DISSERTATION

Multi-perspective Strategic Decision Making

Principles, Methods, and Tools

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ABSTRACT

Multi-perspective Strategic Decision Making:
Principles, Methods, and Tools

Increasingly, governing groups must take into account diverse perspectives (values, beliefs, and expectations) from within the group, from stakeholders, analysts, and adversaries. Multi-perspective strategic decision making is the process of making long-term decisions that shape the course of an organization, while taking into account diverse perspectives. Often, these perspectives affect the group's decision more than "objective" criteria. For complex, deeply uncertain problems, groups considering diverse perspectives can be challenged to agree on strategy. This research defines methods, principles, and tools to help groups agree on strategy despite widely diverse perspectives. It extends exploratory analysis techniques to cover new types of factors driving the choice of strategy: "perspective parameters," including those used for aggregation and scoring variables in a multiresolution model; along with uncertain objective parameters. Six useful simplification techniques are defined to help decision makers see the essence of a complex system and the forces driving it. Finally, this research introduces a heuristic that uses driving forces' time frame and controllability to identify the best strategy and ways to iterate options. The approach is illustrated using a defense acquisition strategy.

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Acronyms

ATR	automated target recognition
CART	classification and regression Tree
CPGS	conventional prompt global strike
CTM	conventional Trident missile
EA	exploratory analysis
FAR	flexible, adaptive, and robust (strategies)
GPS	global positioning system
KEP	kinetic energy projectiles
MPSDM	multi-perspective strategic decision making
MRM	multiresolution model
NRC	National Research Council
PAT	portfolio analysis tool
PGS	prompt global strike
PRIM	patient rule induction method
RDM	robust decision making
R&D	research & development
SAM	surface-to-air missile
SAR	synthetic-aperture radar
SEAD	suppression of enemy's air defense
SLBM	sea-launched ballistic missile
SOF	special operations forces
TCM	Trident conventional missile
WMD	weapons of mass destruction
XLRM	exogenous factors, levers, relationships, measures

Glossary of Terms

adaptive strategy a plan that prepares for the possibility that some factor outside the decision-makers' control may change in the future in ways that may not be predictable now. Adaptive strategies can include hedges and contingency plans along with the associated early warning signs.

adversary an enemy or competitor. Adversaries will tend to look for vulnerable, extreme corners of parameter space to exploit.

aggregation rules algorithms and parameters that specify the method whereby lower-level variables in a multiresolution model are combined to make up a higher-level variable.

beliefs an individual's mental model of how the world works. Beliefs define a decision maker's understanding of relationships between factors based on objective information and inference or deduction. Beliefs include not only relationships between factors, but uncertainty in today's state of the world.

contingency plan a set of executable responses to some signal that may or may not be sensed in the future.

controllability the extent to which factors can be influenced by individual decision maker or the decision-making group.

deep uncertainty the condition where analysts do not know, or the parties to a decision cannot agree upon, (1) the appropriate models to describe the interactions among a system's variables, (2) the probability distributions to represent uncertainty about key variables and parameters in the models, and/or (3) how to value the desirability of alternative outcomes.

differentiating criteria	criteria for which there is a spread of return, risk, or cost between options.
dominance	the degree to which one option performs better than another in some criterion.
drill down	moving from consideration of a higher-level result of a multiresolution model to examine lower-level factors that may have contributed to the higher-level result.
early warning	an indication that the mix of strategic actions that was planned may have to change.
expectations	an individual's view of how the future is likely to unfold.
exploratory analysis	graphical and statistical data-mining techniques to explore outcomes across the entire range of assumption combinations, not simply from excursions from a baseline while varying a few assumptions at a time.
multiresolution model	a model of a system that consists of hierarchical (or nearly hierarchical) elements with multiple levels of resolution, or fidelity. Multiresolution models provide a systematic framework for exploratory analysis, allowing level-by-level exploration. This process may increase the dimensional capabilities of exploratory analysis algorithms.
options	different action-oriented strategic actions the decision makers will consider.
option superiority	a figure of merit for comparing options. For each dimension of return, risk, or cost, relative option superiority for each pair of options is the difference in their scores.

perspective	values, beliefs, or expectations, either individual ones or sets of them.
perspective parameters	variables and algorithms that characterize some types of values, beliefs, and expectations. These variables are evaluated explicitly, along with more objective factors, in the computational experiment.
risk	a measure of concern that the option's actual performance might be less than indicated by the option's return. It reflects consideration of likelihood and consequences of worse-than-expected performance.
scenarios	a specification of a potential mission and the conditions of that mission.
shaping actions	actions designed to affect the likelihood or effect of a driving force. Shaping actions can be aimed at the environment outside the decision makers' organization or internal to the organization.
spanning set of scenarios	a relatively small, manageable set of scenarios chosen to cover a broad but plausible range of factors that is critical to the outcomes of interest.
trip wire	a clear signal that a change has occurred, from which pre-planned actions can be taken quickly.
values	what individuals think is important; what they value.

Chapter 1- Introduction

Significance of the research

In the 21st century, organizations governing every type of institution are experiencing unprecedented demands to consider alternative viewpoints from outside stakeholders, the decision makers themselves, and from new types of adversaries. One factor that contributes to this trend is the information age. Widespread access and rapid dissemination of information brings a high level of scrutiny from public stakeholders to government, business, and civil organizations. Marten and Samuels (2009) report that vulnerable colleges and universities experience "unprecedented external demands for accountability and quality assurance by the public, donors, accreditors, legislative bodies, and the U.S. Department of Education." Decision makers, becoming accountable to a wider group of stakeholders, external to the group must increasingly take these diverse perspectives into account when devising strategy.

In the educational sector, Eherenberg (2004) reports that wealthier institutions of higher education are seeing a dramatic shift in the makeup of their Boards of Trustees. In his book, *Governing Academia, Who's in Charge at the Modern University?* Eherenberg explores the effect of Educational Boards of Trustees becoming more heterogeneous, as they admit the alumni "insiders' voice." Goodstein, Gautan, and Boeker (1994) found that board diversity may be a significant constraint on strategic change.

U.S. Defense policy makers must adjust to a wider scope of considerations as well. Adversaries now include diffuse, non-governmental entities as well as nation states. These new adversaries are fundamentally different than nation states in terms of capabilities, tactics, motivations, strengths, and vulnerabilities. In addition, adversaries will search for and exploit combinations of vulnerable assumptions--combinations that may be hard to predict as systems become more complex. Defense policy must maintain the capability to deal with traditional adversary nations, while adding the capability to protect against non-government opponents (Hough 2008).

In addition to a fundamentally broader set of adversaries to consider, defense strategists must, as always, consider large number of factors that contribute to creating and maintaining alliances with other countries. Domestically, defense policymakers must continue to take into account the perspective of Congress, consider the likelihood of continued funding levels, and predict the political stability of programs in the midst of increased transparency and accountability from the public.

Another factor affecting the heterogeneity of governing institutions is regulatory. In response to perceived financial misdeeds, the Sarbanes-Oxley Act was passed by Congress in 2002. This, along with other, state-specific legislation requires governors of for-profit institutions, and to some extent non-profit institutions, to include more “outsiders” on their Boards of Directors.

U.S. government, for-profit, and non-profit institutions are not the only ones feeling the pressure driving them to consider more diverse perspectives. According to a recent RAND Pardee Center workshop report, regional and international institutions, facing pressure from economic, environmental, and activist forces, “may need substantial modification to contribute towards a stable, free, and just world in the 21st century.”[1]

How do high-level decision makers proceed with the difficult challenge of creating strategy which addresses these diverse perspectives? Classical management theory prescribes methodology for the decision-making group to agree on objectives, often from a shared understanding of the organization’s vision and mission (Hitt, Ireland, and Hoskisson 2009). When groups are homogenous, consensus on objectives is relatively likely. As perspectives within the decision-making group diverge, or when decision makers must consider a wide range of stakeholder, analyst, and adversary viewpoints, consensus on objectives grows less likely. If objectives cannot be agreed upon, then it is improbable that the group will agree on strategies to accomplish those objectives.

There is clear evidence of so-called dissonance when values conflict (Heifitz 1994). Although governing groups rarely break out into fistfights as the Continental Congress

[1] Pardee Center Workshop on Due Diligence for Humanity’s Long-Term Future, January 13, 2008, RAND, Santa Monica, Ca.

reportedly did during revolutionary times, consensus can become more difficult to achieve when a broader group of perspectives must be considered.

What is Multi-perspective Strategic Decision Making?

Strategic decision making theory is often described in the context of strategic management research, with roots extending back to Chandler's (1962) Strategy and Structure and Ansoff's (1965) Corporate Strategy (Hoskisson et al.1999). As early as the mid-1980s, strategic decision making was defined by different researchers in different ways. Chaffe (1985) cites several studies to support her claim that "virtually everyone writing on strategy agrees that no consensus on its definition exists. Mador (2000) lists several definitions of strategic decisions used in the literature:

- "[a decision which is] important, in terms of the actions taken, the resources committed, or the precedents set" (Mintzberg, Raisinghani and Theoret 1976);
- "decisions that determine the overall direction of the firm' (Quinn 1980);
- "[those which] 1) involve strategic positioning; 2) have high stakes; 3) involve many of the firm's functions; and 4) [can] be considered representative of the process by which major decisions are made at the firm."

Eisenhardt and Zbaracki (1992) define strategic decisions as "those infrequent decisions made by the top leaders of an organization that critically affect organizational health and survival." Mador (2000) summarizes these various definitions: "By implication, strategic decisions are complex, and involve a high degree of uncertainty." Although the nature of all these definitions has a somewhat different slant, Dean and Sharfman (1996) conclude that in their research, managers had no trouble identifying strategic decisions.

Strategic decision making, for the purposes of this research, is the process of making long-term decisions that shape the course of an organization. Such decision making is often done by groups of high-level decision makers. Examples of strategic decision makers include Boards of Governors/Trustees/Directors, multi-national or regional groups, and Defense policymakers, among others.

Strategic decision making is distinct from operational or tactical decision making in several ways. First, decision makers must typically consider time frames of months to years, not days to weeks. Uncertainty is deeper, not only because of the longer timeframes, but because the capabilities of adversaries (e.g. competitors, enemies) are not often known in the near term, or are not easily predictable. Also, the strategic decision can affect resources in the millions or billions, instead of hundreds or thousands, as well as affecting the general approach the organization takes to deal with challenges.

Multi-perspective strategic decision making (MPSDM) is defined in this research as the process of making long-term decisions that affect the course of an organization, taking into account diverse perspectives—values, beliefs, and expectations. These perspective can differ between individuals in the decision-making group, analysts, stakeholders, and analysts. This research describes an MPSDM approach: principles, a methodology, and a set of tools designed to help groups agree on strategic actions when decision makers either have amongst themselves, or must consider, perspectives other than their own. A novel heuristic is proposed which suggests strategy type based on the time frame and amount of control decision makers have over the factors driving relative superiority of options. Using these heuristic, strategic options can be modified and the analysis can be iterated. This dissertation then illustrates the approach with a simplified defense acquisition example.

Audience for this research

This research is envisioned to be most useful to consultants and staff to strategic decision makers, and students who will become strategic decision makers, consultants or staff. The approach is designed to be applicable to a wide variety of types of institutions, and it is demonstrated in the dissertation using a simplified version of a real-world defense procurement problem, accessible to a broad audience.

What is meant by perspectives?

Davis et al. (2008) define a perspective as "a way of looking at the problem when assessing the 'balance' within a portfolio of investments" (p. xxxviii), and describe different types of considerations in high-level strategic assessment. For instance, they describe the U.S. Pacific Command perspective as being relatively more concerned about the long term, the “strategic” view, the Pacific region, and big-power balances than the U.S. Special Operations Command. In this framework, a perspective is associated with an organization and includes many assumptions.

MPSDM defines perspectives at the level of individual assumptions, as opposed to a set, and an individual’s assumptions, as opposed to a group’s.[2] MPSDM defines perspectives as:

- Values - what individuals think is important,
- Beliefs – mental models of how the world works, and
- Expectations - individuals’ view about how the future will unfold.

Values, or what individuals think is important, are often difficult to define. The challenge here is to devise a way of characterizing many types of values (or criteria) in an analytic framework. One early practitioner of what is now known as Multicriteria Decision Making (MCDM) theory was Benjamin Franklin, who composed lists of “pros” and “cons” to ideas, crossing off considerations of equal importance before evaluating the remaining considerations. (Figueira, Greco, and Ehrgott 2005). Keeney and Raffia defined Multi-Attribute Utility Theory (MAUT) in a 1976 publication that is a standard reference in decision science tests. More recently, a number of methods have been created to evaluate options against multiple criteria (see Zopounidis and Doumpos (2002) for a review). Many of these methods apply “weights” to the different criteria before computing an aggregate score and ranking the alternatives. Other methods use more complex aggregation methodology. The criteria themselves are considered by MPSDM to represent one type of value, with the aggregation weights and methodology representing relative preference between criteria, another type of value.

Often, analysts and strategists try to anticipate what a stakeholder group might value before developing strategy. This is difficult without the stakeholders being involved in the

[2] MPSDM allows for assumptions to be grouped together into sets but does not assume such grouping. If reliable information about correlated values, beliefs, and expectations can be made, the analysis can vary all the relevant assumptions together. This method serves to reduce the number of combinations of assumptions and simplify the exploratory analysis (conceptually and computationally). However, it is not always possible to predict such groupings before the analysis (even within an organization, individuals may differ in their perspectives), and some assumptions within the groupings may not affect the outcomes of interest to the same extent as the others.

creation of strategy, because sometimes the stakeholders themselves may not know the relative priority of their values before seeing an assessment of the options. For instance, how would an individual "trade" one criterion for another if some predetermined goal cannot be met with any feasible alternative?

If values are difficult to define, characterize, or know ahead of strategy development, the challenge is to explicitly include them in the process of creating strategy. Often high-level decision makers find that they are either unable or unwilling to explicitly define or express their values. Some considerations that are important to high-level decision makers are unspeakable, for a variety of reasons. For instance, keeping certain sensitive information (organization-based or personal) from leaking out may make it difficult to explicitly include some types of values in the creation of strategy. Other "unspeakable criteria" may include considerations that may be viewed as parochial, those that are not fully thought out, or controversial views[3].

One approach sometimes used to address values is to define membership in various groups and then look for and characterize common values within the group. Pfeffer (1973) defined board diversity as representation from different occupational and professional groups. This distinction is used by others studying board diversity (Baysinger and Butler 1985; Kosnik 1990; Powell 1991; Thompson 1967). Their research shows that generally, as constituencies that board members represent grow more diverse, "the greater the potential for conflict and factions to develop based on divergent definitions of organizational goals and policies" (Goodstein, Gautam, and Boeker 1994). Kosnik (1987) and Singh and Harianto (1989) found that the proportion of "outsiders" to "insiders" on the boards that they studied affected organizational compensation. One could imagine different definitions of diversity: Liberal vs. conservative; generational (i.e. age); race; country of origin; socioeconomic status, etc. For strategy development with different stakeholders, another dimension of values might be related to the type of institution the individual represents—family owned, hierarchical, not-for-profit, etc. and that institutions'

[3] The considerable range of such 'unspeakable criteria' came out in discussions with Paul K. Davis.

organizational values. To date, the effects of these types of diversity have not been documented.

The second element of perspective, beliefs, pertains to an individual's view of how the world works, or the relationship between factors. Beliefs could be thought of as if/then relationships, for instance "if our organization pushes this lever then the system will respond this way." MPSDM distinguishes "analytical" beliefs from other types of beliefs. Analytical techniques, for example, include the "best" way to aggregate variables into a higher-order summary. For instance, criterion weights are often used in MCDM to compute an overall score for each option, but algorithms other than weighted sum may seem more appropriate to the analyst. Contrast this analytical belief with a decision-maker's belief that if the organization attempts a military strike, the enemy will respond. The likelihood of an enemy's response depends on many beliefs: the effectiveness of that response, the counter-response, world opinion, etc. Thus, analytical beliefs are of a different nature than other types of beliefs, many of which depend on other types of beliefs.

Beliefs, or views of how a system works, may be even less clear to decision makers than values. Beliefs define a decision makers understanding of relationships based on objective information and inference or deduction. What is meant by beliefs in this research includes not just beliefs about how factors are related, but uncertainty in today's state of the world. Specifically, current capabilities, particularly an adversary's, are critical to the success of strategies in the for-profit and defense areas. If an adversary's capabilities are guarded as private information, the decision makers' beliefs about them may vary widely. Some information is known, some is not. Decision makers must rely on a combination of objective information and inferences, and deductions. These inferences and deductions produced by different individuals with access to the same objective information may vary widely. Sometimes these beliefs are testable, often they are not. To add another layer of uncertainty on top of already uncertain beliefs, the decision makers' beliefs about an adversary's actions depend on beliefs about the *adversary's* beliefs.

Additional areas where beliefs may differ from individual to individual occur between analysts and analysts, or between analysts and decision makers. Analysts often communicate with a variety of math models, but high-level decision makers have their own mental models of how a system will likely respond to one or more assumptions.[4]

The third element in the definition of perspectives is individual's expectations. Webster's equates expectation with anticipation, which is defined as "the act of looking forward." Thus, there is an implication that expectations pertain to a time in the future. MPSDM considers expectations to be decision makers', stakeholders', analysts', and adversaries' views about how the future is likely to unfold. Expectations are one of three types of perspective, but they also include how other types of perspectives—beliefs and values—may change in the future.

Treating perspectives as uncertainties

What types of factors can be considered uncertain? Although many researchers associate uncertainty with incomplete knowledge of the environment or with changes occurring with time (Downey and Slocum 1975), MPSDM treats all types perspective (values, beliefs, and expectations) as uncertain in the analysis for five reasons: First, many of them are uncertain, most notably expectations of the future. Second, perspectives represent *differences* between individuals. In some cases, these differences may be unknown at the time of the analysis. For instance, decision makers themselves may not know they have values different from those of other decision makers. In addition, the adversary's perspectives may be held as private information. Third, analysts may differ in their belief of the "best" way to model aspects of the system. Fourth, since expectations of the future are uncertain, and changes in values and beliefs may change in the future, values and beliefs are also uncertain.

The fifth reasons perspectives are treated as uncertainties in MPSDM is that some analytical treatments of uncertainty are useful for dealing with perspectives. The term

[4] The terms "assumption" and "independent variable" are used interchangeably here, and meant to imply a temporary assertion about an uncertain variable or model. This is a broader definition than, for instance, Dewar et al. (2001) define an assumption as "an assertion about some characteristic of the future that underlies the current operation or plans or an organization." Dewar ties assumptions to expectations of the future, but MPSDM allows for current values and beliefs to be assumed as well.

"deep uncertainty," originally attributed to Arrow (2001)[5], has also been used in research to apply to conditions where uncertainty is ambiguous or vague and/or the relative value of outcomes cannot be clearly established (Bankes, 2003). Lempert, Popper and Bankes (2003) broaden the concept of deep uncertainty even further:

> [Deep uncertainty is] where analysts do not know, or the parties to a decision cannot agree on, (1) the appropriate conceptual models that describe the relationships among the key driving forces that will shape the long-term future, [what MPSDM calls beliefs] (2) the probability distributions used to represent uncertainty about key variables and parameters in the mathematical representations of these conceptual models, [a combination of some types of beliefs and expectations in MPSDM], and/or (3) how to value the desirability of alternative outcomes [a type of value] (p. xii).

One of the lines of research that this dissertation draws heavily from is Robust Decision Making (RDM). RDM is an analytic method for developing robust policies—those that perform well over a large range of uncertain futures. The goal of RDM is not to aim for optimal outcomes, but for robustness (in the sense that outcomes that remain good across a wide range of uncertainties). RDM has been applied to a variety of social policy issues such as: Climate change (Groves, Lempert, Barry, Wainfan 2008; Groves, 2007; Lempert et al. 2004; Lempert and Schlesinger 2000; Lempert et al.1996; Lempert et al. 2000); global sustainability (Lempert et al. 2003); educational investment (Park and Lempert 1998) and science and technology investment (Lempert and Bonomo 1998).

As will be described in more detail later, RDM puts forth a method of exploring uncertain parameter space using graphical and data-mining techniques that is applicable to MPSDM. However, RDM has a somewhat different emphasis than MPSDM. Whereas RDM aims to define strategies that perform reasonably well over a broad range

[5] Lempert, Popper, and Bankes (2003) cite a 2001 presentation by Arrow regarding climate change policy.

of plausible futures, MPSDM focuses on how to define strategies that can be agreed upon by group of decision makers who may never agree on values, beliefs, and expectations. MPSDM's emphasis on decision makers', stakeholders', analysts', and adversaries' perspectives helps groups accommodate minority views and converge iteratively towards consensus on strategic actions.

Goals of this research

This research proposes and demonstrates methodologies, principles, and a set of tools to help strategic decision makers agree on actions despite diverse perspectives amidst deep uncertainty. It extends and demonstrates the concept of exploratory analysis (EA) to simultaneously consider uncertainty about objective factors and so-called perspective parameters: those associated with the different values, beliefs, and expectations including the analytical belief about the best way to aggregate and score parameters in a mathematical model.[6] It offers an extension of multiresolution modeling techniques and frameworks to help analysts and decision makers methodically navigate and gain insights about plausible outcomes in broad parameter space. It proposes graphical techniques to share insights among the decision-making group about a wide range of plausible futures. Statistical data-mining techniques then focus the group's discussion on factors that matter to the choice of options, along with the conditions under which they do, and to refine the group's understanding of different perspectives. MPSDM proposes ways of simplifying the problem so that decision makers can develop a shared understanding of the forces driving the choice of strategy. Finally, it includes a process to modify the options, consider minority views, and iterate the methodology to improve the likelihood of consensus on strategic actions.

