble of plotting the data). They look at the for-sale listings and see that a one bedroom house in Arlington costs about the same as a three bedroom house in Reston, or a five bedroom house in Leesburg. Viewed this way, it may seem like a reasonable tradeoff to accept a longer commute in exchange for much larger house.

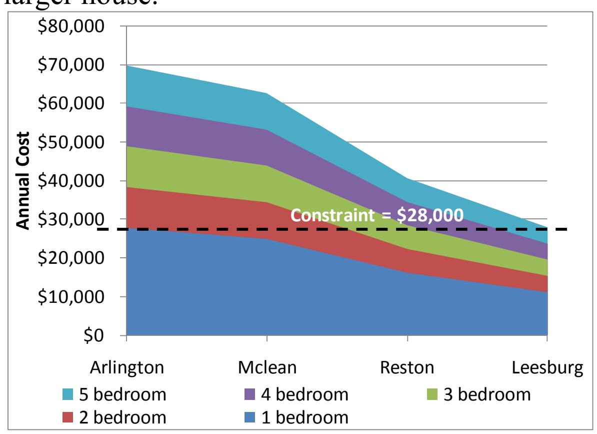

Figure 2: Annual Housing Costs for Various Size Houses in Four Cities.

However, most buyers fail to adequately forecast the extent to which **commuting cost** factors in to the equation. Figure 3 shows what happens when commute costs are added to the equation – a function of the estimated commute distance, the number of work days per year, average fuel consumption of a passenger vehicle, the estimated costs associated with wear and tear, plus the actual cost of tolls for each commute.

While the increase in commute cost with distance is intuitive, the significance of its contribution to the model is surprising. As shown in Figure 3, our notional buyer can barely afford two bedroom house in Reston, and only a one bedroom house in Leesburg. Given visibility into these sensitivities, the buyer must reconsider the alternatives and the underlying (and incorrect) assumption that you can get more house for the money by living farther away. Whereas before it might've seemed like a very attractive proposition to deal with an extra hour a day of commuting in exchange for two extra bedrooms, that same tradeoff might not be so appealing for only one additional bedroom.

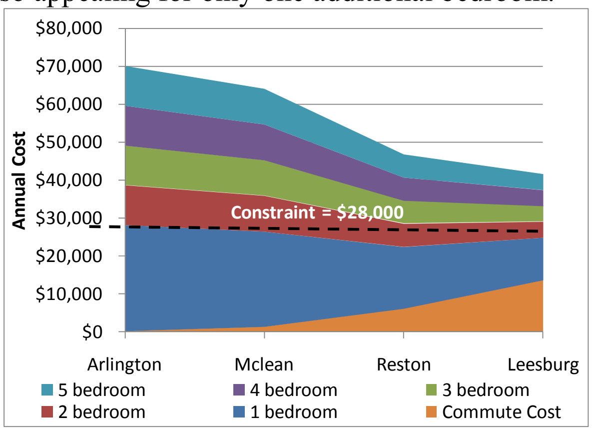

Figure 3: Annual Housing Costs Plus Estimated Commute Costs for Various Size Houses in Four Cities.

Visibility into this information might also cause the buyer to reexamine the "requirement" for a guest bedroom. In fact, this " desirement" was actually a misstatement of the requirement "I would like Mom to have a nice place to stay when she comes to visit." By reexamining Figure 3, it becomes evident that each additional bedroom in Arlington costs approximately $8,000 per year: far more than a weeklong stay in a nearby four-star hotel.

This example demonstrates the sort of assumptions and logical inconsistencies that plague all complex decisions. The requirements are based on assumptions, and the result is a solution that incorrectly considers the seemingly insignificant cost of commuting because it is spread out over a year and quite literally hidden from all but the most neurotic budgeters.

The fix was to build a simple tool that considered many possible significant factors in a dynamic constraint analysis environment (created in Microsoft Excel). By creating "dashboard gauges" of various relationships and performing sensitivity trades using a model based on simple relationships and first principles, the hidden factor of commute cost became glaringly obvious.