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[6] The distinction between objective factors and perspective factors (values, beliefs, and expectations about the future) may not be as firm as has been indicated. Many factors that might be considered objective are in fact subjectively estimated (especially expectations) or subjectively assigned some nominal value. Strictly speaking, objective factors are ones that can be verified as fact, i.e. an event happened, a weapon destroyed the target, etc. What is meant here is to recognize the differences with which individuals may estimate factors and account for these differences in perspectives.

Chapter 2 - Challenges of Multi-perspective Strategic Decision Making, How Others Have Approached These Challenges, and the Principles of MPSDM

Decision makers face several challenges when devising strategy, even when their fellow decision makers are relatively like themselves. As values, beliefs, and expectations of other decision makers, stakeholders, and adversaries are taken into account, some of these challenges are made even more difficult. This chapter addresses the major challenges encountered in coming to consensus on strategy amidst diverse perspectives:

- framing the problem
- addressing perspectives in the analysis
- dealing with the curse of dimensionality
- creating strategy from the analytical results

Much as broader perspectives can bring a richer set of strategic possibilities and tools to a decision-making process, research from a wide variety of disciplines offers a selection of approaches to these challenges. The next sections of this chapter describe each of the major challenges of MPSDM, along with approaches that others have used to address them. The MPSDM approach to each challenge is summarized, and relevant principles are proposed.

The chapter then concludes with a summary of the types of literatures explored for this research, along with key concepts taken from each.

Challenge # 1: Framing the strategic problem for analysts and decision makers

What is framing?

The literature offers a range of definitions for "framing" as it relates to decision making. Entman (1993) defines framing fairly broadly:

> To frame is to select some aspects of a perceived reality and make them more salient in a communicating text, in such a way as to promote a particular problem definition, causal interpretation, moral evaluation, and/or treatment recommendation for the item described (p. 52).

A widely-cited description of framing was introduced by Khaneman and Tversky (1984) as selecting and highlighting some features of reality while omitting others. Nutt (1998) evaluated 350 strategic decisions to evaluate the process of framing a strategic issue "by influencing the directions that are set to guide the search for alternatives." Nutt found that stakeholders (typically activists in his sample) were the most common framers, at least initially. "Decision making was initiated by claims from stakeholders that pointed out salient concerns and difficulties and prompted directions to be set that guided a search for ways to respond."

In policy analysis, framing a problem means figuring out how analysts and decision makers could think about salient aspects of a problem before seeking alternative solutions. It also includes determining the structure that represents the problem amidst multiple criteria and uncertainty.

Why is framing a challenge for MPSDM?

Individual stakeholders may consider one aspect of a system to be most salient but when decision-making groups or stakeholders consider different perspectives, it may be difficult to "get on the same page." Defense planners might think of the problem in terms of meeting future military objectives, but Congress must determine funding priorities, and allies must consider political feasibility. As groups consider more perspectives in their decision making process, it becomes hard to agree on common frameworks. As expectations about the long-term future diverge among strategic decision-making groups, it is easy to understand how reasonable individuals could differ in how they think about a problem.

In addition to differences in ways that decision makers think about a problem, several studies have identified different decision making styles. Alternative judgment and decision-style taxonomies exist, but Hammond et al. (1997) describe empirical studies that show decision modes range from rational to intuitive. Hitt and Tyler (1991) provide a useful summary that includes intuitive or quick judgments (sometimes called naturalistic decision making); rational-normative, external control, and strategic choice models.

Khatri and Ng (2000) compare the relative prevalence of an intuitive strategic decision making style with the rational-analytical style in business decisions. In their interviews of senior managers of computer, banking, and utility organizations, they found that intuitive processes are used often in organizational decision making. Interestingly, intuitive processes were positively correlated with organizational environment in an unstable environment, negatively related in a stable environment.

Sometimes the presence of a group affects the criteria that individuals use for decisions. Janis' famous (1982) study of seven major governmental decisions identified the concept of Groupthink, where the need to be included in the decision-making group can outweigh the rational expected outcome of the group's decision.

Eisenhardt and Zbaracki (1992) review the strategic decision making literature, identifying the dominant paradigms and reviewing empirical support for each. They conclude "that decision makers are boundedly rational, that power wins battles of choice, and that chance matters. It is also clear that a synthesis of bounded rationality and political perspectives provides a compelling description of strategic decision making."

Davis, Kulick, and Egner (2005) point out that there are advantages and disadvantages to different decision-making styles. They identify approaches to synthesize decision processes with some virtues of both rational-analytic and naturalistic styles, pointing out ways that a good staff could work with an intuitive decision maker by finding critical assumptions, building in contingencies, etc.

In what has been called the "standard reference and textbook for many years to come"(Brewer, 2009) on risk assessment, the National Research Council Committee (NRC) on Improving Risk Analysis Approaches Used by the U.S. EPA (2009) concluded that environmental problems are socially constructed and therefore depend on human values, which are mediated by diverse perceptions. Four chapters are devoted to human, institutional, and "irrational" components of risk assessment. The committee cites a two-decade effort to deal with nuclear power plant waste at Yucca Mountain, Nevada and conclude that the issue is not as simple as rational calculation of leaking radiation from storage canisters. Instead, the issue is more about fears and lack of trust among the general population. They urge decision makers to confront and manage the perceptions of those affected rather than the rational expectations and technical assessments.

Another cognitive process that individuals use relates to simplifying complexity. As problems include more variables and relationships between the variables, decision makers frequently make use shortcuts, or heuristics to reduce a problem down to what they conceive as the bare essence of a problem. (Simon and Newell 1958; Kahneman, Tversky, and Slovic 1982; Gigerenzer, Todd, and the ABC Research Group 1999). These simplifications often have a basis in human judgment, experience, or intuition. In an interesting example of a heuristic, Rabin and Weizsacker (2009) demonstrate what they call "narrow bracketing." That is, decision makers sometimes evaluate subsets of choices in isolation, resulting in decisions whose outcome is dominated by other possible choices. They also find that the percentage of people exhibiting the suboptimal choices exhibited in narrow bracketing is higher when the stakes are high, implying a higher chance of narrow bracketing for strategic decision making compared with operational or tactical decision making.

In summary, the research shows that individuals often have different ways of thinking about problems, sometimes analytical, sometimes not. As problems involve more variables and the associated relationships between the variables, individuals and groups may rely on simplified cognitive models of the system being evaluated. [7]

Thus, one underlying principle of MPSDM is as follows:

Principle #1: Perspectives (values, beliefs, and expectations) are as important to strategic problems as more objective criteria.

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[7] Davis and Hillestad introduced alternative "views or perspectives" in early work on strategic portfolio analysis; see, e.g., Hillestad and Davis (1998), p. xv.

Approach taken by MPSDM to address the challenge of framing the problem

This section will describe the four aspects proposed by MPSDM to frame the problem: The multicriteria scorecard; the use of return, risk, and cost as generic criteria; characterization of performance with box-and-whisker plots; and characterization of time-scale and factor controllability.

Aspect #1: The multicriteria scorecard

MPSDM proposes an analytic framework which takes into account more subjective, or "soft" factors associated with perspectives. Strategic problems, by their nature, are complex and deeply uncertain and therefore analytic exploration of the options is called for in order to have adequate conceptual scope while also usefully simplifying and frame the problem for decision makers. As will be described later, MPSDM proposes several ways to simplify the strategic problem which are based on an analytic framework, while taking into account diverse perspectives.

The multicriteria scorecard methodology is quite common in the multi-criteria decision making literature. Originally applied to U.S. Department of Transportation policy in 1971 (Chesler and Goeller 1973), and to environmental policy (Goeller et al. 1977).[8] A multicriteria scorecard shows a score for each option for each criterion. Sometimes quantitative results are shown in a scorecard, with each option represented as a row and each criterion in a column. Often a simpler color code is used in the scorecard decision aid. The colors typically represent results of quantitative analysis, i.e. some numeric score rates a "green" vs. a "yellow" score. Davis has done extensive research in framing a problem for decision makers with scorecard methodologies (Davis 2002; Davis and Hillestad 2002; Davis 2008; Davis, Johnson, Long and Gompert 2008). A sample scorecard from a defense procurement example (Davis, 2008) is shown in the figure below.

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[8] Different kinds of scorecards are commonly used for enterprise management to perform business evaluation (Kaplan and Norton 1996).

The Options

Measures of option goodness: effectiveness (color) by scenario class and overall risk

Measures	Mobile Missiles (2020)	Mobile Missiles (2020) Reactive Threat	Terrorist Site (2020)	Terrorist Site (2020) Fleeting Target	WMD Facilities (2020)	WMD Facilities (2020) Hard Case	Overall Risk (2020)
Investment Options	Detail	Detail	Detail	Detail	Detail	Detail	Detail
Base Case	R (F)	R (F)	LG	R (F)	R	R	R
Penaids	R (F)	R (F)	LG	R (F)	Y	Y	Y
SLBM + Penaids	R (F)	R (F)	G	G	Y	Y	Y
SLBM + Penaids + SOF Vehicle	R (F)	R (F)	G	G	G	Y	Y
SLBM + Penaids + Sensors	O	R (F)	G	G	Y	Y	Y
SLBM + Penaids + Sensors + SOF Vehicle	O	R (F)	G	G	G	Y	Y
Adv. Bomber + Sensors + SOF Vehicle	G	R (F)	LG	R (F)	G	Y	Y

Figure 2.1 - Scorecard Result. Order of goodness (least to best) is Red, Orange, Yellow, Light Green, and Green

In the scorecard presentation above, the first column lists the options being considered to achieve capability for a Prompt Global Strike. The subsequent columns indicate the score for each option against each criterion. In the figure above, effectiveness in each of six scenarios is shown[9], as is the overall risk for each option. Scores are color-coded, with the worst score interval indicated by a red rating, followed by orange, yellow, light green, and green. The color codes are also indicated in the upper right hand corner of each cell of the scorecard by their initial. This initial helps color-blind individuals and those reviewing a black and white copy of the scorecard to interpret the results. Scorecards allow quantitative comparison of multiple options against multiple criteria.

[9] The term scenarios in this research refers to a specification of a potential mission and the conditions of that mission

Aspect # 2: Return, risk, and cost as generic criteria

The scorecard framework described in Figure 2.1, above, implies that there are a set of top-level measures that can be identified for decision makers and analysts. Note from the figure that Davis et al. (2008) have identified a type of return (performance in a number of scenarios) and risk as two generic,[10] top-level option evaluation criteria. Return (operationalized in the figure as measures of effectiveness), risk, and sometimes cost are used often in Davis' research (Davis & Dreyer 2009; Davis et al. (2008); Davis, Shaver, and Beck (2008); Dreyer and Davis (2005)).

This return/risk framework also has a strong basis in the financial management literature. Researchers and practitioners in this domain have long had to deal with simplifying an uncertain and complex problem and expressing findings in terms that are accessible to decision makers with different levels of knowledge or interest. These simplifying considerations have been incorporated in much of Davis' portfolio analysis work (Davis & Dreyer 2009; Davis et al. (2008); Davis, Shaver, and Beck (2008); Dreyer and Davis (2005)).

In his seminal work on Portfolio Theory, Markowitz (1952) distilled risk and return as two useful dimensions to consider in investment decisions. Subsequently, other financial-world portfolio theories have been developed: Modern Portfolio Theory (Elton and Gruber 1991; Elton et al. 2006); Post-Modern Portfolio Theory (Swisher and Kasten 2005) and Focused Portfolio Theory (Hagstrom 1999). All of these branches of portfolio theory feature a small set of summary-level indicators to guide investment decisions.

MPSDM proposes using the two-dimensional risk/return framework long used in Davis' research and financial literatures along with the cost of each option as three generic, summary-level criteria. For this research, it is assumed that the options are all feasibly affordable, but that the preference for an option may be affected by its relative cost.

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10 The term generic here is meant to imply "common." These generic dimensions are envisioned to be useful for a variety of MPSDM applications. As will be discussed later, the subdimensions, or lower-level measures that aggregate up to the top-level dimensions are assumed to be application-specific.

Another benefit of using the return, risk, and cost framing (along with drilling down to lower-level dimensions as described later) is that extensive research has been performed, and will be conducted on ways that people compare these three fundamental variables. The use of these three summary measures may allow the MPSDM approach to benefit from some of the useful insights coming from this important research.

There are some challenges to using return/risk/cost framing, however. The practical usefulness of this simplified framing of returns, risk, and cost depends on many factors: the decision makers' interest in details, the "spread" of the top-level scores once uncertainty is taken into account, and the insights that can be shared about what drives the return, risk, and cost, among other factors. Aggregate measures may be "too aggregated," offering little or no insight into the lower-level factors that affect choice of strategic options. As will be shown in Chapter 4, the top-level scores may be useful for describing the forest of option performance, but not as helpful in understanding why options perform as they do. In addition, although MPSDM prescribes three generic top-level dimensions (return, risk, cost) as financial theory recommends, the strategic problem is often more complicated than the financial one. First, return and risk are not typically measured in monetary terms, especially as the number of subdimensions increases. It is not always obvious how to combine, or aggregate measures that are in fundamentally different units. In addition, decision makers may have special responsibilities that are not easily compared or traded.

Another challenge of this framework shows up in the risk dimension. Financial risk is often measured in terms of variance of price, a very simple measure compared with the multi-dimensional concept of risk that decision-makers with diverse perspectives would need to consider. In this research, risk is defined as a measure of concern that an option's actual performance might be less than indicated by the expected return. It reflects consideration of both likelihood and consequence of worse-than-expected performance. For MPSDM problems, there often does not exist historical data to provide an empirical basis for calculations of risk that are often commonly used in financial assessments.

MPSDM proposes these top-level factors not as a replacement for more detailed characterization of the system, but for two purposes: first, as a structural foundation for the scorecard criteria; and second, as a way for the analyst and possibly the decision makers to get a forest-level view of the system before exploring the trees.

Let us turn next to defining what is meant here by returns. Strategic decision making by its nature typically allocates resources in the present in order to prepare for the future. In financial management, returns can be defined and evaluated in monetary terms. In strategic decision making, the returns are typically of a different nature, for example market share, employee good will, effectiveness in different scenarios, perception of those who provide funding, etc.

The challenge then is to frame the sub elements[11] of return in a way that will cover the values or criteria that are important to decision makers. Since these values are often non-monetary, the subdimensions of return must be crafted to fit the problem at hand. What lower-level factors go into the top-level measure of return? Although the methodology, principles, and toolset of MPSDM are not restricted to the use of scenario performance in return dimensions, scenario methodology is quite common in corporate planning (Shoemaker 1992). The scenario framework is used in the MPSDM example illustrated later.[12]

The use of scenarios in order to bring concreteness and clarity about uncertainty to decision makers has a long history in research. Herman Kahn pioneered the use of scenarios in the 1950s at RAND to aid U.S. military planning (DeWeerd 1967). Kahn combined detailed analysis with imagination to produce “future-now” narratives, reports written as though the author were in the future (Chermack, Lynham, and Ruona 2001). Kahn and Wiener introduced scenario planning to the business community in 1967 (Kahn and Wiener 1967). More recently, Davis’ multiscenario analysis (Davis 1988; 1994) approach has been applied to defense-related planning and the RDM line of research has

[11] Sub elements can be thought of as underlying dimensions

[12] In some literatures, scenarios are known as “worlds” or “states of the world.” Much of the scenario literature focuses on “gaps” between what is expected to exist in the future and what will be needed to meet the demands of a particular scenario, as in “will we have the capability to succeed if this scenario occurs?”

devised methods to discover “policy relevant” scenarios: Sets of assumptions that make a difference to an outcome of interest (see Groves 2005 for more history of RDM).

Outside the research world, scenario planning is quite common in practice. A major survey showed that over 50% of Fortune 500 companies used scenarios in their planning as early as 1982 (Schoemaker 1992). Scenarios are a useful for a number of reasons. Before scenario development, it was common to model the system with uncertainties embedded the model, sometimes in probabilistic terms. Scenarios present a number of “models of the future” to decision makers, each representing possible resolutions for some of the uncertainties with probabilistic claims. This decomposition of uncertainty into distinct states helps individuals to cope with complexity (Schoemaker 1992). In addition, scenarios provide a device for bringing concreteness to a problem. What psychologists call the availability heuristic—the ease with which one can bring to mind exemplars of an event—helps people pay attention to circumstances they can recall from memory or easily imagine (Tversky and Kahneman 1973; Bettman 1979). Scenarios are one way to help decision makers imagine the future more easily.

Along with return, risk, and cost, a useful fourth dimension might be upside potential, in a way that might be a symmetric analog to risk. Davis, Kulick, and Egner (2005) argue that ignoring upside potential can lead to seriously flawed decision making because it biases the group towards risk reduction without considering opportunities. The methodology presented in this research does not preclude evaluation of upside potential as a separate criterion, and in fact allows for any top-level measures of return. In fact, by identifying cases of extremely favorable results graphically in the annotated box-and-whisker plots[13] and exploring the conditions under which they occur with data-mining techniques with exploratory analysis (both of which will be detailed later), upside potential can be explicitly assessed in the MPSDM approach.

There are several ways to characterize risk into its lower-level dimensions. In the financial world, risk is often associated with volatility (Markowitz 1952). In the defense procurement example presented later, overall risk might be composed of several lower-

[13] i.e. outliers or areas of extremely high return or areas of extremely low risk or cost. Similarly, the opposite return and risk edge of the box-and-whisker plots are important because it is precisely these vulnerabilities that adversaries will seek out and exploit.

level measures: There may be a risk of funding not being continued for an unpopular weapon system; collateral damage in wartime may be higher for one option compared with another; or another option may be risky due to the potential use of the capability to be misinterpreted in a crisis as a nuclear attack (National Research Council, 2008), among other considerations.

Cost can also have lower-level dimensions, which would be important if there are significant uncertainties in some aspects of the system's cost estimates. Cost dimensions could be, for example, fixed and variable; time-related (near/long term, by year, etc.); proportion of costs allocated to different bill payers, including allies; and the "pots of money" associated with funding, among other dimensions. Another factor to consider is any cost constraint: what are the budgetary limitations? Constraints can be explicitly included in the analytical model, or explored to see the conditions under which constraints are exceeded. Depending on the problem at hand, lower-level cost dimensions can be defined to address these factors, as well as areas where the cost estimates contain more or less uncertainty.

Although the illustrative example of MPSDM given in Chapter 4 treats cost factors as relatively more certain than other factors within return and risk dimensions, real policy issues often have highly uncertain cost factors. Consider the current national health care debate: although decision makers agree on the goal to improve the quality of health care in the United States, much of the debate has been about cost factors. For instance, highly uncertain factors include the total cost, how the costs are allocated to different bill payers, whether the costs will be near term, long term, or spread out in time, whether the total cost will increase compared with the current policies, etc.

Even in defense acquisition policy, where historical data can provide a basis to derive cost estimates, policy makers must consider sub-dimensions within the cost dimension: near-term vs. long term; cost sharing with allies; which programs to cut in order to afford new ones; cost inflation or risk; life cycle costs; operating vs. support costs, etc.

The concept in MPSDM is to define a number of return, risk, can cost subdimensions that are relevant to the strategic issue at hand. Depending on the types of uncertainties or the factors that are most salient to the decision makers or stakeholders, a number of subdimensions can be defined and assessed for each option. Identifying and communicating the subdimensions of return, risk, and costs can help decision makers understand the scope of what was considered, can help analysts to identify specifically how one option differs from another in return, risk, and cost, and can focus discussion on more finite aspects of return risk, and cost, compared with a top-level measure of each.

Thus, the initial analytical framework used for MPSDM is a scorecard of measures and submeasures of returns, risk, and cost for each feasible, action-based option, with the objective to avoid the necessity of agreeing on values, beliefs, and expectations while evaluating each option against the others.

The risk/return/cost scorecard framework offers several advantages over other methods to summarize analytical results and elicit discussion of relative option performance.

1. It presents a summary of all options against all criteria simultaneously, allowing decision makers to identify each option's area of good and poor performance.
2. This visualization has been used in a variety of domains for decades, and is familiar to decision makers.
3. The scorecard shows explicitly which options and criteria were evaluated, allowing the decision makers to understand the scope of the strategic analysis.
4. The scorecard methodology provides a top-level structure that can be used for the more detailed strategic analysis. Each criterion can be divided into lower-level criteria that are evaluated for each option. Thus, the scorecard visualization tool provides a framework that can be used in what is called a multiresolution model. This model structure will be discussed in more detail later.
5. The scorecard methodology, as implemented by Davis et al. (2008) allows for real time "drill downs" on individual criteria. These drilldowns can help decision makers understand the lower-level factors in a multiresolution model

that drive the higher-level aggregate score. Not only can this drill down serve to share insights, but it may elicit a discussion of the likelihood or characterization of those driving factors.

There are several challenges to using a scorecard methodology with MPSDM, however.

1. Good scorecard technique, particularly selection of the evaluation criteria to aid decision making, requires a mix of art and science. A scorecard can easily become too "busy" with multiple criteria and options, making it difficult to gain any insight from the scoring presented. The scorecard can be simplified if a few aggregate or summary-level scores per criterion can be presented for each option, but showing measures that are too highly aggregated can obfuscate insight.

2. If decision makers within the group vary in their perspectives, then they may also vary differently in their knowledge of, or interest in, technical details. One person may have deep knowledge of the problem, and need to understand and validate the detailed technical assumptions and parameters in an evaluation. Another individual may have only a top-level awareness or interest in the technical aspects of the problem.[14]

3. There may be no simple set of criteria that the group members all agree are important.

4. Even after analysts have resolved matters of fact, decision makers may disagree on the value of an absolute score that merits a specific (red, yellow, green) rating. For instance, one criterion might be viewed as "unacceptable," or given a red score by an individual with one set of beliefs, or a "yellow" by another with a different set of beliefs. Current economic policies, for example, are expected by some to be successful and others to be counterproductive.

14 As perspectives become more diverse, wider differences can be expected in the interest in understanding the details of an analytical model. Davis has had good results with the technique of real time "zooms" to lower-level results in a hierarchical model that explain the top-level scores.

5. The analyst must decide and communicate what the score for each option and criteria represents. One way to do this is to show one or more edges of the distribution, for instance the best or worst case results (or both, using two colors or two columns for each criterion). Another alternative is to show the central tendency, such as the mean of the measure being evaluated. This central tendency may blur some important combinations of assumptions that might give plausible, extreme results. Often these are the exact combinations of variables that adversaries will seek to exploit. Sometimes the central tendency can be annotated to give more information.

Aspect #3: Characterization of the performance with box-and-whisker plots

Of the scorecard challenges above, items 1-3 will be addressed subsequently. Item 4 (decision makers may disagree on the value of an absolute score that merits a specific--red, yellow, green—rating) and Item 5 (the analyst's decision on what the score represents, a central tendency or some other measure) can be addressed in some cases by another framing aspect proposed by MPSDM, the annotated box-and-whisker plot.

An example of an annotated box plot is shown below.

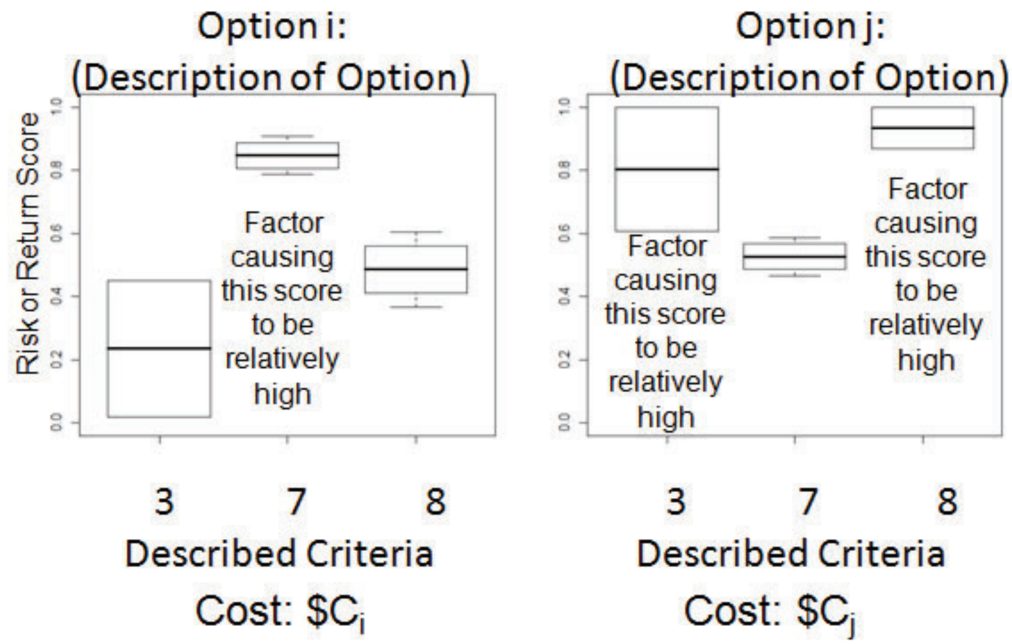

Figure 2.2 - Example of an Annotated Box-and-Whisker Plot

Starting at the top of each option's graph, the option is described in words. The Y axis shows each option's return or risk scores (although this score could be for any subdimension, let's assume for the moment that it is an Overall Retum score) for each option. Lower-level criteria that went into the Y-axis score (Overall Return score) are described in words along the X-axis. (Here, lower-level criteria might be effectiveness in scenarios 3, 7, and 8). Factors contributing to each option's relative performance are described in comments within the plot. Cost for each retained option is listed on the X-axis. [15]

[15] As described earlier, the three generic dimensions recommended for the decision-makers' consideration are return, risk, and cost. What is illustrated in this diagram, and in the illustrative example later, is that cost is treated as a simple variable. That is, it is represented on charts but cost uncertainty per se is not explored as an uncertain variable, and elements of cost are not modeled in detail. MPSDM allows for different kinds of cost to be treated as an uncertain variable, and modeled using multiple resolutions. The examples shown for uncertain returns and risk demonstrate the procedure that would be used. The "retained" options and criteria, as described later, are the options that are not dominated by others, and the criteria which differentiate the options.

The boxes and lines on the graph represent statistical results from running a large number of "cases", where assumptions are allowed to vary together. The upper edge of the box represents the 75th percentile score, the lower edge of the box is the 25th percentile score, with the difference between these scores being defined as the interquartile range. The bottom horizontal bar outside the box (the lower whisker) is 1.5 times the interquartile range below the 75th percentile. The top horizontal bar outside the box (the upper whisker) is 1.5 times the Interquartile range above the 25th percentile. The heavy horizontal bar inside each box represents the median score. Outliers, if they exist, are defined as points outside the whiskers and shown as hollow circles.

It is important to note that it is not possible to deduce true statistical results for these outcomes because no effort is made to accurately represent the distribution of uncertain assumptions, nor are assumptions necessarily independent from each other. However, as will be seen in the illustrative example, box-and-whisker plots can be used to gain first-level insight into factors that drive one option to perform relatively better or worse than others.

Aspect #4: Characterization of time-scale and factor controllability

Thus far three aspects of an MPSDM framework have been described: a multicriteria scorecard framework; top-level criteria of return, risk, and cost as a useful way to think analytically about the problem; and an annotated box-and-whisker plot to characterize performance in order to distill results down for decision makers and to focus discussion on factors that drive option choice. A fourth framework aspect that MPSDM introduces is a heuristic that uses the analytical results to identify the best type of strategy to be used. MPSDM postulates that time frame and controllability (the amount of control the decision makers have) of the factors driving option choice are the two generic, summary-level measures that are useful in determining the best type of strategy to pursue. This will be discussed further in the next chapter.

Of course this heuristic assumes that the factors driving option choice can be identified. As problems become more complex, either because of the high number of perspectives, or the large numbers of uncertain factors and relationships, it is not always obvious which factors drive the outcomes of interest to decision makers. This challenge is best met with exploratory analysis (EA), which will be described in more detail later.

Challenge # 2: Addressing perspectives in the analysis

Recall from the previous chapter that perspectives have been defined in this research as values, beliefs, and expectations. We are still faced with the problem of evaluating the options against soft, or non-quantifiable risk/return/cost criteria. This is typically handled in the multi-criteria decision making literature by leaving fundamentally different types of criteria separate, coming up with a precise score for each criterion for each option and letting the decision makers discuss which criteria are of higher value. The problem with this approach is that in a multi-perspective decision-making environment, this discussion may not lead to consensus. Individual decision makers may focus on one column of the scorecard (or the score that separates a red rating from a yellow) and never come to agreement on which is more important.

Approach taken by MPSDM to address perspectives in the analysis

The MPSDM approach was designed specifically to address the challenge of evaluating options against soft, or perspective-based criteria. As will be described next in more detail, many types of perspectives can be represented parametrically in an analytic model.[16] These "perspective parameters" can be explored in parallel with more objective parameters to find the factors that affect the choice of options.

Incorporating values into the analysis

As defined earlier, values are what individuals consider important; what they value. A good example of an approach to include values in the analysis comes from the so-called balanced scorecard methodology used in business. Kaplan and Norton (1996) define four generic dimensions, or values to measure companies: The financial dimension (how owners view the company); the customer relationship dimension; the business

16 Davis and Hillestad introduced alternative "views or perspectives" in early work on strategic portfolio analysis; see, e.g., Hillestad and Davis (1998), p. xv.

process dimension; and the learning and innovation dimension. Scenario approaches propose performance in a number of scenarios, or sets of assumptions, as criteria. Here, decision makers must decide the relative value of the different scenarios: How likely are they? Is one a better measure of how well the organization will do in the future? Are there important criteria that the scenario set ignores? What if two or more criteria conflict? What if one criterion is so challenging that it would cost an inordinate amount of money to meet it? All of these questions relate to the decision makers' sets of values, and are not easily answered, especially before the performance of the system is well understood.

Using the scorecard framework, one type of value is operationalized in MPSDM as the choice of criteria, or column definitions against which each option will be evaluated. Sometimes decision makers can agree on a set of criteria, but sometimes they can't agree upon important criteria, or relative importance. Sometimes the decision makers themselves don't know ahead of the analysis, which criterion is paramount. Perhaps the validity of a criterion "depends" on other factors which the decision makers can't characterize before the analysis. These factors could include the cost, the relative trade-offs between meeting one criterion vs. another, what the adversary will do in response to the strategy being developed, etc. Although many of these factors can be refined with an iterative approach, and by re-visiting strategy in light of new evidence, some types of values can be modeled analytically. The choice of initial criteria is clearly an attempt at finding a common set of values for the decision makers to use initially.

Similarly, the relative importance of each of the criteria is a relative value that can be represented analytically. Weighted sum or more complex logic to aggregate overall return, risk, and cost can be analyzed and explored to determine which parameters (i.e. weights or logical variables associated with each aggregation method), if any, drive the choice of options.

By discussing the results of the analytical exploration, it is sometimes possible to elicit decision makers' values. For instance, if one option has slightly more return but significantly more risk than another, the decision makers may face the risk/return tradeoff at that point. The MPSDM methodology proposes starting with a broad criteria set initially, one that covers the range of factors the decision makers' view as important. The methodology explicitly analyzes different values, winnows them down to include the set that differentiates the options, focuses discussion on the values that affect relative option superiority, and includes an iterative approach to refine the analysis of the options if new values are elicited in the face of plausible return, risk, and cost.

Incorporating beliefs into the analysis

Beliefs, or views about how the system works, define relationships between factors. Examples include a set of if/then relationships, correlations, and more complex associations and models. One type of belief is the likely actions of an adversary in response to a strategic option being picked. These actions are influenced by a variety of factors: An adversary's perceptions of the action; their capabilities; their expectations of future actions by the decision makers' organization and its associates; the adversary's perception of *others'* perceptions, and so on. Beliefs can be based on history, conjecture, intuition, or logic and thus can differ significantly within the decision making group. When an adversary holds private information, the beliefs about their responses within the decision making group may differ significantly from what actually occurs.

Beliefs are operationalized analytically in two ways in MPSDM. The first is by different mathematical models or algorithms representing relationships between factors. Often analysts have incomplete information when formulating these models and must insert their own beliefs into the process. The second way beliefs are represented in MPSDM is by the choice of plausible range and distribution of the uncertain variables for exploratory analysis. For example, the analyst may believe that a product being introduced has a performance within a given range, or that the risk of misinterpretation of intentions by an adversary could be quite high. Often models can be refined (for instance, to include additional related factors) or tested to more accurately specify performance.

MPSDM proposes two tools for incorporating beliefs explicitly into the strategic problem analysis. The first is the multiresolution model (MRM), which will be described in detail later. In an MRM, a model element's resolution can be refined as exploratory analysis finds that some factors affect the choice of options more than others. The second is through the use of logical “belief variables” as uncertain variables. During the numerous runs of a computational experiment, the belief variables are assigned different logical values.[17] For instance, if three different models of an adversary’s response are plausible, a logical variable can be assigned to take on the values 1, 2, or 3. Depending on the value of that variable in a particular run of the computational experiment, the algorithm can pick the associated model to use.

A related belief can be considered more analytical: How two or more lower-level measures should be aggregated and scored “upwards” in the multiresolution model. As described earlier, aggregation and scoring algorithms are sometimes obvious (as in the case of probabilities) and sometimes they are a matter of beliefs. Aggregation beliefs in MPSDM are handled as just described, with logical variables that define the different plausible aggregation and scoring methods. Note that aggregation methods define how two or more variables should be combined into a higher-level result; scoring methods define the result according to the result’s scale and take into consideration nonlinear scoring thresholds.

The final type of belief that MPSDM defines relates to the scoring thresholds in the colored scorecard of Figure 2.1. It is sometimes a matter of perspective, for example, which score should rate and unacceptable (or a red) rating for a particular option and criterion. As before, these thresholds can sometimes be bypassed by using annotated box-and-whisker plots or can be treated as uncertain parameters, varied in different runs of the computational experiment, and explored analytically to identify the factors that affect option superiority.

Incorporating expectations into the analysis

Recall from the previous chapter that expectations are defined in this research to be associated with how factors may change in the future. Strategic decision making considers time frames that are longer than operational or tactical decision making. As uncertainty grows, sensitivity analysis around some presumed baseline projection

[17] In this dissertation, the term “run” is the same as the term “cases” and refers to a set of independent variables associated with a run of the computational experiment used in exploratory analysis.

becomes less applicable for three reasons: First, large ranges of plausible values of factors necessitate identifying plausible combinations of uncertain parameters that produce extreme results. Second, nonlinear effects may be introduced. Third, time-changing factors in MPSDM include not only objective ones, but also values and beliefs. As will be described in the next section, some types of values and beliefs are best represented analytically as different structural models, for which sensitivity analysis is not applicable.

Parameterizing perspectives

The table below presents some examples of how many types of values, beliefs, and expectations can be represented by model parameters.

Table 2.1 - Types of Perspectives and How they
Can Be Parameterized in a Model

Type of Perspective (Value, Belief, or Expectation)	How it could be parameterized in the model
Value 1: What is important to consider in evaluating returns, risk, or cost?	Choice of return, risk, or cost subdimensions[18]
Value 2: How one criterion is valued over another	Aggregation algorithms and parameters used to roll up subdimensions of return, risk, or cost into higher-level measures
Belief 1: How some part of the system works	Logical variables associated with different structure elements of the model. MPSDM allows a number of different models to be explored simultaneously
Belief 2: Capabilities and risks, either of the decision makers' organization or of an adversary's	Plausible range or distribution of input parameters (or assumptions) used in exploratory analysis
Belief 3: How two model elements should "best" combine to create a higher-level assessment	Choice of aggregation rules and parameters
Belief 4: What is an "unacceptable" or "good enough" result of some element in the model?	Scoring algorithms and thresholds
Expectations: how a factor is likely to change in the future	Plausible range or distribution of input parameters (or assumptions) used in computational experiment

Although returns and risk have been identified as generic summary-level dimensions, what are the lower-level subdimensions of each? For the balanced scorecard example, what comprises financial performance? Which time frame should be considered? As Value 1 in the table above indicates, the choice of subdimensions reflects the lower-level criteria the decision makers value.

[18] Cost could be considered along with return and risk, but here it is assumed that it is less uncertain.

As indicated in the discussion of multicriteria scorecards, much research has been done in evaluating performance against multiple scenarios, so scenarios might be a good choice depending on the problem at hand. Clearly the domain and the views of the stakeholder in a specific problem must be chosen to consider as broad a set as possible, at least initially. The approach taken in MPSDM is to initially include many subdimensions of returns as feasible and then identify and winnow down the criteria to the subdimensions that matter to the outcomes of interest.

Value 2, how one criterion is valued over another, is conceptually more difficult. As is often seen in the multi-criteria decision making literature, the concept of assigning weights to each subdimension of risk or return is useful. An extension of multi-criteria decision making theory that is offered here is to assume those weights are uncertain variables for the computational experiment. Another extension of multi-criteria decision making theory is the assumption that other aggregation rules besides a weighted sum are possible when rolling up any lower-level measures into higher-level results. The following types of aggregation rules can be easily incorporated into any hierarchical model (Hillestad and Davis 1998):

- Weighted Sum
- Multiplying (as in logical "and" considerations)
- Logical "or" considerations
- Taking the highest value
- Taking the lowest value
- Nonlinear thresholds

The weighted sum approach is well known, but there are situations where other aggregation rules might be called for. A multiplying rule would be used if two elements were both necessary in order to achieve a higher-level effect. For instance, if in order to field a new weapon, two technological capabilities must be operational at the same time, a failure of either one would mean that the system would not be available when needed.

Logical “or” combinations are a bit more difficult to consider conceptually. They may occur, for instance, if a weapon could be carried on either one of two or more platforms. Either platform A is available or platform B is available, and the appropriate aggregation methodology for that situation would be to use an “or” aggregation rule that selects the “best” platform. This is another area where multiresolution modeling pays off. Trying to aggregate two factors that are related by an “or” condition by, for instance, averaging them, obfuscates the true behavior of the system. Consider the distribution of a variable that was a result of an averaging aggregation rule vs. an “or” rule. The “or” rule might produce a bimodal distribution, corresponding to the outcomes associated with the variables being aggregated, whereas an averaging rule would more likely produce a unimodal distribution. Explicitly allowing this “or” condition gives a more accurate and useful model.

It may be appropriate to take the highest value or lowest value of two lower-level measures when risk is being evaluated. For example, this approach might be used by a decision maker to combine development risk with risk of stable funding. The combination method, as described in the table above, is a matter of perspective. If one is particularly risk-sensitive, it might make sense to take the worse of the two (or more) sub elements of risk as the aggregate measure. Other individuals may believe that an average is close enough, or even better, especially if there are many underlying measures to consider.

A more complex concept of rolling up lower-level measures into higher-level ones is a nonlinear threshold scoring method. The figure below illustrates this.

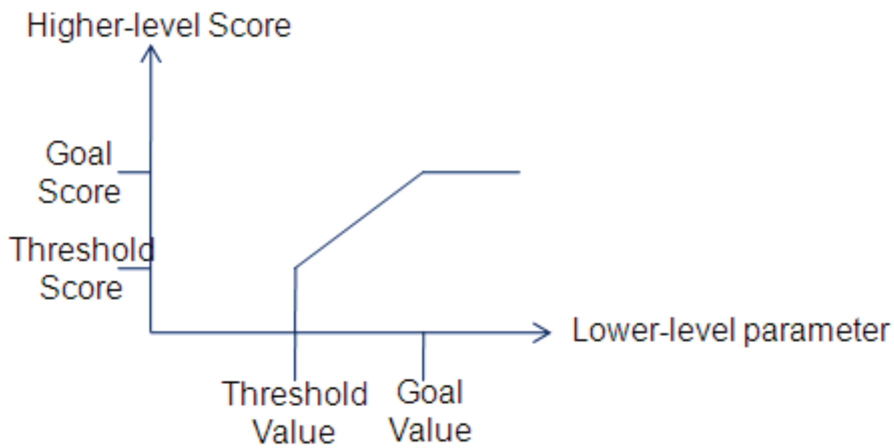

Figure 2.3 - Nonlinear Threshold Scoring

Postulate that a higher-level score in the multiresolution model was related a lower-level parameter, but in a nonlinear fashion such as a floor or ceiling effect. For example, in a technology development, some level of performance might be considered “good enough” to meet a higher-level requirement. Any performance increase above that threshold level would be of little or no benefit. Any number of nonlinear functions could be represented mathematically in the model, but a simple example is shown in the figure above. Here, only four nonlinear threshold parameters need be specified: the threshold and goal values of the lower-level parameter, and the scores associated with those threshold and goal values in the resulting higher-level result. Since “good enough” may be a matter of perspective (as might be the associated score), these parameters can be represented in the model as uncertain variables and explored to find conditions where they affect outcomes.

Similarly, recall that a scorecard has different colors associated with the various levels of returns or risk. The value of the parameter associated with a “red” rating is a matter of perspective. This is yet another example of a perspective parameter that is easily treated as an uncertain parameter in exploratory analysis.

For cases like this, where the scoring and aggregation methodology itself is a matter of perspective, MPSDM takes the approach of considering many plausible scoring and aggregation rules, assigning them each a logical value, and running the computational experiment on the full range of plausible scoring and aggregation rules. Exploratory analysis can then discover which rules "matter", or affect the outcomes of interest.

Referring back to Table 3.1, this same method also applies to Belief 1: how some part of the system works. For different beliefs, or views of how the system works, alternate models of lower-level elements can be created. Each model can then be assigned a logical value. For some of the runs in the exploratory analysis, model A will be used and other runs will use model B and so forth.

The final rows in the table above pertain to beliefs and expectations about the future that are uncertain. The approach here is similar to the previous discussion: The ranges (or distributions, if they can be derived) are treated as uncertain variables, assigned different values for different runs in the computational experiment, and assessed using exploratory analysis to see which parameters matter and under what circumstances (i.e. for what ranges of parameters) they affect the choice of options.

The uncertain variables, or assumption parameters in the model, can be continuous, discrete, or logical. Logical variables can, for instance, define which sets of parameters or which algorithm should be used for a particular run of the computational experiment. Thus parametric as well as structural variation can be explored. As mentioned before, these parameters include objective factors (e.g. those defined by the laws of physics) and more subjective, or perspective-related factors such as the relative value of one criterion over another, beliefs about the relationships between elements of the system, or expectations about the future.

This approach builds from the next principle used in MPSDM research:

Principle #3: Many types of perspectives can be parameterized and evaluated in parallel with more objective factors.

How is MPSDM's analytical treatment of perspectives related to other treatments?

MPSDM drew heavily from two lines of research in its approach to perspectives. Davis et al. (2008) consider logical groupings of subjective factors as one type of perspective. For instance an "optimistic assessment" could include favorable values of sets of uncertain parameters. As will be detailed later, MPSDM does not preclude this logical grouping, but also includes the capability to assess individual measures of perspectives, in order to determine which ones affect the choice of options.

RDM (Lempert et al. 2003) defines an XLRM framework that can be mapped to many of MPSDM's types of values, beliefs, and expectations. Exogenous factors, those outside the decision-makers' control, are most closely related to MPSDM's concept of expectations about the future, although not all expectations are exogenous. Levers that decision makers can push are called options in MPSDM. Relationships, or ways that the future evolves over time in response to the decision makers' levers, correspond to a type of beliefs in MPSDM. Measures, or performance standards that are used to rank the desirability of various options, corresponds to a type value in MPSDM.

MPSDM builds on these previous works, but treats perspectives somewhat more systematically in two ways. First, it proposes two types of uncertain variables: objective parameters that are typically associated with the future or adversaries' capabilities, and "perspective parameters," those subjective factors used to represent the values, beliefs, and expectations of the decision makers, analysts, stakeholders, and adversaries. In some sense, all uncertain values could be considered to be a matter of perspective. Those that pertain to an uncertain future could represent expectations. Those that represent, for instance, adversary's current capabilities could be considered beliefs. The intention here is to differentiate between objective parameters, which relate to, for instance, laws of physics, and perspective parameters, which represent the more subjective judgments, deductions, and inferences.