4.2 Case Study: Aerodynamic Optimization

This example documents a technology selection exercise where the goal was to evaluate several alternative technology concepts for increasing the aerodynamic properties of an aircraft. The overall objective of this work was to identify a solution that would enable an aircraft to fly at least one additional flight segment per day in order to increase revenue. The assumption was that this goal could be accomplished by increasing the speed of the aircraft while also maintaining or increasing the aircraft efficiency. The secondary assumption was that the key to achieving this goal was to increase the aerodynamic performance and/or propulsive efficiency of the aircraft. As a result, the analysis focused on high-fidelity modeling of technology concepts that could either improve the aerodynamic properties of the aircraft or enhance the propulsion system.

The performance of each of the technologies was estimated using various high fidelity physics-based models. Originally, these technologies were evaluated solely based on their ability to provide the largest increase in aerodynamic or propulsive efficiency, and the technologies were prioritized based solely on these performance metrics. After the results of the high-fidelity models became available, a surrogate model was created to simulate the impacts of each of the technologies on the performance of the aircraft as a whole. The results showed (to everyone's surprise) that even the highest ranking technologies had virtually no detectable impact on the speed or overall performance of the aircraft. None of the technologies came close to the goal of an extra flight segment per day.

The common mistake here was that all of the solutions where optimized for the wrong performance metrics. The assumption (that aerodynamic and propulsive improvements were THE way to meet the goal) severely limited the number of solutions that were investigated for this problem. A QUEST should have been employed prior to the high fidelity modeling efforts in order to determine what metrics have the biggest impact on the ability to reach the stated goal and how large of a change in performance was needed to achieve the goal.

To demonstrate this recommendation, a simple discrete event simulation tool was created in ExtendSim to simulate the amount of time the aircraft spent in various portions of the day-to-day operations – including both the in-flight mission profile and ground-based operations such as refueling, and boarding passengers. Variable ranges were based on the reasonable amount of improvement that might be achieved through technology infusion. A Monte Carlo simulation was run around the discrete event model to vary the amount of time spent performing each operation and the probabilities of delays. Surprisingly, a sensitivity analysis on the Monte Carlo results indicated that aircraft cruise speed had the smallest impact on the overall objective. The Pareto plot in Figure 4 shows the relative impact that each of the factors had on the variability of the number of flight segments per day.

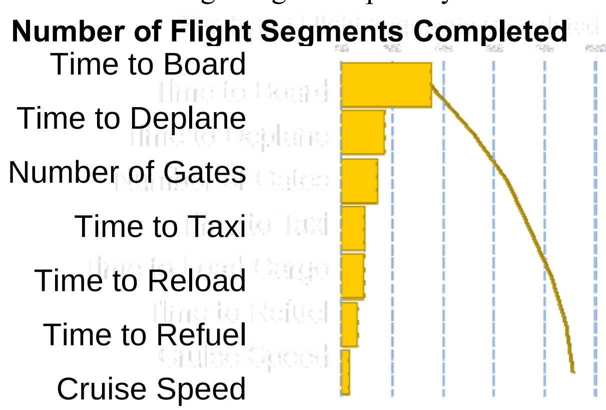

Figure 4: Pareto Plot showing the sensitivities on the number of flight segments per day.

To meet the desired goals, aircraft speed would need to be increased far beyond the margins that could be provided by ***any of the alternative technology concepts being evaluated***. The results highlight the fact that the most significant impacts come from solutions that improve the boarding time, deplaning time, and number of gates, but the high-fidelity modeling activities were focused on modeling the wrong solutions due to the faulty assumption that aerodynamics and propulsion advances were the only significant technology advancements.

A quick-turn trade-study tool could have been used earlier in the process to identify those areas of the design space that stand to provide the maximum potential benefit and guided more detailed simulation efforts. In this case, the results of the Monte Carlo simulation indicate that it might be worthwhile to give some serious consideration to wide-body concepts that accelerate loading and unloading.

This example highlights the common problem where emphasis is placed on high-fidelity modeling due to the perception that high fidelity correlates to high accuracy and reliability. This sometimes robs attention from efforts to ensure that the model being created is the "right" model or that the concept being modeled is the "right" concept.