Secondly, the MPDM methodology treats different perspective as uncertain variables, and initially intermingles these two types of outcome drivers. Once the parameter space is explored in a computational experiment, the factors that most drive the choice of option are disentangled into lower levels of the model as necessary to gain insights about the system. These factors are then presented in a simplified form (the annotated box-and-whisker plot) that aims to share insights and to aid discussion of the factors that affect choice of option.

Challenge #3: Dealing with the dimensionality of addressing uncertainties and perspectives

What is the curse of dimensionality?

As discussed in the previous section, many criteria may be important to strategic decision makers. As multiple options are compared against multiple criteria, the number of parameters can grow quite large. With additional uncertain input parameters (both objective and subjective) in a long, strategic timeframe, the number of parameters can easily swamp capabilities of analysts and decision makers to make sense of them. Hillestad[19] identifies the "curse of dimensionality" as being problematic for defense acquisition problems.

The advent of desktop computing brings new computational capability for this type of problem, but in order to build shared understanding of a problem to multi-perspective decision makers, the problem must be simplified to a level where a decision-making group can discuss a manageable number of criteria, options, and uncertain factors in order to reach a conclusion.

Sometimes an analyst can find a useful simplification, or way of boiling a problem down to the important elements. However, as perspectives vary along with other parameters, the curse of dimensionality makes it difficult for the analyst to "get their arms around" a problem. In order to simplify results in a meaningful way, the analyst may have difficulty presenting results that do not inherently contain biases produced by their attempts to simplify results of analyses.

How does MPSDM address the curse of dimensionality?

MPSDM proposes a number of ways to address the curse of dimensionality by structuring the analytical model and simplifying the problem usefully without losing thoroughness or the essence of a problem. These approaches include the use of a multiresolution model, along with a number of useful simplifications.

[19] personal correspondence.

The use of a multiresolution model

Recall scorecard challenges 1 and 2, which speak to the need to balance the oversimplification of aggregate return/risk/cost measures with the thoroughness and precision of including multiple detailed submeasures. This is where a technique that Davis calls multiresolution modeling is particularly helpful. (Davis and Bigelow 1998; Davis and Bigelow 2003; Davis and Hillestad 2002). An MRM provides a systematic way of structuring the analysis that assists both the analysts and the decision makers.

Resolution refers to the level at which something is described. Multiresolution modeling, as defined by Davis and Bigelow (1998) is "building a single model, a family of models, or both to describe the same phenomena at different levels of resolution, a family of elements which multiple levels of abstraction." Abstraction here is meant to imply a simplification without losing the essence of the phenomenon being modeled. The figure below illustrates the concept.

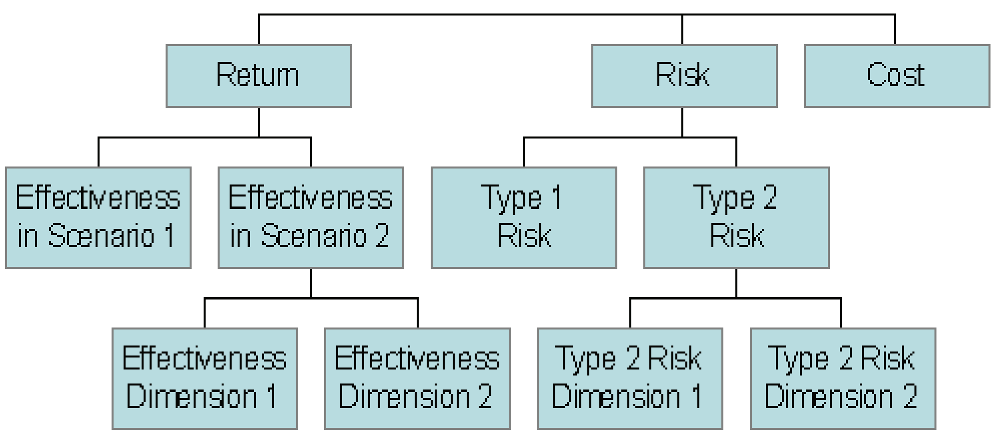

Figure 2.4 - Example of a Multiresolution Model

Starting at the top of the figure, the high-level measures return, risk, and cost can be broken down into lower-level subdimension measures. Measures can have as many levels of detail as required to give the needed insight into the critical dimensions of the problem at hand. For instance, as discussed earlier, dimensions of return might be performance in any problem-specific criteria such as effectiveness in a number of scenarios, performance against fundamentally different types of considerations, etc. Return and cost measures can be further broken down as required.

Thus, with MRM, one can reason about different input assumptions and outcomes at different levels of detail. MRM produces one or more relatively high-level measures, (for example, Return/Risk/Cost[20]) but the illustrative problem presented later evaluates Return as Overall Effectiveness for six subdimensions (scenarios), which is a large number of criteria. Aggregated measures of return, risk, or cost provide an opportunity to winnow down the dimensions of the problem.

Davis and Bigelow's (1998) research on multiresolution models has identified them as a useful tool for several reasons:

- Humans reason at different levels of detail, a point particularly true for the application here where decision makers may have different knowledge of, or interest in seeing, the details of the system being evaluated.
- Knowledge comes at different levels of resolution, and different laws operate at different laws of detail.
- A detailed model may ignore some relationships that operate at the higher-level, such as strategy and adaptive behavior.
- A higher-level model is typically quicker and less expensive to generate.
- More detailed (lower-level) models require much data, which is often unavailable or unreliable.

The first consideration also applies well to strategy domains where decision makers naturally think hierarchically. Corporate and nonprofit decision makers are well used to breaking a system down into lower-level organizations, subcontractors, etc. Defense

[20] The names of model parameters are capitalized in this dissertation.

policy makers are strongly rooted in system engineering tradition, where a complex system is often decomposed in a hierarchical structure.[21]

Beyond the analytical advantages, Davis has demonstrated the power of sharing multiresolution analysis with groups of high-level decision makers in defense-related applications. (see for example Davis, Shaver, and Beck 2008; Davis, Johnson, Long and Gompert 2008; Dreyer and Davis 2005). High-level decision makers typically do not have an abundance of time to gain familiarity with detailed analytical models. If a model is represented in multiple levels, it allows for real-time "drill downs" to lower levels with other analysts and decision makers. This ability to quickly zoom to lower levels of the model allows the model builder to show underlying assumptions and share insights about why aggregate variables behave as they do.

Another advantage of multiresolution models, which is particularly important for decision makers of varying knowledge about the problem, is that individuals can easily see the higher-level aspects of the assessment. If a model is not understood, then the decision maker has to either simply trust the analysts, or employ his own staff to validate the model. Even if decision makers are unfamiliar with some of the technical details of the problem, presenting the model in various levels of abstraction allows them to grasp the essence of the analysis.

A final advantage of multiresolution models comes from a method defined for MPSDM where the analyst explores uncertain parameter space in a stepwise manner. Instead of evaluating all independent variables (i.e. assumptions) at once, the user can "step down" the multiresolution model one layer at a time, finding the most influential variable to explore before refining that part of the model and exploring at a lower level. Thus, a multiresolution model can help the analyst navigate a large, complex model in a logical, piecewise way.

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[21] Bracken, Birkler, and Slomovik (1996) describe a principle, "structure should match strategy" that considers an organizational structure derived from strategy. A natural structure for a multiresolution model might be to reflect organizational hierarchy, i.e. subcontractors' products and services at a lower level than prime contractors, etc. Some practitioners of methods to structure so-called "wicked" problems start with organizational entities as discrete elements (Horn and Weber 2007). A notable counter-example is the Department of Defense, where capabilities-based planning was adopted as a strategy. Organizing in terms thereof has been disruptive because was inconsistent with funding paths and required an extra layer.

Thus, another principle of MPSDM is as follows:

Principle #4: A multiresolution model is useful for strategic decision making analysis when perspectives vary.

The main challenge of multiresolution models lies in the aggregation techniques used to form the higher-level summary measures. Sometimes the proper technique is obvious. For instance, if two lower-level factors represent probabilities of two necessary components, such as a wing and a tail of an airplane being available, then the logical aggregation rule is to multiply the two probabilities.

Other times, however, it is not obvious how lower-level variables should be combined. In particular, computing overall risk from two fundamentally different types of risk is a challenge. This may be a matter of the decision makers' beliefs about how to evaluate risk.

The value of a multiresolution model for exploratory analysis has not been widely understood. Davis, Shaver, and Beck (2008) call for advancing the science of exploratory analysis to portfolio-framed (i.e. multiresolution scorecard) problems: "Significant research will be needed to extend the current theory and methods and to make them practically available to the Department of Defense" (p. xxx). MPSDM addresses this need.

Useful simplification #1: Using Relative Option Superiority as a figure of merit

Recall scorecard challenge # 3, that there may be no simple set of criteria that the group members all agree are important. This challenge can be addressed by focusing on the figure of merit Relative Option Superiority in order to gain and share insight into the underlying conditions that affect choice. Relative Option Superiority for one option over another is defined for each dimension or subdimension as the difference in scores for each pair of options.

$$S_{jkR} = R_j - R_k \text{ where}$$

$$S_{jkR} = \text{Relative Option Superiority for option } j \text{ over option } k \text{ for risk / return measure } r$$
$$R_j = \text{Risk / return measure score for option } j$$
$$R_k = \text{Risk / return measure score for option } k$$

Since a return/risk/cost framework has been proposed, relative option superiority includes the differences in some return, risk, or cost measure for each pair of options.

If criteria can be quantified numerically and an absolute prediction of an outcome can be made precisely, then it is a simple matter to compute the performance of one option over another. In most cases, however there are criteria for which absolute scores can be neither computed nor agreed upon. Even more difficult is the challenge of agreeing on the absolute threshold for a "red" vs. a "yellow" score on a scorecard, or the threshold of acceptability for a given measure. Discussing Relative Option Superiority may bypass certain disagreements, i.e. model specifics. Although individuals may disagree about the specifics, they may be more likely to agree that one option is relatively superior in some measure than another.

Another advantage of using Relative Option Superiority as a figure of merit is that it may be easier for the group to agree on relative return or risk of one option over another. Such consensus, even if grudging, can bypass disagreement about details of the analysis which may or may not affect the choice of options.

In addition, focusing on the figure of merit Relative Option Superiority enables some comparisons to be made without detailed analysis. For instance, there may be an option that has a potentially disastrous outcome for some combinations of assumptions, making it an inherently riskier option than others. A quick look at relative option superiority may rule this option out without need for any additional, more detailed modeling.

Another advantage of this Relative Option Superiority in return/risk/cost framing is that it focuses the evaluation. Specifically, the scope of the multi-dimensional parameter space for several assumptions and multiple options can grow to the point where it quickly becomes overwhelming to analytical capabilities and decision makers' ability to form insights, especially when perspectives vary. The important factors can be obscured by being buried in a large amount of relatively unimportant information to strategic choice (for instance, areas where all options perform relatively the same). Focusing on areas that are important—in this case, the conditions under which one option performs relatively well or relatively poorly in return, risk, or cost compared to another option, can simplify the evaluation. This simplification may help guide decision makers to shared understanding.

Although the general methods described in this dissertation are applicable to other figures of merit (for instance regret), MPSDM focuses on Relative Option Superiority for a number of reasons:

- The concept of relative superiority is easily understood by decision makers who may have little knowledge about the technical details of the problem. In addition, it may help them explain the group's choice to stakeholders with even less knowledge about alternative perspectives.

- The process allows exploration of the relative upside and downside of the options. Identifying factors that drive an option being highly preferred in return, for instance, can lead to strategies to affect those factors. This brings forward the possibility of "upside potential" or "game-changing option" without inventing an additional criterion.

- As will be seen in the next chapter, concentrating on relative superiority focuses exploratory analysis. Rather than setting an arbitrary threshold for separating options' performance into "good" vs. "bad," and using exploratory analysis to find the factors associated with the bad areas of multi-dimensional parameter space, MPSDM sets specific thresholds for explorations: the levels of risk or return where one option performs better than another.

Thus, MPSDM proposes the following principle:

Principle #2: Relative Option Superiority is a useful discriminating figure of merit.

Useful simplification #2: Starting with a finite set of feasible options

This research assumes as a starting point that a relatively small initial set of feasible options (or alternative actions to take) has been identified for evaluation. Keeney (1992) prescribes a group beginning decision making by focusing on values, but notes that "decisionmaking usually focuses on the choice among alternatives." The premise of MPSDM is that decision makers may never agree on values, beliefs, or expectations. Therefore, MPSDM methodology starts with a relatively small set of feasible options, and includes a process to iterate the analysis and group discussion once values and other factors that drive the choice of options are understood.

Useful simplification #3: Using exploratory analysis to navigate uncertainty and determine forces driving Relative Option Superiority

Once the options have been identified, the analytical evaluation of those options against multiple criteria can begin. As discussed earlier, various strands of research begin with this options/criteria framework: MAUT, MCDM, among others. Nguyen (2003) defines some categories of methods used in the research to compare options against criteria:

- Value/utility Methods
- Scoring
- Ranking and outranking methods (Roy 1993; Barns et al. 1986)

All these methods appear to have the same first step: identifying a priori which outcomes or criteria might be of interest to decision makers.

Many of these methods assign weights to the different outcome criteria, either to compute an aggregate measure of value for each option, or to aid the option ranking calculation. Clearly criteria and weights can be directly related to what MPSDM defines as the values dimension of perspectives. For example, consider a group that identifies several criteria. If they all agree on the relative importance of these criteria, the task of ranking the strategic options is relatively straightforward.

Recently, it has been recognized that the weights for each criterion may not be known before the analysis, or may differ between decision makers. A variety of questioning techniques have been developed to quantify the weights that represent each criterion's importance to the decision makers before the assessment of the options (see Nguyen 2003 for a review). Of course this method applies only if decision makers can quantify their relative values before seeing the results of the option assessment. Sometimes individuals can't characterize their values ahead of the analysis; their relative preference for one criterion over another "depends" on factors that aren't accessible to the decision makers ahead of the analysis. For instance, there may be a "show stopper" condition or a level below which an option is ruled unattractive, despite its good performance against other criteria.

It is also recognized that such weighted-sum characterizations of a problem may not faithfully represent how real decision makers decide. One example is where an option that receives a particularly high score against one criterion may be deemed a "game changer", despite its relatively low performance score against other criteria. MPSDM allows for nonlinear scoring techniques such as this.

A primary goal of any effective decision-making tool is to focus the decision-makers' attention onto factors that have a significant effect on the final outcome produced by the decision, while ensuring that the parameter space has been covered thoroughly. Although differing perspectives can make it difficult for decision makers to focus their discussions on strategic actions rather than the validity of the perspectives themselves, some types of perceptions may not affect the decision much at all. For instance, the analytical belief of which lower-level model is "best" may not, in the end, make a difference in Relative Option Superiority. The MPSDM methodology provides a way of simplifying the problem, focusing the discussion on parameters that significantly affect outcome.

One of the simplifying approaches proposed by MPSDM is to use exploratory analysis (EA) techniques to mine out the parameters--perspective or more objective ones--that make a difference to Relative Option Superiority. EA is analysis that examines projected behavior of the system across the "assumptions space" or "scenario space."

That is, the assumptions (inputs) that drive the model are varied—simultaneously, not merely one by one—so that the analyst can identify combinations of assumptions that lead to good, bad, and ambiguous results. Exploratory analysis was originally associated with scenario space analysis (Davis and Winnefeld 1983; Davis 1994) and is a generalization and renaming of "multiscenario analysis" (Davis 1988). EA is closely related to what was originally called exploratory modeling (Bankes 1993) and applied in RDM (Lempert et al. 2003).

Although EA will be described in detail in the next chapter, at the top level, it can be thought of as the opposite of conventional analysis. In traditional modeling techniques, the analyst designs and builds a model, specifies the inputs, or assumptions, and the model produces the associated outcome. EA, on the other hand, involves designing and constructing a computational experiment where assumptions are varied simultaneously as sets of independent variables, with the outcomes of interest making up the dependent variables. A large number of assumption sets or "cases" are analyzed, with the computer producing a multidimensional database consisting of assumptions and outcomes for each case. Starting with this database, graphical and data-mining techniques are then used to work backwards, trying to determine the driving forces—the assumptions and combinations of assumptions that affect the choice of options.

Applying EA to MPSDM problems presents a few challenges. Currently, for national security applications, the practice is to identify perspectives as sets of alternate, self-consistent sets of assumptions (Davis et al.2008a). These sets could consist of, for instance, optimistic assessments of groups of unknown variables. For example an adversary's capability, risk measures, or likelihood of stable funding from Congress could be assigned to take on a range more favorable than a pessimistic assessment. The scores from these groups of assumptions are then rolled up into what becomes, in effect, a new criterion or column in a scorecard, e.g., the optimistic assessment. The idea is to identify a type of perspective made up of several related measures. The resulting optimistic assessment can then be compared against an analogous pessimistic assessment. To compute an overall assessment, two practices are used currently: the first is to leave the optimistic and pessimistic assessments separate for the decision maker; the second method is to compute an aggregate assessment using a weighted average of the different assessments (Davis et al. 2008a)

MPSDM proposes two extensions to EA as it is used in national security applications. It permits the analyst to:

- methodically "step" through the exploration, navigating downward through the MRM, exploring further as the driving forces at each level are identified
- identify categories of perspective parameters: values, beliefs, and expectations. Beliefs include analytical beliefs about the "best" way to model, score, and aggregate parameters in a multiresolution model.
- treat perspectives as individual parameters. Although the experimental design is made simpler if one can collect *sets* of perspective parameters, it is sometimes hard to tell ahead of the analysis how decision makers' and analysts' values, beliefs, and expectations tie together. Sets of perspectives can be assembled after the EA, as RDM does, to define the perspectives that matter—those affecting the choice of options.
- describe preliminary exploratory analysis using inspection and graphical methods to gain insight from the suite of runs.
- use data mining techniques employed in the RDM research to determine the "important" perspective and objective factors (i.e. those that affect the outcomes of interest).
- identify categories of perspective parameters: values, beliefs, and expectations. Beliefs include analytical beliefs about the "best" way to model, score, and aggregate parameters in a multiresolution model.

The first extension, above, is a stepwise exploration of parameter space, moving "down" the MRM with each subsequent exploration. This stepwise approach examines fewer assumptions at a time, in series rather than in parallel, and offers a few advantages over a single, complex model structure:

- It allows the analyst to "maintain their bearings" during the exploration, keeping the model as simple as possible for as long as possible. Often, explaining a multiresolution model to decision makers in a logical, system-engineering structure will help them gain confidence in the model. If decision makers are used to a hierarchical way of thinking, for instance in national security or competitive fields, they may be particularly receptive to this type of structure;
- Using a multiresolution model development method which starts with a simplified model and letting the EA guide the model refinement may save time and money; and
- It may extend the dimensional capabilities of analytical algorithms. Two tools—the one used to generate the results of the computational experiment, and the EA data-mining algorithm—have computational limitations which can be extended by evaluating fewer assumptions at a time.
- It permits a disaggregation

In the social policy stream of research, RDM practitioners have made advances in using and comparing algorithms to find clusters of independent variables that affect the outcomes of interest. MPSDM uses this approach to EA, but also contributes to the Exploratory Modeling approach used in RDM applications in multiple ways.

First, MPSDM defines a multiresolution modeling structure that may appeal to decision makers with little or no knowledge of the technical details of the problem. RDM is currently being tested with actual high-level decision makers. The author worked on one experiment where RDM was compared with other methodologies to evaluate the impact of climate change on California Water planning. Although RDM performed well against other methods, it was viewed as too complex for some participants. Only a minority of participants felt strongly that RDM was easy to understand, and that it was easy to explain to stakeholders. The six useful simplifications described in this chapter, plus the use of multiresolution modeling techniques are aimed at providing thorough yet simplified representations of the strategic decision to high-level decision makers.

In addition, a novel contribution of this research is to define perspective parameters, including those associated with aggregation rules, as uncertain variables, to be explored at the same time as more objective factors. Unlike other analytical techniques, where perspectives are considered after the analysis is complete, here they are analytically represented in the model and explored simultaneously with more objective factors to find which ones matter to the outcomes of interest, and under which conditions they matter.

Other useful simplifications

Thus far, MPSDM proposes three ways that problems can be usefully simplified: Using Relative Option Superiority as a figure of merit; starting with a relatively small set of feasible options; and using EA to find forces driving Relative Option Superiority. Three other useful simplifications are proposed by MPSDM:

1. Using a process that includes a mix of aggregating (to represent top-level results) and disentangling (to parse out the key factors driving the top-level results) in order to navigate the uncertain parameter space and share insights gained along the way.
2. Identifying options that are dominated, or inferior in important criteria to others. These options can be eliminated from consideration.
3. Identifying criteria which differentiate options. That is, criteria for which one or more options are relatively superior to others. If all options perform relatively the same for a particular criterion, then that criterion is of little use in helping decision makers choose between strategic options. That criterion can be eliminated in that iteration of the MPSDM methodology.

The first method of aggregating and disentangling in a step-wise exploration of an MRM will be described in more detail in the next chapter.

The second method, looking for dominated options to eliminate, may not always yield results. An option may be inferior to others for some sets of uncertain parameters for a measure, say return, but not in all of them. Or it may be inferior to another option in return, but not in risk. MPSDM proposes starting with the baseline option as the “current plan,” so that other options can be evaluated relative to the “do nothing differently” strategy. With this choice of baseline, the failure to reach a decision on strategy results in the baseline strategy being adopted, and decision makers will have a clear indication of its relative strengths and weaknesses. Since presumably other options improve in at least one aspect of the strategic problem, it is somewhat likely that the baseline option will be dominated, in return or risk or both.

The third method, above, starts with a broad set of criteria and then evaluates each option's performance against each criterion. If all options perform relatively well or poorly for a criterion, that measure can be eliminated since it doesn't affect the choice of options—it is not an option differentiator. Later, after options are modified and the MPSDM method is iterated, that criterion may need to be re-included for consideration.

Thus, MPSDM offers seven ways to address the curse of dimensionality: the use of MRM with a return/risk/cost framework; the choice of Relative Option Superiority as a figure of merit; starting with a relatively small initial set of feasible options; extending EA methodologies to discover forces (including perspectives and MRM aggregation techniques) driving the system; an aggregation/disentangling process to efficiently navigate uncertain parameter space; eliminating dominated options; and eliminating criteria that don't differentiate options.

Challenge #4: Creating strategy from the analysis

One possible method to derive strategy is for the decision makers to discuss the annotated whisker plots and all agree that an option is clearly superior to the others. This happy circumstance is more likely to occur if uncertainty is relatively small, decision makers' perspectives are closely aligned, and an option's score on a scorecard is so much better in all criteria that it dominates the others. This situation is relatively rare, and it is clear that a workable decision-making methodology cannot be predicated on its regular occurrence.

Other methods can be used by a group to create strategy. RDM regularly evaluates each option (or policy lever) to find the vulnerabilities—conditions under which an option performs poorly (Groves et al. 2008). The decision makers then discuss or vote on the likelihood of the factors driving the vulnerabilities turning out in a way that favors one option over another. Savage's (1950) work on minimizing the maximum regret is related to this concept of choosing options by considering the downside potential, or risk. RDM uses a related but not identical measure in its definition of regret to find strategies that work "reasonably well" over a large number of plausible futures. This approach has clear appeal, especially when the worst case is unacceptable as in the potential for disastrous global climate change, national security-related vulnerabilities, or for corporations that have the potential to fail. As will be described in the next chapter, MPSDM adopts the RDM approach of identifying vulnerabilities for options of interest as one factor guiding the iteration of options.[22]

Still another method to create strategy is to look for ones that are flexible, adaptive, and robust (Davis 2002, Davis, Kulick, and Egner 2005). The FAR philosophy prescribes strategies that—within economic constraints—generate capabilities that are flexible enough for multiple missions and uses; adaptive enough to deal with diverse circumstances; and robust enough to withstand shock and recover.

Although it is necessary to assess a number of options relative to outcomes of interest, strategy does not necessarily consist solely of decision makers choosing an option. Instead, decision makers can use insights gained from the above methodology to create paths forward. These paths forward can take into account the different beliefs and expectations, once the key ones that affect the outcomes of interest are mined out.

One of the goals of MPSDM is to usefully simplify complexity, as described in the previous section. Continuing this theme, a simple heuristic is proposed which uses driving forces' time frame and controllability (the level to which decision makers can affect a factor) to determine the type of strategy that should be considered to affect option superiority. The figure below shows this heuristic.

[22] Although the use of Regret as a figure of merit is not precluded in MPSDM's methodology, Relative Option Superiority is currently defined as a simple difference in some measure of return, risk, or cost between two options.

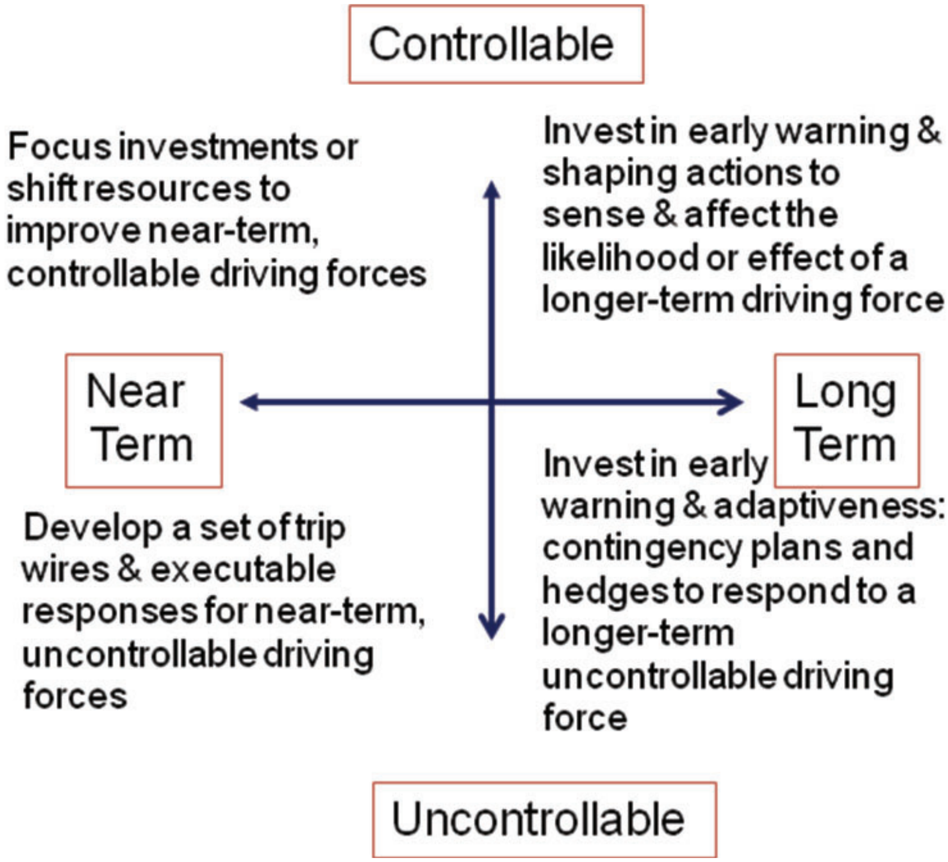

Figure 2.5 - Heuristic to Derive Strategy Type Based on Time Frame/Controllability of Driving Forces

The upper right hand corner pertains to driving forces that are longer-term and still somewhat controllable. An example of this might be a technology to overcome a capability that the adversary may or may not be developing. A good strategy in this quadrant would be two-pronged: develop early warning capabilities to give the organization more time (hence more alternatives) to address the capabilities gap; and invest in shaping actions.

Shaping strategies change the likelihood or effect of a driving force. They can come in two forms: efforts to shape the environment in desirable ways (what Davis (1989) calls “environmental shaping strategies” (Bracken (1990) applies business principles to the national-security concept); and actions to change the decision-makers’ organization in desirable ways, what MPSDM calls “internal shaping strategies.” Since driving forces in this quadrant are by definition longer term, there may be sufficient time to affect such shaping actions. An example of a driving force in the business domain for this quadrant would be market presence. A competitor may be planning a market entry into a new country. Here, the two-pronged strategy would be to develop early warning of that possibility (are they running focus groups? Moving distribution centers closer to that country, etc?); and a shaping action to affect the likelihood or effect of the action external to the decision-makers' organization: acquire a company in that region, put plans in place for a pre-emptive entry, etc. An example of an internal shaping strategy in the defense world would be to create a training program to prepare for the possibility that military forces will need to be deployed for a new type of mission.

MPSDM's concept of an early warning is related to Dewar et al.'s (1993) concept of a signpost. They define a signpost as "an event or threshold that clearly indicates the changing vulnerability of an assumption." The term "early warning" in MPSDM is meant to imply an indication that the mix of strategic actions that was planned may have to change. This could be due to a change in expectations, i.e. the future is not unfolding in the way expected, or the change in effects, i.e. a new belief has emerged.

Regardless of the differences in exact meaning, Dewar's advice for signposts applies to early warning mechanisms as well: They should be unambiguous and genuine, especially when adversaries may use deception practices. Dewar recommends use of multiple indicators, and that the sensing be implemented by the same organization that does the planning. He also describes the use of a sequence of indicators that is activated once one signpost appears.

Continuing on to the lower right hand quadrant of the figure above, we find driving forces that are longer term but predominantly outside the decision-makers' ability to control. An example from business might be the emergence of a new competitor into the marketplace. In the defense world, a driving force in this lower right hand quadrant might be the political instability of a potential adversary country. The emphasis in this lower half of the figure is in formulating *responses* to uncontrollable factors. For this case, the best strategy is again two-pronged: The first prong is to develop early warning capabilities designed to detect the change. The second prong of the suggested strategy type involves those responses themselves, which should be adaptive.

What is meant here by adaptiveness? The word "adaptive" as it pertains to strategy has been used by many authors, with slightly different shades of meaning. Hofer (1973) was perhaps the first to characterize an adaptive model of organizational strategy, characterizing it as

> concerned with the development of a viable match between the opportunities and risks present in the external environment and the organization's capabilities and resources for exploiting these opportunities.

More recently, Davis (2008) defines an adaptive strategy as "one able to be effective in a wide range of operational circumstances." (See also Davis 1993; Davis, Gompert and Kugler 1996; Davis 2002). Lempert et al.'s (2003) methodology for quantitative, long-term policy research defines adaptivity as "identifying, assessing, and choosing among near-term actions that shape options available to future generations."

Common to these definitions of adaptive strategy is the concept that some factor in the environment (i.e. outside the decision makers' control) may change in the future, in ways that may not be predictable now, and an adaptive strategy is a plan to respond in a way that accounts for that change.

Clearly there is some overlap between these three definitions of adaptiveness. The intention here is to take advantage of the time frame/controllability framework and separate shaping actions, which are by definition controllable by the decision makers' organization, from adaptive *responses* to forces beyond the decision makers' control. MPSDM defines an adaptive strategy as a plan that prepares for the possibility that some factor in the environment (i.e. outside the decision makers' control) may change in the future in ways that may not be predictable now. Adaptive strategies can include hedges and contingency plans along with the associated early warning sign.

A contingency plan is a set of executable responses to some warning sign that may be sensed in the future. It may or may not involve a near-term investment, and may or may not necessitate replanning at the time the sign is received. An example of a contingency plan for the business example might be to acquire competitive intelligence and devise a way to market the decision makers' product as superior to the new entrant, should the competitor enter the marketplace. For the defense example, a contingency plan might be to increase the number of reserve resources to prepare for additional threats, should they emerge.

The concept of a hedge appears to have somewhat different connotations, depending on the domain in which the term is used. In financial literature, a hedge is an investment intended to protect oneself from the risk of an unfavorable shift in the price of a security.[23] Davis (1989) and Bracken (1990) define a hedging strategy as one that "copes with external contingencies arising from other environments (insofar as shaping strategies cannot cope with them)." Dewar et al. (1993) define hedging actions as actions "taken to better prepare an organization for the failure of one of its important assumptions."[24] In all three definitions, the concept of hedging presupposes one type of investment now based on an assumed expectation of the future, but a hedge is an additional near-term investment "just in case" that expectation proves false.[25]

A hedge, as the term is used here, differs from a contingency plan in that it requires a near-term investment, and does not involve replanning as do some types of contingency plans. A contingency plan assumes that some signal in the future will prompt a shift in the set of actions the organization takes. Both are in response to a driving force in the environment, outside the decision-makers' control, and both are more common in longer-term planning.

A hedge in the business example might be to invest in developing new products for a different market to diversify the company's offerings in case a competitor develops a

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[23] Longo (2009) identifies two sources for the original hedging strategy: Alfred W. Smith is generally recognized as creating the first hedge fund, but Warren Buffet reported that Benjaman Graham operated the first hedge fund in 1926.

[24] Dewar et al.(2003) say that hedging actions are distinctly different from shaping actions, in that hedging actions, which prepare for the world of violated assumptions, and require an act of replanning. MPSDM's concept of a hedge does not require replanning, because it includes the possibility of preplanned shifts in actions in the future that would be activated by a signal. Davis, Kulick, and Egner (2005) refer to branches, or contingency plans in response to monitored changes, as distinct from hedges that allow appropriate responses to problems that arise for which there are nonexistent or inadequate plans.

[25] Hedges are typically associated with uncertain expectations about the future, and MPSDM's heuristic uses hedges for longer-term driving variables. An extension of MPSDM would consider hedges for uncertain values and beliefs as well.

game-changing capability. A hedge in the defense example might be to form a coalition of countries and agree on a unified response "just in case" an aggression occurs. Note that some adaptive response plans, if known to the adversary, might in themselves act as a deterrent.

In differentiating the two types of long-term strategies (those on the right hand side of the heuristic: shaping actions vs. adaptiveness) two considerations are useful to remember: First, that these are responses to *driving forces* that are either within, or outside of the decision makers' control. (The strategic actions themselves are completely within the decision makers' control); and second, that shaping actions assume the decision makers can affect the likelihood or effect of some factor and adaptiveness is a response to some change in the environment, outside the decision makers' control.

MPSDM proposes two ways in which hedges can be incorporated into the decision-making methodology. The first is to use the EA process to identify those assumptions which most affect option superiority and define a type of hedge. This is the process described so far.

The other way hedges could be incorporated into the MPSDM process is by taking into account the different expectations about the future that individual decision makers may hold. Consider two investment strategies: "all in" investment strategy designed to address one future state of the world; or a diversified portfolio of investments including hedges that could reduce the total risk exposure. The first strategy presupposes that decision makers could agree on one future state of the world. As perspectives vary, the likelihood of this agreement diminishes. One method sometimes used to reach consensus on expectations is by voting on the likelihood of alternate futures. Although the voting process may seem impartial, it contains some problems: do all votes count the same? What if one decision maker has little confidence in their expectations? Is there someone in the group whose special expertise that is diluted by the voting process? Arrow's impossibility theorem (Arrow 1951) demonstrates that with three or more options to choose from, no voting system can produce a community-wide ranking from the ranked preferences of individuals while also meeting three criteria: unrestricted domain; non-imposition; and non-dictatorship.

One variant of a hedging strategy is a so-called mixed strategy; pick some of Option A, some of Option B, etc. An example from the defense or business world might be to invest in one phase of Option A, such as the development phase, and to proceed with Option B until it is well into production. The building-block approach used by Davis to define components of a system could also be applied in the time domain by breaking options into smaller, milestone-based phases. Of course a mixed strategy could include dimensions other than phases: it could include number of units produced, a fixed investment amount in each option, etc.

The diversified investment approach can mitigates consensus issues. It addresses minority perspectives by explicitly considering, and planning for futures that may be unlikely but high consequence. The remaining issue, however, is how much of the portfolio to invest in each of these alternative expectations of the future. Here is where the value of the early warnings comes into play. Early warning of, for instance, an adversary taking unexpected action allows time to shift the investment to counter that action.

Other approaches to strategic decision making identify early-on the levers that the decision makers can push; MPSDM proposes waiting until the driving forces are understood. This has two potential advantages: It may save time by avoiding discussion of actions that don't affect outcomes of interest; and it may expand the option set. By focusing in on one or two driving factors, groups may come up with creative ways to affect things that they might not have considered in the broader context.

This "controllifying" activity is not to be underestimated. Often, when a factor seems completely outside the decision makers' control, influences from other domains can be brought to bear. An agreement with a third party, a game-changing breakthrough, or even an unforeseen circumstance may bring the factor into indirect control. Sometimes the group (especially when stakeholders are included) has resources far beyond what any individual decision maker may recognize.

Continuing clockwise to the lower left hand quadrant of the figure above, we find uncontrollable driving forces in the near term. This is perhaps the most challenging quadrant of all, because there is insufficient time to invest in shaping or adaptive strategies. An example from the business world might be the brewing political instability of a country in which the company does business. In the defense world, a driving force in this quadrant might be an upcoming meeting of a terrorist leader in a known location. Here, the idea is to develop a set of pre-planned executable responses in case the driving force turns out unfavorably. Rather than sit and wait, a set of trip wires can be developed, with associated actions so that decision making, should the future unfold as indicated, can be quick. A trip wire is different from an early warning in that it is intended to be a clear signal that a change has occurred, from which pre-planned actions can be taken quickly. For our business example, this might mean developing set of clear indicators associated with different levels of responses up to and including plans to evacuate employees from the country. For the defense example, a response in this quadrant would be to invest in unambiguous intelligence and develop doctrine for making decisions such as striking an adversary during a brief moment of their vulnerability.

Continuing to the upper left hand quadrant of the figure above, we find driving forces that are near-term and controllable. Examples of this in the business world might be the probability for winning a proposal for the first product in a new product line. A defense example might be availability of resources for a new trouble spot brewing. Since these are near-term, there is not sufficient time to develop adaptive strategies. Similarly, there is no need to put signposts in place, although it may be useful to verify underlying assumptions. The type of strategy recommended for this quadrant is to focus investments (perhaps by using resources previously used for hedges) or shift resources. For instance, in the business example, a strategy here might be to apply more resources to the proposal. In the defense example, one strategy might be to develop doctrine regarding location of bases or deployed forces.

Note that even though strategic decision making has been defined as the process of making long-term decisions involving large amounts of resources, a brief discussion about time frame is in order. Strategic decision making, by definition, considers long-term outcomes, but it is useful to consider whether each driving force is predominantly near-term or long-term for the following reasons:

- Although strategic decision making looks further into the future than operational or tactical decision making, resources must be split between investments with near-term and longer-term results. Strategic decisions are intended to have long-term effects, but the decision itself will lead to actions beginning in the short term.

- This heuristic may also be useful for shorter-term decision making as well, by focusing the group's discussion on what factors can be brought under the control of the decision making group.

- Some driving forces may appear to be not under the group's control in the long term, but there may be actions that can be taken to drive them towards controllability. For instance, a potential ally's desire to cooperate might seem uncontrollable in the near-term, but tactics might be created to incentivize them to change their participation.[26] Doing so would increase the number of ways to deal with the driving force. Such shaping actions are long-term in nature, but must be initiated in the near term in order to have maximum effects.

- Some factors that affect long-term outcomes can be affected in the near term. In the example described earlier, shifting resources to cover a proposal can affect the likelihood of winning the longer-term program.

Next, in a process that will be described in more detail later, options which are relatively superior to others can be modified to improve their returns, risk, or cost using the type of strategy suggested in the time frame/controllability heuristic. The MPSDM process is then repeated, iterating options and/or criteria (that may have been revealed or refined during the process) as resources allow or one option becomes clearly superior.

[26] Here we have another example of a distinction between the XLRM framing used in RDM and the approach taken here. Recall that the X refers to Exogenous variables, and that decision makers start by identifying exogenous factors before the analysis. MPSDM has a different view of exogeneity. While it is clearly critical for decision makers to understand their span of control, there are times when creative strategies can be derived to increase a factor's controllability. Similarly, a decision maker may sometimes have indirect controllability, that may only come out after a few driving forces are determined. For instance, there may be tools in the decision makers' toolkit that can be used to influence an adversary, even when an adversary's actions seem, at first blush, to be exogenous to the decision makers.

The preceding discussion illustrates another underlying principle of MPSDM.

Principle #5: Time frame and controllability of driving forces are two critical factors that drive the choice of type of strategy to employ.

Types of literatures explored in deriving the MPSDM approach

A variety of disciplines contributed to the literature review for the MPSDM approach. The figure below shows the disciplines that contributed methods, principles, frameworks, or tools in this research.

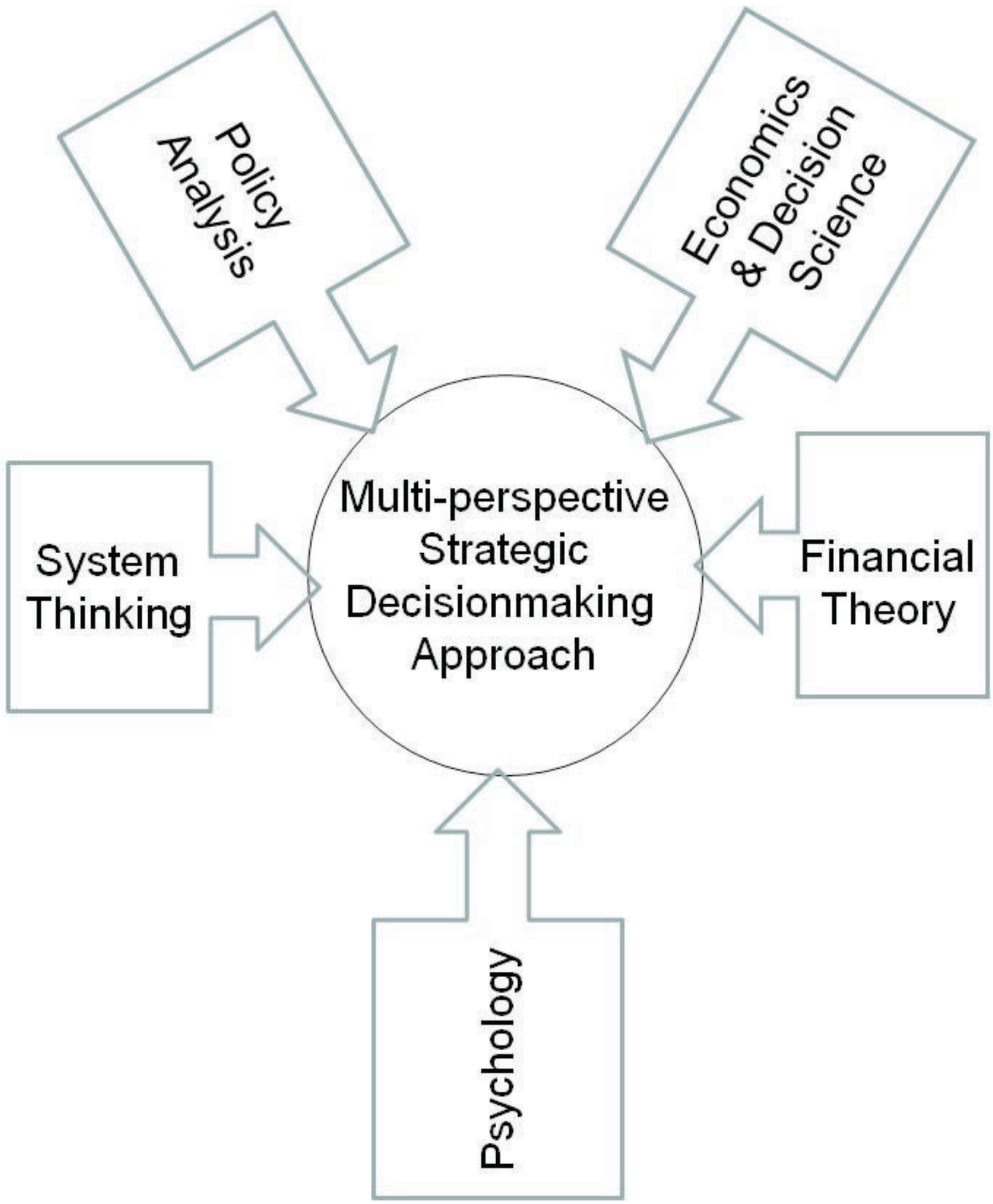

Figure 2.6 - Literatures Contributing to MPSDM

From policy analysis literature comes the methodology of identifying options, facilitating discussion of those considerations for which high-level decision makers' experience and judgment are most useful, and selecting an action-based option (e.g. "invest in that set of capabilities"). Some of the data mining applications and tools used in Exploratory Analysis come from policy domains. As discussed earlier, the MPSDM approach builds on Davis' line of research, the RDM methodology, as well as Dewar's work in policy analysis.