4.3 Case Study: Long Range Strike Aircraft

The first case study investigates a notional strike aircraft where the impact of hidden factors is misinterpreted by engineering intuition, and a simulation-based approach yielded surprising yet illuminating results. One trade under consideration was the relative merits of speed, range, and persistence of weapons versus the same factors on the aircraft platform. A high-fidelity physics-based simulation of a combat scenario was developed over the course of eleven months [4]. This simulation used an agent-based model for battle management and real-time retargeting and a six degree-of-freedom model of aircraft flight. One example output from this study is shown in Figure 5.

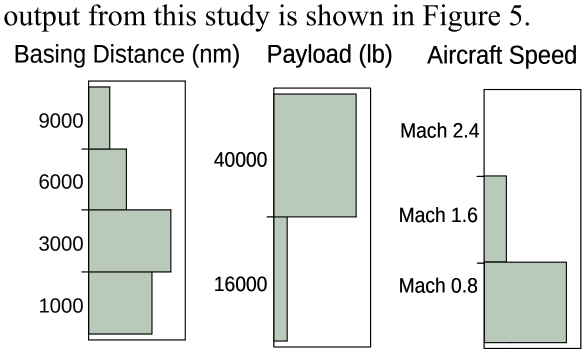

Figure 5: Distribution of the Properties of Successful Aircraft (Notional Strike Mission).

This figure shows the properties of aircraft designs that successfully prosecute more than 90% of candidate targets (mission success) in terms of a distribution of the total population of designs considered. The results show that:

- A majority of successful missions use aircraft based closer to the theater (left)
- Aircraft with larger pay load are more successful (center)
- Aircraft **with a <u>slower</u> cruise speed** are more successful (right).

While it is intuitive that aircraft based closer to the theater (left) and aircraft with a larger payload (center) are desirable, engineers were at a loss as to why subsonic platforms consistently outperformed their supersonic brethren. In fact, none of the Mach 2.4 aircraft considered could successfully complete the mission. This result was counterintuitive and was suspected to be a flaw in the model.

After extensive debugging, the "error" was found to be a flaw in the stated tactics of the vehicle (an assumption). Since it is very difficult to change tactics by modulating continuous variables, early in the study the tactics of the vehicle was stated as an assumption. Using the "Roving Linebacker" tactics employed by B-1 bombers in Operation Enduring Freedom, the aircraft fly from base to a predesignated loiter point outside the area of operations. Each aircraft is assigned a prioritized target by an agent-based battle manager [5]. It then cruises into the battlespace, deploys one or more weapons, and returns to the loiter point. Since the drag on the airframe goes up exponentially with speed, supersonic platforms not only required a massive platform size (mostly fuel), but consumed this fuel quickly during the loiter and cruise segments.

Because of the way the platforms were programmed to cruise and loiter (an assumption stated by experts at the beginning of the study), the supersonic aircraft spent most of the simulation flying back to base to refuel and was seldom at the loiter point or near the battlespace when the battle manager attempted to assign targets. In contrast, the subsonic aircraft was often either at the loiter point or still inside the hostile country when the next target assignment was made and was often able to successfully prosecute the target using a range of candidate weapons. To "tweak" the simulation to enhance the supersonic aircraft's performance, the loiter marker was placed inside the hostile country so the platform was always "on station." However, with a 1g turn radius of 280 nm and a 2g turn radius of 43 nm, the Mach 2.4 aircraft could not reposition itself to properly target and deploy weapons on a new assignment.

The surprising result that "subsonic aircraft outperform supersonic aircraft" required a time-consuming rewrite of the code to allow subsonic loiter and supersonic dash, as well as a dozen other tactical variations that were not conceived at the outset of the study.

As stated earlier, it is a common assumption that an increase in speed, range, or payload capacity is always a good thing. In this example, it is true that speed is one of the driving factors, but not in the way engineers initially assumed. The mistake in this case was that traditional "faster-is-better" logic was applied as an assumption to jump start an analysis that relied on a model that was too complex. Simulation designers did not observe the "flaw" during tens of thousands of simulation runs. It was immediately obvious that something was awry in the visualization of the results. Simple physics and first principles offered an explanation.