Economics and decision science seek to describe ways in which people choose. Much work has been done on the different models describing human choice. The initial framework chosen here, the scorecard methodology used frequently in multi-attribute decision theory, allows decision makers to view the performance of a few options to discussion. The so-called balanced scorecard methodology (Kaplan and Norton 1996) has been used in a variety of organizations over the years.

Financial theory often works to simplify complex financial measures into a few simple metrics, such as expected risk and return, as well as to create two-dimensional representation of complex market behavior for decision makers. As described earlier, portfolio theory and its variants seek to simplify and reduce total risk exposure through diversification, a type of hedge.

Psychology researchers recognize that people are not always rational actors—that decisions are sometimes made not on the basis of increasing expected return, but rather on rules of thumb, biases, and heuristics used (sometimes without being explicit about the basis of the decision). Psychology literature also discusses the amount of complexity that people can usefully absorb, and encourages useful simplification of a problem. The author has been involved with psychological experiments aiming to help us understand how people prefer to characterize uncertainty, as well as some additional experiments involving high-level decision makers. One of the most interesting findings is that the problem must be simplified usefully, in order for the decision maker to not only understand it, but to communicate it to his or her superiors or stakeholders. Finally, the recent brain research involving imagery of different parts of the brain during decision making looks quite promising to help us understand biological factors that influence choice (Camerer 2008).

System thinking tells us how to structure a problem in order to simplify it. The multiresolution model, which will be discussed in detail later, is one such useful structuring approach. Lower-level measures are aggregated up to higher-level measures, with data analysis and scoring algorithms used to put multiple dimensions of goodness for multiple options on a single scorecard. This method almost literally gets everyone on the same page, discussing action-based options rather than the underlying values, beliefs, and expectations upon which individuals may never agree. In addition, the multiresolution model permits real-time “drill downs” to lower-level parameters which greatly helps build credibility of the presenter and allows high-level decision makers to do real time “what if” analysis. Systems thinking also emphasizes the relations between elements (e.g. beliefs and aggregation methods) that can be parameterized, analyzed and understood.

All of these disciplines were explored for their usefulness in MPSDM, and the bibliography can be considered a sampling of the works consulted.

Chapter 3 - Methodology and Toolset of Multi-perspective Strategic Decision Making

Methodology

Overview

Classical management thinking prescribes group discussions about objectives, followed by development of corresponding strategies and plans (Hitt, Ireland, and Hoskisson 2009). This traditional approach includes on an underlying assumption that the risk, returns, and cost of options being considered can be predicted with a relatively high level of confidence, and that uncertain variables can be identified and characterized.

MPSDM seeks to be more realistic about uncertainty, and about the existence and importance of differing perspectives. It develops strategies and plans focused on actions (options) while accommodating diverse and sometimes uncertain perspectives. The figure below illustrates the MPSDM methodology.

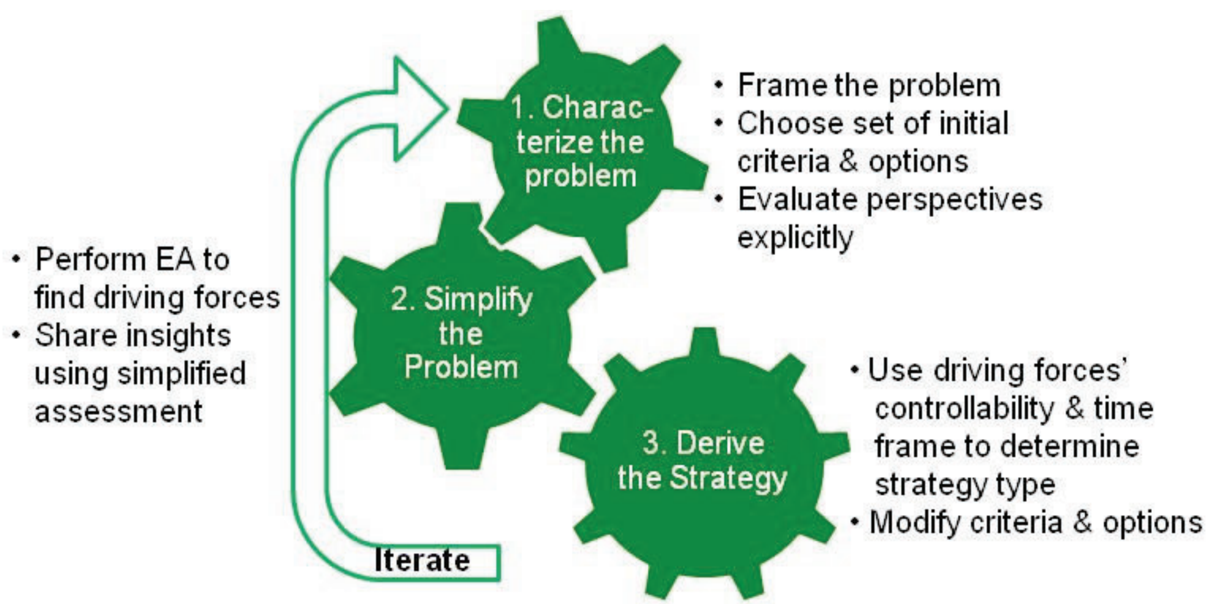

Figure 3.1 - MPSDM Methodology

MPSDM calls for 1) Characterizing the problem for analysts and decision makers using a return/risk/cost framework and an initial set of criteria in a multiresolution model; choosing a feasible, action-oriented initial set of strategic options; and evaluating perspective parameters explicitly; 2) Simplifying the problem using a multi-pronged approach; 3) using the driving forces' controllability and time frame to determine type of strategy which best addresses the choice of options, and modifying options and criteria as required. Once insights about the problem are gained and shared, the problem is iterated, repeating the analysis on the revised set of criteria and options based on initial experience. At any phase of this methodology, decision makers can be consulted for their perspectives, but experience shows that high-level decision makers want a combination of credible results and discussion at a level where their expertise and judgment can be most useful.

At the top level, the MPSDM methodology looks similar to other three-phase strategic decision making process models (Schwenk 1995), although the phases are sometimes described using different words. MPSDM, more specifically than other approaches, focuses on decision makers', stakeholders', and adversaries' different perspectives. This different focus is more evident in the detailed description of the methodology

MPSDM step #1: Characterize the problem

The management and policy analysis literature proposes several ways to frame problems but, as discussed earlier, in order to derive strategy, MPSDM starts with return/risk/cost framework and an initial set of criteria, against which options will be evaluated. There are many ways to identify an initial set of criteria, for example by defining some capability desired in the future and assessing the current capability. Closing the capabilities gap could be one criterion. Other criteria could the highest considerations held important by different constituencies. Typically constraints are identified at this early stage of characterizing the problem.

Although the MPSDM methodology can use any type of returns or risk measures, performance in scenarios is a good starting criterion for assessing different strategic options, for reasons described earlier.

Davis et al. (2008) define an analytical approach for devising a so-called spanning set of scenarios.[27] This approach is similar to how a design engineer would specify a set of design points which, together, would stress the key requirements for a system. The approach follows careful thinking about the entire scenario/parameter space and identifies the critical dimensions of the problem. If well chosen, the spanning set of scenarios stresses the options in all critical dimensions. Often these critical dimensions can be identified before the more detailed analysis, sometimes not. RDM methodology (Groves and Lempert 2007) includes a procedure for discovering so-called policy-relevant scenarios: sets of assumptions which are most relevant to the policies. As will be shown later, MPSDM starts with the criteria of option performance in a spanning set of scenarios, and allows for iteration of the scenarios if new critical dimensions are discovered in the exploratory analysis.

As mentioned before, MPSDM assumes that an initial set of feasible options has already been identified. How might this be accomplished? Perhaps decision makers or analysts have already identified a list of possible strategic actions to take. In some cases stakeholders or advocates have identified their preferred options.

Davis et al. (2008) define a methodical approach for developing this list of options that expands the possibilities beyond what analysts or decision makers may initially consider. The procedure identifies multiple objectives with the intention of generating a portfolio of investment options; identifies building-block options that address a portions of the problem (i.e. individual objectives), generates all combinations of building blocks (i.e. all composite options), and then performs a screening evaluation to winnow the list to those that perform relatively reasonably well (e.g. that are close to the efficient frontier) across multiple objectives, by at least one perspective. Good strategic options are almost

[27] In mathematics, a spanning set has a somewhat different definition than used by Davis et al. Mathematically, a spanning set is a set of points from which all other points in a set can be constructed by a linear combination of those points. A spanning set of scenarios is not meant to imply that would could construct all other scenarios by linear combinations of the spanning set. Davis, Shaver and Beck (2008) define a spanning set of scenarios as “a small set of scenarios chosen to stress a design or investment plan in all critical dimensions. An option that does well across the spanning set of cases should do well in real-world situations (assuming good use of resources at the time), even though those situations will usually differ from the test cases” (p. xxxviii).

always composite options because of the multiple objectives and considerations. This method ensures that a broad set of possibilities is considered initially.

A key principle of MPSDM is evaluating the options using both traditional, objective criteria, simultaneously with decision makers' perspectives (values, beliefs, and expectations). As was described in the previous chapter, many types of perspectives can be identified and characterized analytically and included in a multiresolution model to assess the options.

MPSDM step #2: Simplify the problem

The second step of the MPSDM methodology is to simplify the problem. This is challenging because of the curse of dimensionality—the number of options, the profound uncertainty inherent in strategic decision making (especially when adversary's capabilities and responses must be considered), and the wide range of perspectives that have been incorporated into the problem. The approach taken by MPSDM to simplify the problem using a multiresolution return/risk/cost framework and six useful simplifications:

1. defining Relative Option Superiority as a figure of merit;
2. starting with an initial, relatively small set of feasible options;
3. extending EA methodologies to discover forces (including perspectives and MRM aggregation techniques) driving the system;
4. using an aggregation/disentangling process to efficiently navigate uncertain parameter space;
5. eliminating dominated options; and
6. eliminating criteria that don't differentiate options

The first few of these simplifications—using a multiresolution return/risk/cost framework, using Relative Option Superiority as a figure of merit, and starting with an initial, finite set of feasible options--has been described earlier. The next sections describe the other simplifications.

Exploratory analysis

EA is described in the Figure below.

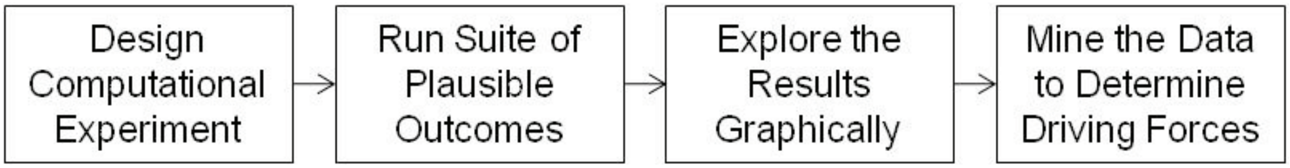

Figure 3.2 - Steps in Exploratory Analysis
(Figure Adapted From Bankes 1993)

The first exploratory analysis step is to design the computational experiment. As mentioned earlier, the dependent variables are the outcomes of interest, i.e. performance in a number of scenarios and risk dimensions. Each “run” of the computational experiment produces risk and return results at different resolutions as a function of independent variables (sets of assumptions). Consider an aggregated return measure, such Overall Effectiveness which could be calculated as a weighted sum of performance in multiple scenarios.

The independent variables, or assumptions, can include continuous, discrete, or logical variables indicating uncertainty or different perspectives. The variables consist of objective factors and the more subjective perspective parameters which represent different values, beliefs, and expectations of decision makers, stakeholders, and adversaries. The design of the computational experiment includes determining the independent variables, and establishing the plausible range they will take in the multiple analytical runs of the experiment. In addition, the independent variable sampling technique must be established. It is important to cover the full range of parameter space, defined as the assumptions and outcomes associated with the extreme ends of assumption plausibility. For instance, if one assumption can plausibly take on a value between zero and one, and another assumption can plausibly be between 10 and 100, then all four combinations (0,10; 0,100; 1,10; 1,100) should be evaluated. It may turn out that, due to nonlinear effects, some middle-ground combinations produce more extreme combinations than the points on the extremes. The sampling methodology is left to the experimental designer.[28]

The next step in designing the computational experiment is to set up a table of the independent variables, or sets of assumptions that will be considered. The variables are not varied one at a time as in traditional sensitivity analysis, but all together according to the computational experimental design. During the computational experiment, the independent variables are set to different values within their plausible range, and the mathematical model produces a suite of plausible outcomes corresponding to each set of assumptions.

Running the computational experiment involves taking the table of independent variables, running it through a model of the system, and a set of outcomes for each set of independent variables. Several tools currently exist to model the system in support of EA; the most common appear to be Analytica, developed by Lumina Systems (Davis, McEver, and Wilson 2002) and the Computer Assisted Reasoning System (CARs) developed by Steven Bankes and maintained by Evolving Logic (Lempert et al. 2003). Both tools include the capability for initial graphical exploration of the parameter space.

The resulting matrix of independent variables and dependent variables (outcomes) is of dimension (X, $[N_i+N_d]$) where X is the number of "runs", or combinations of independent variables considered in the computational experiment; N_i is the number of independent variables, and N_d is the number of dependent variables.

The third step in EA is graphical (visual) exploration of the results of the computational experiment. Here is another area where the multiresolution model helps provide structure and clarity to the problem. Sometimes a visual inspection or "drilling down" within the multiresolution model or suite of results from the computational experiment points to input assumptions (or combinations) that produced extreme

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[28] As mentioned earlier, deep uncertainty includes the case where the distribution of uncertain parameters cannot be determined or agreed upon. There may be cases where a distribution of one or more parameters can be assumed and used in the experimental design. The resulting "probabilistic EA" would be significantly complicated if the parameters were not independent. The presumption here is that the analyst will use good judgment about representing the distribution of input parameters, but the important point for MPSDM is that the extremes of plausible parameter space should be explored. After the exploration, the analyst can determine whether a particular combination of parameters that produces extreme results is plausible, but in many types of problems, adversaries will seek to find and exploit these extreme conditions.

outcomes. In addition, simple graphical techniques include histograms of the frequency of certain outcomes, box-and-whisker plots, or scatter plots of assumptions vs. outcomes can be used to find the forces that drive extreme outcomes. In the process of this graphical exploration, the goal is to gain insight and understanding about what drives the complex, multidimensional system at hand. As described earlier, annotated box-and-whisker plots show the distributions for outcomes of interest for the different options and criteria and serve as a useful starting place for gaining insight into the relative performance of the options.

Finally, statistical data mining techniques can be employed to determine the driving forces, or independent variables that most strongly affected the outcomes, and under what circumstances they do. A number of data-mining techniques exist, most recently documented in Nisbet, Elder, and Miner (2009) and Hastie and Tibshirani (2009).

Lempert, Bryant, and Bankes (2007) identify two that are particularly useful for policy applications. (See also Bryant and Lempert 2009). The Classification and Regression Tree method (CART: Brieman et al. 1984) and the Patient Rule Induction Method (PRIM: Friedman and Fisher 1999) both start with the results from the multiple runs of the computational experiment: a matrix consisting of several independent variables and at least one outcome for each run. Each independent variable defines a dimension in multidimensional parameter space. For the moment, consider each point (i.e. value of the independent variables in that space) to be associated with an outcome that is either above or below a threshold. These outcomes can be considered “good” or “bad” outcomes, or visualized as black and white points in space, where the dimensions of space correspond to each input assumption.

To understand the data mining process, it is helpful to imagine a set of points in multidimensional space. Each dimension corresponds to one independent variable (input assumption). The points are either black or white, with black points being defined as points of interest. For example, black points are associated with performance above a specific threshold. We wish to find the input assumptions, or dimensions, associated with primarily black points. Not only do we wish to find which assumptions are associated with black points, but we wish to draw “boxes” around the black points such that the space inside the box (defined values of assumptions) contains primarily black—or good--points. These boxes would define which assumptions, and the range of those assumptions, that are associated with the points of interest.

Both the PRIM and the CART algorithms place limiting restrictions on the dimensions that can be used to form sets of boxes characterizing the independent variables and their range that are most associated with the cases of interest.

Lempert et al. (2006) identify three goals that the algorithm should seek when defining boxes:

1. Good coverage: a high ratio of “good” cases in the box to the total number of cases in the database
2. High density: a high ratio of “good” cases to total cases within the box set.
3. Interpretability: fewer boxes and dimensions in each box to make it easier to understand and characterize the boxes conceptually.

The CART algorithm doesn’t produce the boxes explicitly, but produces output in the form of a decision tree that can be used to identify box sets. The algorithm divides up the multidimensional input space, one parameter at a time (although multiple splits of the same parameter are allowed), with the goal of creating multiple regions of space containing only “good” or “bad” outcomes. The algorithm partitions the parameter space in series of binary splits, creating sets of boxes that are orthogonal to the independent variable axes. The series of splits, or regression tree, can be continued until it defines regions of purely “good” or “bad” outcomes. For most applications, however, these regions would be quite complicated (hurting the interpretability measure), and noise in the data may cause over-fitting.

After growing the initial tree, the CART algorithm “prunes” the tree to find the combinations with the best predictive power, accounting for statistical noise. Thus, several boxes are produced by CART: the initial, complicated one and one or more pruned trees. The user can choose the one that best balances coverage, density, and interpretability.

Like CART, PRIM starts with the full range of input parameter space and successively restricts the size of the space, but uses a so-called "peeling" and "covering" process. Consider the ratio of the number of "good" cases to the number of total cases, or the mean in the unrestricted parameter space box. The PRIM algorithm identifies and removes a thin layer of whatever "face" from the current box will increase the mean in the new (restricted) box. This series of restrictions is called a "peeling trajectory."

A number of boxes are produced by this step, and the user is presented a plot of density for each box vs. its "support" (the fraction of good points inside the box to the total number of points—a factor related to coverage). As Lempert, Bryant, and Bankes (2007) point out, coverage is a better figure of merit than support for the type of policy applications they considered. The user then selects the boxes of interest, balancing the competing goals of density and support. In a process called pasting, the candidate boxes can then be expanded by allowing the dimensions that may have been overly restricted to relax.

The user then chooses from the set of pasted boxes, and the PRIM algorithm can be iterated using what is known as a covering process: the data within the selected box are removed from consideration and the peeling/pasting process is repeated for the remaining data. The user can continue this two-step process until the algorithm no longer finds useful box sets.

Lempert, Bryant and Bankes compared the CART and PRIM algorithms using known shapes of points of interest and determined that neither algorithm provides a perfect description. To be fair, the known parameter spaces were not simple rectilinear boxes, or the shape that both algorithms return, but rather more complex regions. They found that PRIM has a tendency to restrict too many dimensions and span disjoint regions with single boxes. CART tends to generate too many and inappropriately asymmetric boxes. For simple parameter space regions, CART generated boxes with better coverage/density performance than PRIM, but the authors noted that PRIM was generally more useful for actual policy analysis because CART required an unfeasibly large number of boxes before reaching acceptable levels of coverage.

MPSDM recommends the PRIM algorithm be used for the following reasons:

- PRIM's general applicability to higher-dimensional parameter space regions noted above
- PRIM offers more interactivity than CART, allowing the user to balance the sometimes-competing figures of merit (coverage, density, and interpretability). This interactivity advantage could be somewhat offset by the resulting variation of results from analyst to analyst.
- PRIM has been updated by Evolving Logic (Bryant, 2009) to address some of the weaknesses noted, including
    - even more interactivity and graphical indications to help the user select boxes
    - tests associated with statistical significance of variables
    - reproducibility calculations, performed by comparing results from two box sets generated on different resamplings relative to the number of points in their union.
    - the ability to generate data for post-processing.

Other simplifications

Recall the MPSDM methodology shown in Figure 3.1, and the six-pronged approach to simplifying the problem. The fourth prong is to a process that includes a mix of aggregating (to represent top-level results) and disentangling (to parse out the key factors driving the top-level results) in order to navigate the uncertain parameter space and share insights gained along the way. The disentangling is accomplished by adding more fidelity to the models of underlying factors that drive the choice of options. Once these driving forces are understood and modeled in sufficient detail, another exploration can find even lower-level factors driving the choice of options. At some point, the fundamental factors driving Relative Option Superiority of one option over another (or a retained option's vulnerability) are sufficiently characterized. The resulting insight can be used with the time frame/controllability heuristic to modify the options. Alternatively, the factor can be identified to decision makers to aid a discussion of the likelihood of this factor behaving as characterized.

The fifth simplification technique is identifying and eliminating any dominated options. Dominance in one dimension (risk, return, or cost) occurs when one option is inferior to others for almost the complete set of plausible outcomes. If an option is superior to another option, for example, in 98% of the cases considered, it is a matter of judgment whether it is truly dominated. However, examining the 2% of the cases where the option is not dominated can sometimes provide useful insights. For instance, this combination of assumptions may be considered sufficiently unlikely to warrant further consideration of the option.

Similarly, by examining the results of the computational experiment, the criteria which differentiate the options can be identified. Differentiating criteria are the criteria for which one or more option is superior to others. If all options perform relatively the same for a particular criterion, then that criterion is of little use in helping decision makers choose between strategic options. Although it may be useful to know that the current options do not address a particular criterion, that criterion can be eliminated in the current iteration of the MPSDM methodology. This winnowing down of the criteria represents the sixth prong of the simplification approach.

MPSDM step #3: Derive the strategy

The third step in the MPSDM methodology as illustrated in Figure 3.1 is to derive the strategy. One type of strategy would be to simply choose the option that performs “best” for the criteria identified. MPSDM proposes using the insights gained about the forces driving relative option superiority to guide selection of the *type* of strategy. As described in the previous chapter, by mapping the time frame and controllability of the driving forces onto the two-dimensional heuristic described earlier, the best type of strategy to account for that driving force can be discovered.

Once the strategies are developed to affect or respond to the driving forces, the options that are the most attractive can be modified according to the prescribed strategy type. EA can be repeated using the new option set. The criteria can either be the original set, or, if new understandings about the relative value of the criteria have been revealed during the previous iteration, the criteria can be modified. As before, the criteria that do not affect relative option superiority can be winnowed down, along with dominated options. The iterative process can continue as resources permit, or until an agreed-upon option and strategy (for instance, option 3 plus hedges) emerges.

Toolset of the MPSDM approach

The toolset of the multi-perspective strategic decision making approach builds on tools developed in other policy domains; the exploratory analysis tools used by RDM in the social issues sector (Lempert et al. 1996; Lempert and Bonomo 1998, Lempert and Schlesinger 2000, Lempert et al. 2004, Lempert et al. 2005, Groves 2005), and the multiresolution modeling tools used by Davis et al. in the defense sector (Davis 1993, Davis and Bigelow 1998, Davis 2000, Davis 2003, Davis 2005, Davis and Dreyer 2009). Tools developed or refined for MPSDM include:

- Methodology to characterize and model some types of perspectives
- Multiresolution models for rapid, clear assessments at levels appropriate to the problem and to structure a methodical exploratory analysis
- Exploratory analysis techniques to simplify the problem to its important parts (non-dominated options, differentiating criteria, and driving forces)
- Annotated box-and-whisker charts to focus discussion on values, beliefs, and expectations that affect choice of options
- A heuristic that suggests strategy type as a function of driving forces' controllability and timeframe
- The method to use the heuristic to modify options for iteration

Thus far, this chapter has described the methodology, principles, and the toolset of MPSDM. The next chapter illustrates the methodology and principles defined here for MPSDM with a more concrete example.

Chapter 4 - Demonstration of the Approach

The strategic problem chosen

To illustrate the principles, methodology, and toolset of the MPSDM approach, the procurement strategy of achieving capabilities to deliver conventional prompt global strike (CPGS) was chosen. This problem represents a long-term policy decision involving large resources and illustrates many of the features of MPSDM.

A 2007 report to Congress by the Secretary of Defense and Secretary of State identified the CPGS mission, which is to plan and execute small, discrete, conventional-weapon (non-nuclear) strikes around the globe within one hour as authorized by the President. The United States does not currently have military capabilities to carry out this mission (National Research Council of the National Academies, 2008, hereafter called NRC 2008), unless the target is a relatively short distance and then only if existing aircraft (tactical aircraft and cruise missiles, bombers, unmanned aerial vehicles (UAVs)) are pre-positioned and have extensive mission support resources available. The NRC Committee also concluded that the development of sophisticated air defenses may cause problems for forward-deployed forces unless defense-suppression attacks could be developed to disable the air defenses.

What is the value of achieving CPGS capability beyond what is currently available? The NRC (2008) concluded that the U.S. could gain meaningful political and strategic advantages by developing this capability. Specifically, in some scenarios, CPGS capability would eliminate the dilemma of being forced to choose between responding with nuclear weapons and not responding at all.

Several factors make achieving CPGS capability a challenge. These include the US restructuring of its forces based overseas, the need to fight adversaries further away from US Bases, and the broader set of possible adversaries.

In addition to the above mission challenges, the CPGS requirements themselves are somewhat soft. In the NRC 2008 report, the Committee on CPGS Capability did not interpret the term "global" literally. They anticipated that attacks in Antarctica, Patagonia, or Tasmania will not be likely, and that there would be time for redeployment if the world situation changed in that regard. With respect to promptness, the NRC committee concluded that "setting a goal of one hour for execution time in a conventional strike is sensible when viewed in terms of feasibility, value, and affordability. Although the report deemed the one-hour goal "sensible", it was not considered a strict criterion. Davis, Shaver, and Beck (2008) considered activities that precede the strike in the timeline and concluded that "Most currently plausible Global Strike scenarios involve many hours or days of warning and preparation, and the time to actually execute a mission is much less important than the ability to achieve surprise or avoid detection." However, some targets might be vulnerable for only a short time, in which case the timeline would be very important.

Certain considerations were not included in this illustrative example, as they do not appear to be within the traditional scope of CPGS analysis: network attacks and other matters related to cyber war; and other non-kinetic attack mechanisms. In addition, the mathematical model is intended to illustrate the MPSDM approach using a real-world application, not to give a definitive answer to a strategic policy question. The author's judgment was used to simulate expert judgment to: Select initial options from previous research that were "generally" the most cost-effective (where effectiveness is a matter of perspective); temporarily drop three options with the least cost but relative inferior performance and define an aggregation method for one variable (scenario effectiveness) that balanced the desire for clarity against other plausible aggregation algorithms.

MPSDM step #1: Characterize the problem

Recall from Figure 3.1 that the MPSDM methodology can be represented as a three-step process: Characterize the problem; simplify the problem; and derive the strategy. For the first step, the recommended framework includes evaluating a number of feasible, action-based options against a set of return, risk, and cost criteria in a multiresolution model. The evaluation explicitly considers perspectives simultaneously with more objective factors.

Prompt Global Strike scenarios

Although the measure “return” could be any of several types of measures, performance in a number of scenarios was chosen as the high-level return measure for this demonstration because scenarios bring concreteness and clarity to the capabilities being evaluated. The term “scenario” here is meant to refer to a specification of a potential mission and the conditions of that mission.

Two studies define sets of scenarios evaluated for CPGS acquisition research: Davis, Shaver, and Beck (2008); and NRC (2008) report. Although they are quite similar, the scenarios chosen for this demonstration of MPSDM were Davis Shaver and Beck’s (2008) spanning set of scenarios. This choice was driven by two considerations. The first was that the NRC committee included a scenario in which a CPGS strike would serve as the leading edge of a larger global strike. Since the criteria for that scenario would consist of effectiveness against a set of goals that is broader than CPGS as defined in the literature, it was not included in this illustrative problem. The second consideration was that Davis, Shaver, Beck defined three sets of scenario *classes*, against which relatively benign and more challenging conditions could be explored. This ability to vary the assumptions within a scenario class was deemed useful to gaining insights about the effect of these assumptions.

Davis, Shaver, and Beck (2008) describe a procedure for defining a set of scenarios and related parameter values that span the critical dimensions of the problem at hand. In what could be called preliminary exploratory analysis, or exploratory thinking, they evaluated several dimensions considered in developing this set of scenarios. These dimensions included: target type (in increasing order of difficulty they are: point target; hard point target; large, deep, underground; large, deep, underground, ambiguous); the number of targets; whether there was a time sensitivity for the strike; whether the targets were mobile; level of enemy air defense (low, medium, high); and strategic issues (bases and permissions; collateral damage; perceptions; escalation risk; and overall “plausibility”).

After considering the various dimensions listed above, Davis, Shaver, and Beck (and the NRC, 2008) concluded that three classes of scenarios would be represented by attacks on: 1) mobile missiles, 2) terrorist leaders in an urban meeting; and 3) weapons of mass destruction (WMD) facilities. These test cases stress sensors and detection systems, timeliness, and ability to attack hard targets, respectively.

The first scenario class is an attack on enemy mobile targets, such as a transshipment of one or more mobile intercontinental ballistic missiles (ICBMs) by truck or by ship. This scenario assumes that there may be more than one target, that the targets may be weapons of mass destruction, perhaps nuclear, and that the targets are stationary at the time of the strike.

The definition of a successful outcome for this scenario provides an example of a perspective affecting the assessment. In addition to evaluating the objective effectiveness of a weapon system option, the decision makers must evaluate the following subjective questions:

- What if all but one of the targets is destroyed, but the remaining weapon is used in retaliation for the strike?
- How likely is the site to be protected by air defenses?
- What if part of the force could be attacked successfully but the strike had little effect on other parts?

This first scenario of this class stresses the ability to find and strike the target accurately since the targets are to be found in a large land area and there may be ground clutter. The effectiveness of that response is likely to be related to the effectiveness of the original strike.

The second class of scenario is a strike on fleeting targets, which are only vulnerable for brief periods. A representative example would be a meeting of high-ranking terrorist leaders. The U.S. would know in advance that the meeting is planned to take place in a particular city, but may not know until close to the meeting time the exact time or location of the meeting. This intelligence may come from electronic intercepts or from operatives on the ground.

For this second class of scenarios, we have two different types of challenges, both of which are a matter of perspective:

- Since the setting is urban, what is considered "acceptable" collateral damage risk?
- How firm are the requirements for one-hour response time?

This second scenario class has a historical basis. Various strikes have been aimed at killing al-Qaeda leaders during brief times of vulnerability, including a 1998 strike on an Al Qaeda training camp reportedly narrowly missing Osama bin Laden. The firmness of the requirements for a one-hour response time is not only a matter of decision makers' expectations, but also adversaries' perspectives on U.S. capabilities at the time.

The third scenario class is an attack on facilities for weapons of mass destruction (WMD) such as a nuclear-weapon facility or one involving biological or chemical weapons. A strike may need the assistance of on-the-ground intelligence agents or Special Operations Forces (SOF). Here the following questions must be addressed:

- What type of air defenses might be encountered?
- Will the facility be above ground and well located, or below ground and not precisely known?
- Will U.S. resources be deployed near the facility?

This third class of scenarios stresses the ability to penetrate air defenses and locate the target accurately, since its position may not be known precisely. It also risks the leak of toxic materials and/or damage to international perceptions.

For each of these classes of scenarios, Davis, Shaver and Beck identified a nominal, along with a more challenging (or "hard") scenario. For instance, for the first class, an attack on mobile missile weapon systems, the more challenging case assumed a reactive adversary with technical and tactical countermeasures. For the second class, an attack on terrorist leaders in urban setting, the more challenging case assumed that the terrorist leaders would be vulnerable for a shorter time than the less challenging case. For the third class, an attack on a WMD facility, the baseline case assumes that intelligence information would be sufficient for a successful attack involving a hypothetical joint operation. This type of attack would have more precision and therefore might be able to avoid collateral damage caused by unintended release of materials. The more challenging WMD-facilities case assumes intelligence would be inadequate or that a number of facilities were invulnerable to a modest attack of any sort. The table below summarizes these scenarios.

Scenario Name	Description
S1n	Mobile missiles
S1h	Mobile missiles, reactive threat
S2n	Terrorist site
S2h	Terrorist site, fleeting target
S3n	Weapons of mass destruction facilities
S3h	Weapons of mass destruction facilities, hard case

Table 4.1 – Summary of Scenarios Used for Illustrative Example

The idea of choosing a spanning set of scenarios is that they cover a broad range of factors that are critical to the outcomes of interest. These factors can sometimes be analyzed and identified in advance of the computational experiment, and sometimes not. The problem may have so many uncertain variables that it is not obvious ahead of the EA which factors affect relative option superiority. To address this issue, RDM proposes a process of "scenario discovery" that employs exploratory analysis and to identify the critical factors. The factors are then combined into a set (or a scenario) and decision makers are asked to rate the importance of the scenario. MPSDM proposes starting with an initial set of scenarios (or criteria), including perspective parameters in the EA along with uncertainties, and the use of discussion aids to elicit additional criteria that decision makers may not have identified before the EA. The additional criteria can be iterated along with the options themselves as more information is revealed.

The relative advantages of each approach depend, in part, on the ability to define, a priori, a broad set of factors and criteria that may be important to the decision makers. Sometimes decision makers might say “it depends” if asked before the analysis which criterion was more important. Their relative values may depend on how one option performs relative to another; if one option offers a “game changing” capability, then that criterion may suddenly become very compelling. As the range of perspectives within the decision-making group grows broader, criteria may be more difficult to anticipate, and the iterative approach proposed by MPSDM may be very helpful.

An example of the usefulness of this iterative approach comes from the NRC (2008) assessment of CPGS options. It was noted that some committee members differed as to the value of the illustrative scenarios chosen. Some members thought that the mobile missiles and terrorist site scenarios were more useful than a third scenario class, representing immediate response or preemption of imminent attack. Others thought that the deterrent value of achieving capability for the third scenario class would be most useful and were less convinced about the usefulness of classes one and two. This difference in values can be addressed analytically by treating relative weights of the different scenarios as perspective variables, running a range of numerical values in the computational experiment, and finding how these relative preferences “matter” in the choice of options.

Having established the mission and the criteria for evaluating outcomes for each option, we next turn to choosing an initial set of options.

Conventional Prompt Global Strike options

For the CPGS illustrative example, several options are discussed in the most recent unclassified literature. Woolf (2008) focused on long-range ballistic missiles and the NRC committee (2008) evaluated a broader set of seven options, including hypersonic cruise missiles and a ballistic missile option that the committee created. Their so-called Conventional Trident Modification-2 would be a modification of the Conventional Trident Modification, a system proposed by the U.S. Navy to replace the nuclear warhead on its submarine-launched Trident missile with a conventional warhead.

Davis, Shaver, and Beck (2008) describe a method of ensuring that a broad set of options is considered initially, and then methodically evaluated. They started by identifying the building blocks that might help to achieve CPGS capability, such as penetration aids to overcome enemy air defenses, space-based radar to enhance detection of mobile targets, a variety of vehicles to carry weapons including a Special Operations Forces (SOF) vehicle and a number of weapons types. Next, they performed a preliminary cost/benefit analysis of every combination of building blocks (sets of so-called building block composite options), focusing on those options that were "closest" to the efficient frontier (plus the baseline option which used current capability). Their analysis showed that the proximity to the efficient frontier depended on the relative emphasis placed on the different scenarios, and thus even if an option performed well for only one set of scenarios, it was retained.

Next, they computed effectiveness of each of these thirteen options against their six scenarios. For this illustration of the MPSDM approach, the six most effective of Davis, Shaver, and Beck's options were chosen[29]. Several considerations went into this choice: First, it offered a broader capability range than Woolf's (2008) focus on long-range ballistic missiles. Secondly, both Woolf and the NRC included options such as the hypersonic cruise missile which the NRC found to be a higher risk and longer-term solution than other options. Thus, the choice reflected a broader set of feasible options than the NRC or Woolf research, and appeared to better demonstrate the MPSDM approach than other sets.

As will be seen later, the MPSDM iteration methodology in the present work led to creating essentially the same option that the NRC devised in its study. This convergence

[29] More precisely, nine of the Davis, Shaver, and Beck options were chosen, because three of their options consisted of building blocks identical to other options, but forward based. As will be shown later, forward basing was treated in this research as an uncertain parameter, to be varied simultaneously with other variables in the computational experiment.

demonstrates two benefits of the MPSDM approach: First, that the initial set of options doesn't necessarily eliminate possibilities. Using insights about the factors that drive one option to be superior to another, plus the time frame/controllability heuristic, new options can be created using the MPSDM methodology that improve return, risk, and/or cost performance. The second benefit this demonstrates is that the MPSDM methodology leads to the same novel idea that a high-level task force of experts created.

The first option, and in fact a recommended generic Option #1 is the baseline case; i.e. no change to status quo. This option includes existing B-2B bombers, Air Force and Navy tactical aircraft, advanced conventional cruise missiles, Tomahawk missiles, or gravity bombs, (or a combination of both), Special Operations Forces, precision weapons, satellite communications, national intelligence systems, regional command, control, communications, computer, intelligence, surveillance and reconnaissance systems such as J-STARS, etc. These systems have the range and payload necessary to strike targets globally. These capabilities, including satellite communications, exist today so the development risk is minimal and operations concepts have been developed and tested.

These baseline systems may be vulnerable to enemy air defenses, which could limit access to certain target areas and put aircraft and crew at risk. In addition, they could take hours or days to reach remote targets, depending on whether the resources were forward based. Other concerns raised by this long flight time are the issue of crew fatigue and the need for tanker support to refuel the strike aircraft during the missions. Manned systems such as included in Option 1 also carry risk to crew during ingress and egress, as do options such as this one that use Special Operations Forces (SOF). In addition to locating targets, SOF forces are currently used for small leading-edge attacks such as defeating or disrupting the enemy's air defense; command, control, and communications; or most-feared weapons.

Each of the additional options adds capability to Option 1. Option 2 includes penetration aids to increase the ability of an Air Force or Navy strike vehicle to penetrate the enemy's advanced surface-to-air missiles.

Option 3 adds a Navy submarine-launched ballistic missile (SLBM), the first of which would be the conventional Trident Modification (CTM) to Option 2. The CTM is the proposed near-term solution to CPGS capability by the U.S. Strategic Command. The CTM program would convert two submarine-launched Trident II (D5) ballistic missiles on each of the U.S. Navy's twelve nuclear-powered ballistic missile submarines from nuclear-armed to conventionally-armed warheads. Each missile would nominally carry four MK4 reentry vehicles, modified by the addition of a "backpack" consisting of an aerodynamic control system, a Global Positioning System (GPS) receiver, and an inertial navigation package to improve weapon accuracy.[30] Each re-entry vehicle would contain a kinetic energy projectile (KEP) warhead, consisting of multiple tungsten rods deployed by an explosive charge. This altitude-determined explosion allows the warhead to attack an area of soft targets if their position is known with accuracy on the order of meters (NRC 2008). Alternatively, the warhead can be set to not explode, giving the capability to penetrate somewhat harder targets, again if their position is known. Using this mode, the CTM would have better (but still limited) ability to penetrate buried or hardened structures such as command-and-control bunkers and hardened aircraft or missile shelters.

Because the submarines are mobile and the missiles are long range, the system can reach targets around the world, provided the submarines are positioned in the area. Development risk, although not as low as the baseline option, is not severe. The main development items include the backpack. Although GPS receivers can be jammed, the combination of an inertial navigation system and GPS updates, when available, to account for location drift, is considered sufficient for navigational accuracy within a few meters (NRC 2008). The delivery vehicle and command and control systems have been developed for nuclear use amidst the need for prompt decision making and launch during a crisis.

The fact that conventional warheads would be carried along with nuclear warheads on the same submarine gives rise to two types of risks. First, a third-party potential adversary, for example Russia or China, which was not the target of the strike, might misinterpret the launch of a non-nuclear warhead as a nuclear attack. This is of particular concern if the third party was a nuclear-armed nation with delivery systems that could

[30] The existing nuclear Trident warheads are unguided after they leave the third stage, since not as much accuracy is required for nuclear weapons as it is for conventional weapons.

strike the U.S. In fact Congress rejected most of the Department of Defense's 2007 Conventional Trident Modification (CTM) budget request because of concerns about "nuclear ambiguity" along with the belief that other systems would better address the political, military, and technical issues surrounding CTM. A national-academy report described that Congressional decision as a mistake and disputed key elements of the underlying reasoning in considerable detail (NRC 2008).

Secondly, if conventional weapons are launched from the same submarine as missiles with nuclear warheads, questions may arise as to the command and control of those missiles. As will be discussed later, various mitigations have been proposed.

Option 4 adds an enhanced insertion vehicle for Special Operations Forces to Option 3 to enhance deep, covert penetration into defended areas. Currently, a variety of SOF vehicles are in different stages of research and development (R&D) within the aerospace industry, involving different levels of technological risk. What is envisioned for this option are capabilities for stealthy SOF penetration which is achieved by a combination of factors, including the launch platform, low detectability of the insertion vehicles, and the tactics of choosing flight paths. Examples of SOF vehicles include armed unmanned Predators or stealthy helicopters.

Option 5 starts with Option 3 and adds two types of sensors onboard penetrating aircraft. The first is an automated target recognition (ATR) system to enhance detection and identification of targets by distinguishing them from ground clutter. The second type of sensor included in Option 5 is a space-based synthetic-aperture radar (SAR) which would enhance detection and tracking of semi-mobile targets. Semi-mobile missiles would leave casernes (military barracks or garrisons) and then sit in unknown positions. This option of course assumes that the aircraft could penetrate to a level where the sensors would be useful.

Option 6 starts with the sensors described in Option 5, adds the SOF vehicle from Option 4, and includes an advanced bomber to increase penetration of even the most advanced surface-to-air missile and to avoid discovery and aid egress. This bomber could either be a very stealthy, high-capacity, long-range bomber or a medium-range aircraft.

A summary of Options chosen for this demonstration is shown in the table below.

Option	Name	Description
1	Base Case	uses existing systems: tactical & long-range stealth aircraft, cruise missiles, special operations forces (SOF) and cruise missiles command, control, communications, computers, intelligence, surveillance, and reconnaissance, combat search and rescue, and suppression of enemy air defenses.
2	Penaids	adds penetration aids to Option 1 to overcome adversary's air defenses
3	SLBM + Penaids	adds submarine-launched ballistic missile (SLBM) to Option 2. The SLBM would be a modification of the conventional trident missile:
4	SLBM+ Penaids + SOF Vehicle	adds a special operations force vehicle to option 3. This vehicle is stealthy for deep, covert penetration into defended areas
5	SLBM + Penaids + Sensors	starts with option 3 and adds sensors to detect, identify, and track targets among ground clutter
6	Adv. Bomber + Sensors + SOF Veh	Uses Option 1 and adds advanced bomber + sensors + SOF vehicle. The advanced bomber increases penetration of advanced air defenses and avoids detection

Table 4.2 – Summary of Options Used for
Illustrative Example

Other options from Davis, Shaver and Beck (2008) were not included in this example, for one of two reasons. First, it was judged that they did not score as well in performance against the six scenarios described above. Second, because they simply added forward basing to another option. For this research, the consideration of whether the aircraft is forward based (or near the strike location) was included in this analysis, but treated as a variable, as described below. This approach helped to reduce the dimensionality of the problem.