The fix: a simple back-of-the-envelope calculation early in the design process would have shed some light on some of the "systems-of-systems" effects, and would have identified the need to explore multiple tactical variations for each aircraft design. A facilitated workshop with experts may have elicited some combinations worth considering. These workshops and/or back-of-the-envelope calculations could have served as the QUESTs for identifying the critical tactics and design alternatives that should have been the focus of the more complex modeling effort. The resulting simulation was not only of marginal value to answering research questions, but the presence of a glaring and obviously intuitive logical flaw diminished the credibility of the modeling process and highlighted the need for increased transparency and composability in model development.

5 Recommendations

The authors advocate the use of QUESTs earlier in the design process in order to assist in problem definition and understanding. The overarching objective of a QUEST is to provide insights into the problem that can be used to guide and narrow the focus of future analytical endeavors and ensure that expenditure of model development effort results in the best possible "bang for the buck." To support this goal, QUESTs can be used to perform one or more of the following functions:

1. Minimize assumptions. Where possible, leverage simple tools to explore system-of-system impacts that may not be well understood.
2. Identify (and/or define) the overarching Measures of Effectiveness (MoEs) that will be used assess the success of the solution with respect to capabilities or missions
3. Map these high level MoEs to the technical performance parameters that influence them.
4. Assess the sensitivities of the MoEs to the technical performance parameters as well as any operating conditions.
5. Identify and clearly articulate the objective of the study. Is the goal to design a highly optimized solution that is to perform a well-defined, limited set of functions? Or is the goal to identify a robust solution capable of handling uncertain future scenarios?
6. Identify the "Opportunity Landscape". Is the better value proposition to act quickly or to proceed with careful diligence? The answer to this question will help gauge the amount of effort and time that should be invested in the analysis.
7. Eliminate degrees of freedom from the problem. QUESTs are based on the premise that it usually takes far less information to eliminate a bad solution than it does to identify a good one. Thus, we can use cheaper, faster, more efficient methods (QUESTs) early on to weed out alternatives, and then successively employ more advanced, accurate, higher-fidelity methods to hone in on valuable solutions.

There are many tools and methodologies that support various aspects of the decision/design process, and any one of them can function as a QUEST if used to quickly and efficiently provide one of the 7 functions outlined above. The field of systems engineering contributes various graphical tools for managing complexity (QFD: Quality Function Deployment, Functional Flow Block Diagrams, N-squared charts, etc) as well as various Enterprise Architecture Frameworks (the Zachman framework, TOGAF, etc). The statistics field provides various enablers that support modeling and simulation (M&S), or for conducting analyses on the M&S outputs (regression techniques, sensitivity analyses, multidisciplinary optimization techniques, etc). The field of psychology presents useful information and theories on the cognitive processes involved in decision making [6]. Additionally, many of these tools and disciplines have been combined to create various business management strategies like Six Sigma, Failure Mode and Effects Analysis (FMEA), system dynamics, lifecycle cost analysis, etc.

By their very nature, real engineering problems range from complex to "wicked." They are ill-behaved, unique problems that can't be solved by simply following a pre-defined series of steps. No single approach or standard recipe exists for solving all complex problems. The approaches must be adapted, combined, and tailored to the nuances of each individual problem. This is why advanced decision making for complex problems is part science, and part art. The person facilitating the process must possess a good understanding of the science behind each of the methods, but they must also be adept at the art of picking the right tool(s) for the job.

This challenge is complicated by the plethora of tools, strategies, processes, and methodologies that ebb and flow with popularity and are occasionally elevated to "buzzword" status. Too often, analysis focuses on using the method *du jour* rather than realizing that an effective analysis must use the right methods, at the right resolution, with the right assumptions, at the right time to enhance the decision making process. A broad-based education in design methods and their fitness-for-use is required to select the right simulation tool and apply it correctly.

Another common trap in the use of simulation tools to support decision making is the flawed belief that the outcomes of the tool represent a pseudo-truth and hypothesis validation. The traditional and proven scientific approach to disprove hypotheses through experimentation has fall by the wayside as simulation-based approaches have become more common. This leads to a narrowly focused view that fails to consider alternative explanations, scenarios, and hypotheses. As CIA Psychologist Richards Heuer notes: “If an analyst cannot think of anything that would cause a change of mind, his or her mind-set may be so deeply entrenched that the analyst cannot see the conflicting evidence” [7].

QUESTs provide a low-cost and analytically sound approach to analysis consistent with the scientific method: it takes far less rigorous analysis to eliminate a bad solution or invalidate a hypothesis than it takes to identify the 'right' answer. QUESTs also help to identify variables irrelevant to capabilities and objectives and eliminate scenarios that are improbable or insignificant.

Finally it is important to note that this property of QUESTs can be misused. Many analysts erroneously believe that disproving the opposite of their hypothesis, by deduction, they validate the original hypothesis as true. Engineers must recognize the need to compare alternative hypotheses with the same scrutiny and rigor while considering all sources of information without bias to a particular hypothesis.

The key to choosing the right QUEST at the right time is to consider the combination of factors that includes: 1) the question to be answered (usually the question is related to one of the previous 7 objectives), 2) the available timeline and resource constraints for answering that question, 3) the type of problem being investigated (does it involve complex systems-of-systems interaction, uncertain operational scenarios, revolutionary concepts, etc) and 4) any readily available resources that can be leveraged (existing models, accessible SME’s, etc).

Figure 6 outlines a few examples of tools, methodologies, and approaches that can be used to create QUESTs that address these aforementioned functions that help analysts “solve the right problem.” This list is not meant to be an all-inclusive list of QUESTs; it is merely intended to function as a general guideline for determining which tools can provide which functions.

	Minimize Assumptions	Identify Overarching MoEs	Map MoEs to Performance Parameters	Identify/ Articulate Objectives	Identify the Opportunity Landscape	Eliminate Degrees of Freedom
Heilmeier Questions	●			●		
Seven Management and Planning Tools						
Six Thinking Hats	●				●	●
Visual Thinking Codex		●	●	●		
Quality Function Deployment (QFD)		●	●	●		
Cause and Effect Diagram			●			●
Architecture Frameworks (ie. Zachman)				●	●	●
Crowdsourcing	●	●		●		
Facilitated Workshops	●	●	●	●	●	●
Interactive Dashboard			●	●		●
Surrogate Model			●			●
First Order MATLAB Code		●				
Failure Mode and Effects Analysis (FMEA)			●			●

Figure 6. Utility of Common QUEST Approaches for “Solving the Right Problem.”

6 Conclusions

Engineers and analysts have been led to believe that high-fidelity models, precise measurements, and validated results ensure a correct answer. In reality, *the right answer to the wrong question is still the wrong answer*.

Ironically, the example in Case Study 1 showed how insignificant factors could be significant. Case Study 2 demonstrated a scenario where experienced experts thought some factors were significant but they turned out to be the least significant. In Case Study 3, the experts were right about the significance of a key factor, but embarrassingly misinterpreted its impact on a complex problem. All of these situations are common in problems with hidden factors.

The authors recommend employing QUESTs as a multiresolution modeling technique early in the design process as a means to uncover potentially hidden factors, avoid faulty assumptions, and identify the factors that truly drive the success of the solution. Use QUESTs to:

- Elicit the real requirements and focus analytical resources on the right factors by leveraging highly visual and dynamic QUEST approaches
- Eliminate bad alternatives versus picking the "best" solution using agile, quick-look, variable-fidelity models
- Map out a broad scenario space to account for many possibilities, not just "likely" scenarios or "scary" (1%) ones.
- To ensure that you are solving the right problem before employing design and operations research methods.
- Encourage "positive dissonance" to resolve conflicts effectively
- Balance tools, processes, and people – QUESTS can provide a framework for seamless communication between stakeholders and analysts.

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