The decision making process must address wide variations in expectations of the capabilities of both friendly and adversarial forces. Some of the critical option-related questions that are a matter of perspective include:

- Will the option be able to strike within the time that the target is vulnerable, especially in the terrorist site scenarios?

- Will the option be sufficient to overcome enemy air defenses at the time of the strike?
- Is the payload capability sufficient, especially for the WMD scenarios where the target may be hardened or deeply buried?
- What is the level of collateral damage that will likely occur with the intended warhead, and how acceptable is that level?
- What is the likelihood that the systems that are being considered for development now will be ready when needed, i.e. what is the development risk?
- What is the likelihood that the program will remain funded through operationalization?

The analysis tools

There are two conceptually distinct types of tools used in the mathematical analysis for MPSDM. The first is a model to run the computational experiment. The second type of tool is one to perform statistical data mining in order to identify the factors most affecting the outcomes of interest.

A few tools exist to create multiresolution models of the type described above. One of the earliest such tools was Hillestad and Davis' (1998) DynaRank Decision Support System, and PAT, the Portfolio Analysis Tool (Dreyer and Davis 2005, Davis and Dreyer 2009). In PAT, there are separate worksheets for each level in the multiresolution model. Macros perform the aggregation and scoring process to fold variables to successively higher levels in the model.

For the PGS illustration, careful consideration was given to the choice of tools for running the computational experiment. One of the goals was to create a model which could easily be shared with other analysts. Sometimes a specialized tool is developed that uses an operating system that is difficult to learn, or contains embedded macros. These naturally make it difficult for others to contribute to the model, and it is not uncommon to find that only one person in the organization really understands how to make changes to the model, despite the existence of carefully written users' manuals. Perhaps even more relevant to strategic decision making, models that are mysterious to the decision makers or their staff are easily discounted, and results met with suspicion. As experienced analysts would agree, it may be essential to convince staff to the decision makers along the way. When budgets and timeframes are tight, this can be a critical road block.

An additional challenge occurs when two or more models of different types are used in sequence. For instance, in exploratory analysis, one model is sometimes created to do a single projection on a combination of input assumptions. Then another tool generates the suite of plausible outcomes, and then a third tool performs the exploratory analysis on that suite of plausible outcomes. Every interface between these tools creates an opportunity for technical difficulties.

For the PGS illustration, the PAT model was chosen as a starting point. Davis and Dreyer (2009) incorporated several features that allowed PAT to be extended for the purposes of running a computational experiment. The first one was the clear structure of the Microsoft excel-based tool that matched the structure of the multiresolution model; a separate worksheet existed for every level of the model, with rules-based aggregation algorithms rolling up results from one level to the next. To set up the computational experiment, the first extension to PAT was replacing the scoring and aggregating macros with embedded equations. This was necessitated by the second extension to PAT, using the data table function to creating a suite of plausible outcomes from tables of input parameters. These extensions continue the theme throughout this dissertation of useful simplifications and building on earlier work.[31] A number of considerations went into the selection of Microsoft Excel-based PAT for this illustration:

[31] The author is grateful that such extensibility was designed into PAT's capabilities (Davis and Dreyer 2009)

- Microsoft Excel is commercially available, known to a large number of analysts (and high-level decision makers), and has substantial product support and online documentation.[32]

- Excel allows almost instantaneous drill downs into underlying variables that may affect aggregate measures. If a decision maker wants to understand why one option in one scenario resulted in a surprisingly low or high effectiveness, it is a simple matter to go to a different worksheet in the file.

- Excel has a capability for data tables, which were extremely simple and quick for running the computational experiment.[33] In essence, a data table works as follows: an indicator variable is defined which points to a row in a spreadsheet containing a set of independent variables. The data table then computes the outcomes of interest as a function of the set of independent variables automatically. Outcomes can be plotted, and for subsequent experiments, the plots are automatically updated.
- Excel now has the dimensional capability to handle very complex models. Excel's row and column limits have been extended for Excel 2007. The total number of rows allowed has been increased from 64,000 to 1,000,000. The total number of columns available has been increased from 256 to 16,000.[34] Although the number of cases run in the illustrative model was relatively small, it is not uncommon to run tens of thousands of cases. In the event that a model exceeds these capabilities, additional worksheets can be created. The multiresolution modeling approach makes this relatively simple; different levels of the model can be represented in different worksheets.
- PAT has been documented and tested for CPGS and other applications, and support was available at RAND.

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[32] Analytica is quite capable and is also used by a number of analysts, although decision makers and their staff may not be as familiar with it as they are with Microsoft Excel.

[33] For a very useful tutorial on Microsoft Excel data tables, refer to http://www.homeandlearn.co.uk/excel2007/excel2007s7p1.html.

[34] In addition to the row and column capability, Microsoft Excel accommodates many worksheets which can be used to model hierarchical "levels" in a multiresolution model.

The model used to run the computational experiment will be described in more detail in the next section.

The second type of tool, used to perform statistical data mining on the results of the computational experiment, incorporates the PRIM algorithm. Chapter 3 describes the reasons for selecting the PRIM algorithm for MPSDM. Currently, there are two versions of PRIM that are free for download, the original algorithm (Friedman and Fisher 1999) version 2.0[35] and another version that has been modified by RAND (Bryant, 2009).[36] For reasons described in Chapter 3, the modified version was chosen for MPSDM.

PRIM runs in an operating system called R, which includes a language and a run-time environment (Ihaka and Gentleman 1996). R is available as a free download and fairly straightforward to learn.[37] R includes the capabilities to write scripts (or sets of commands), call the PRIM algorithm, and produce statistical and graphical results.

The CPGS model

The multiresolution model used to run the computational experiment for the CPGS example is shown below.

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[35] Rev 2.0 is available at http://wareseeker.com/download/prim-algorithm-rev-2.0.rar/3508740.

[36] Version 2.22 was used in this research and is available at http://cran.r-project.org/web/packages/sdtoolkit/index.html.

[37] R is available here: http://cran.r-project.org/

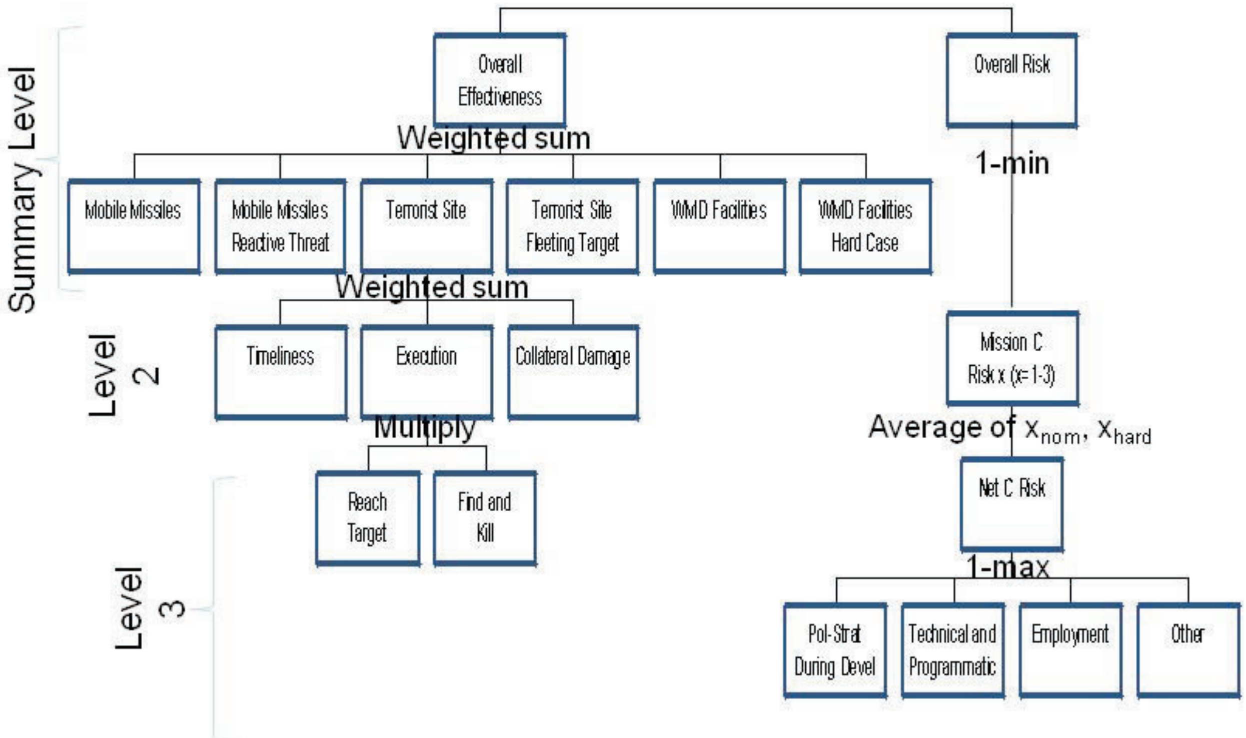

Figure 4.1 - Multiresolution Model for Prompt Global Strike

For each of the six options considered, the same model structure is used, although parameters vary from option to option. Starting top of the figure above, recall MPSDM defines generic dimensions of return, risk, and cost. Return for each option here is operationalized as the overall effectiveness, a result obtained by taking the weighted sum of effectiveness in each scenario (Mobile Missiles, Mobile Missiles Reactive Threat, etc.). The left side of the figure above indicates the level of each variable in the model. The summary level includes Overall Effectiveness, Effectiveness in each scenario, an Overall Risk measure, and Cost relative to the baseline. This summary level can be represented to decision makers as a scorecard where each column represents scores for each effectiveness dimension or overall risk, and each row is the score for each option.

Continuing down the left side of the diagram, we see that the summary level effectiveness scores for each scenario are comprised of weighted-sum aggregations of level two parameters Timeliness, Execution, and Collateral Damage.[38] Timeliness is a score that indicates how quickly the strike could be executed from its initiation. Execution measures whether the attack would accomplish the larger military purpose. Collateral Damage measures the number of unintended casualties associated with the strike, particularly important for the WMD scenarios where there is a substantial chance of releasing toxic chemicals, biological materials, or even radioactive material. The reason for the weighted sum aggregation rule is that different scenarios place different emphases on these parameters. Recall that Scenarios three and four, the Terrorist Site scenarios, call for more timeliness since the terrorist meeting may not last very long. Scenarios five and six, the Weapons of Mass Destruction strikes, have less stringent requirements for timeliness as presumably the WMD site is not fleeting.

Moving to the right, we see that the summary-level score for Overall Risk is simply (1-min(Mission C Risk x; x=1-3)); the sign reversal works to transform summary-level risk into the same color-coded scheme as effectiveness, where a low score of risk corresponds to an unacceptable result.

Continuing down and to the left in the diagram above, we see that the Level 2 variable Execution is an aggregate measure of two Level 3 parameters, Reach Target and Find and Kill. Reach Target represents the likelihood of the target being within range of the weapon and the weapon system's ability to penetrate air defenses, if any. Find and Kill measures the weapon system's ability to destroy the target, particularly challenging for Scenarios 5 and 6, the two WMD scenarios. Find Target, a lower-level parameter, is especially difficult for the mobile missiles scenario. Since the PGS weapon must perform both of the critical tasks Reach Target and Find and Kill, the aggregation methodology chosen was to multiply the scores for each, representing the logical "and" combining rule for probabilities.

Moving to the right, the figure shows that the variable Mission C Risk x (x=1-3) is an aggregate of two risks--the nominal and the hard case for each of three scenario

[38] Capital letters are used to denote variable names.

classes.[39] This variable Net C Risk is itself an aggregation of four types of lower-level risks (although Net C Risk and the four lower-level risks are all implemented in Level 3 of the model). The first of these lower-level risks is Political-Strategic Risk During Development. This dimension includes the chances that the program will remain funded by Congress. It also includes the likelihood that the U.S. will have the cooperation of allies if an option includes forward basing or staging for SOF operations. Continuing to the right, Technical and Programmatic Risk measures the likelihood of technical failure to achieve the assumed capability. Some options have relatively low technical risk, as the technology and operating procedures are relatively mature; in other cases, it may not be clear that technical challenges don't defy the laws of physics and engineering. For the options involving sensors, achieving adequate automated target recognition involves considerable technical and programmatic risk, especially in areas with complex terrain or ground clutter. For options further out in the future, such as advanced bomber, there is the question of whether the industrial base will be able to accomplish what is needed.

Employment Risk refers to the availability of the capability at the time it is needed, i.e. whether the resources might be tied up elsewhere such as those required to penetrate air defenses. Employment Risk also includes the perceived risk of nuclear misinterpretation (higher in the SLBM options[40]) and the possibility that adversary's surface-to-air missiles used for air space defense have capabilities more advanced than expected (e.g. more resistant to electronic countermeasures). It also includes the risk of the adversary getting warnings of U.S. operations by infiltration or penetrating U.S. military networks. Other Risks include the possibility that the consequences of the attack will be other than planned—a strike intended to deter or coerce might be misinterpreted as the leading edge of a more comprehensive attack, or allies reacting badly. This risk dimension includes the possibility that the strike will firm up an adversary's resolve rather than influence him to act in ways the U.S. would prefer.

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[39] The nomenclature "C Risk" indicates that risk is measured on an inverse scale: a higher number is good.

[40] As discussed in the NRC study, the actual risk appears to be quite low, assuming that reasonable actions are taken.

Compared with the effectiveness dimensions, many of the risk measures are matters of perspective. In contrast with a testable parameter such as the likelihood reaching the target, risk measures are generally more subjective. In the case of ambiguity, Congress may not fund the Conventional Trident Missile modification out of concerns that it might be misinterpreted as a nuclear strike by allies, or may prompt a nuclear response by countries such as China or Russia. Here we have several layers of perspectives: the analyst and decision-makers' view, along with Congress' view of China or Russia's perspective.

The third generic dimension, cost, is based on simple estimates of cost relative to the baseline option in the summary scorecard but not in the model. If cost estimates included a higher level of uncertainty, they could be modeled as uncertain variables (using any number or type of lower-level parameters), but the options chosen are viewed to be feasibly affordable, and the estimates treated as certain variables.

As the figure shows, the top level measure Overall Effectiveness is an aggregate measure of lower level scores. This aggregation introduces a perspective parameter important when multiresolution modeling is used: the aggregation rule itself. One could simply choose to take an average of the effectiveness scores for each scenario, but that would imply something about the decision makers' perspective; that they valued each of the scenarios the same. Alternatively, one could take a weighted sum of the effectiveness in each scenario, but that would imply that the relative value of effectiveness for each scenario could be both known a priori, or could be agreed-upon by the decision makers.

The aggregation beliefs are another area where the risk dimension appears to be more a matter of perspective than the return dimension. The return dimension includes parameters for which a logical "and" methodology is obvious, but it is not as clear how to combine disparate types of risks. For instance aggregating Net C Risk into Mission C Risk x consists of taking the nominal scenario and the more challenging scenario (or "hard" case) from each of the three scenario classes. Again, the choice of aggregation method—averaging--is a matter of belief about how risk should be treated. As we will see, the MPSDM approach is to assign a logical variable to plausible aggregation methods and treat this logical variable as an uncertain one, to be varied in the computational experiment.

The return dimension is not without its perspective parameters, however. Note from the figure that Overall Effectiveness is represented as a weighted sum of the effectiveness scores from the different scenarios. The approach taken in MPSDM is to treat the relative values of these scenarios as sets of uncertain parameters. This allows the analyst to adjust the weights and explore how the decision makers' relative values affect option superiority.

There are two concepts important in multiresolution modeling. The first is the choice of aggregation rules. The second is the choice of scoring methodology from the various sub measures up to a measure score. The technique used by Davis and Dreyer (2009) is used in MPSDM to normalize all top-level variables to a scale of zero to one. This technique also includes the possibility of nonlinear threshold scoring, as described by the figure below.

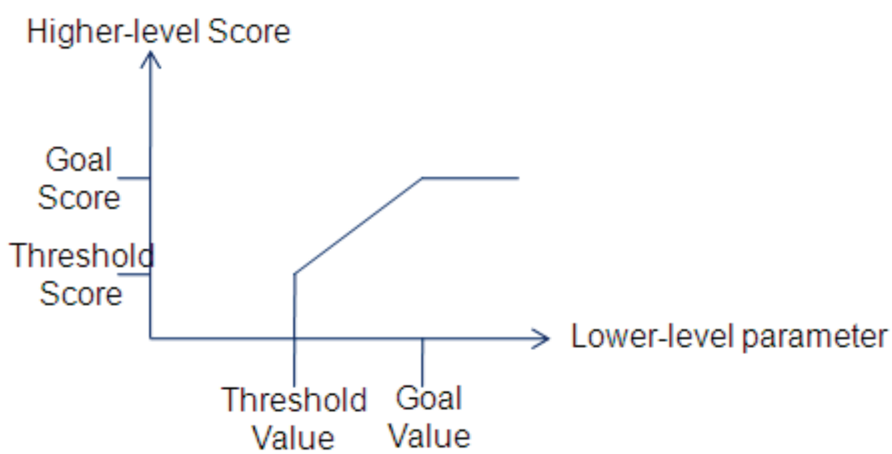

Figure 4.2 - Scoring Methodology to Compute Nonlinear Thresholds

The reason for nonlinear scoring is that sometimes there exists a threshold of "good enough" in capability; adding more of an input does not necessarily add more effectiveness. An obvious example is that above a certain level of Kill Target, Execution Score does not improve.

Referring to the figure above, the composite (or higher-level) score in this method is computed in the math model by the following equation

$$S_{i,j,k}=0 \qquad \text{if } V_{j,k}<V_{j,k}^{T}$$

$$S_{i,j,k}=G_{j,k} \qquad \text{if } V_{j,k}\geq V_{j,k}^{G}$$

$$S_{i,,j,k}=T_{jk}+\frac{V_{i,j,k}-T_{jk}}{V_{jk}^{G}-V_{jk}^{T}}(G_{jk}-T_{jk}) \qquad \text{If } V_{jk}^{T}\leq V_{j,k}\leq V_{j,k}^{G}$$

Where

$S_{i,j,k}$= the score for the measure i, the option j, sub measure k

$V_{i,j,k}$= the values of the sub measure for measure I, investment option j, sub measure k

$V_{j,k}^{T}$ = the threshold values for option j, sub measure k

$V_{j,k}^{G}$ = the goal values for option j, sub measure k

$T_{j,k}$ = the threshold score for option j, sub measure k

$G_{j,k}$ = the goal score for option j, sub measure k

Thus, each sub measure is scored according to whether it is below the threshold, above the goal, or in between. This formulation also accounts for the case where the score *decreases* with increasing values, with the equations modified accordingly.

As with aggregation parameters, nonlinear threshold parameters are treated as perspective parameters in MPSDM, modeled as uncertain variables, and allowed to vary in the computational experiment.

Note that this model is meant to illustrate the principles and methodology of MPSM. As such, is uses simplified representations of factors contributing to CPGS capability procurement strategy.

MPSDM step #2: Simplify the problem

As Figure 3.1 illustrated, the second step in the MPSDM methodology is to simplify the problem using EA to find the forces driving relative option superiority. The problem can be further simplified by eliminating any dominated options and criteria that don't differentiate the options.

Exploratory analysis

Recall the steps of exploratory analysis defined earlier in Figure 3.2, repeated below.

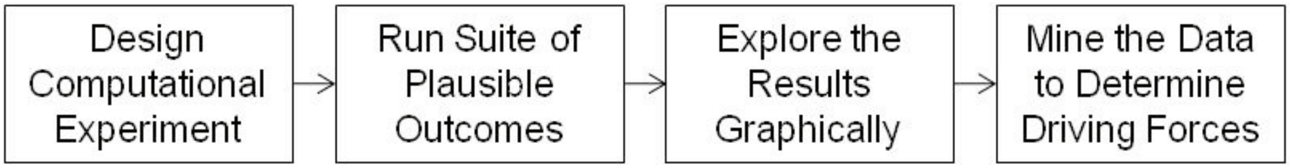

Figure 4.3 - Steps in Exploratory Analysis
(Figure Adapted From Bankes 1993)

Each of these steps for the CPGS example will be discussed in the following sections.

Exploratory analysis step 1: Design the computational experiment

EA starts with designing a “computational experiment.” As in a traditional experiment, input assumptions are varied and resulting outcomes are evaluated. For the CPGS illustrative case, the input parameters represent a set of uncertain assumptions, and the resulting measures—return and risk measures—are outcomes associated with each combination of inputs. The concept in exploratory analysis is that if the assumptions vary within their plausible ranges, then the resulting dependent variables represent a suite of plausible outcomes.

The choice of inputs (or independent variables) for the computational experiment was based on multiple criteria:

- Varying multiple dimensions of parameter space. Traditional sensitivity analysis varies one parameter at a time, around some baseline set of assumptions. Exploratory analysis, on the other hand, varies multiple independent variables simultaneously.
- Exploring effects of nonlinearity
- Including representative values, beliefs, and expectations from Table 3.1
- Demonstrating a methodology that explores parameter space systematically
- Demonstrating the management of the curse of dimensionality where practical

Thus, the computational experiment began by choosing independent variables: All Level 2 parameters within the model, along with the aggregation parameters used to compute Level 1 Overall Effectiveness from Level 2 Effectiveness for each scenario; and the aggregation rule used in computing Level 2 Mission C Risk x from Level 3 Net C risk. In the figure below, the arrows indicate which parameters were selected as independent variables for the computational experiment.

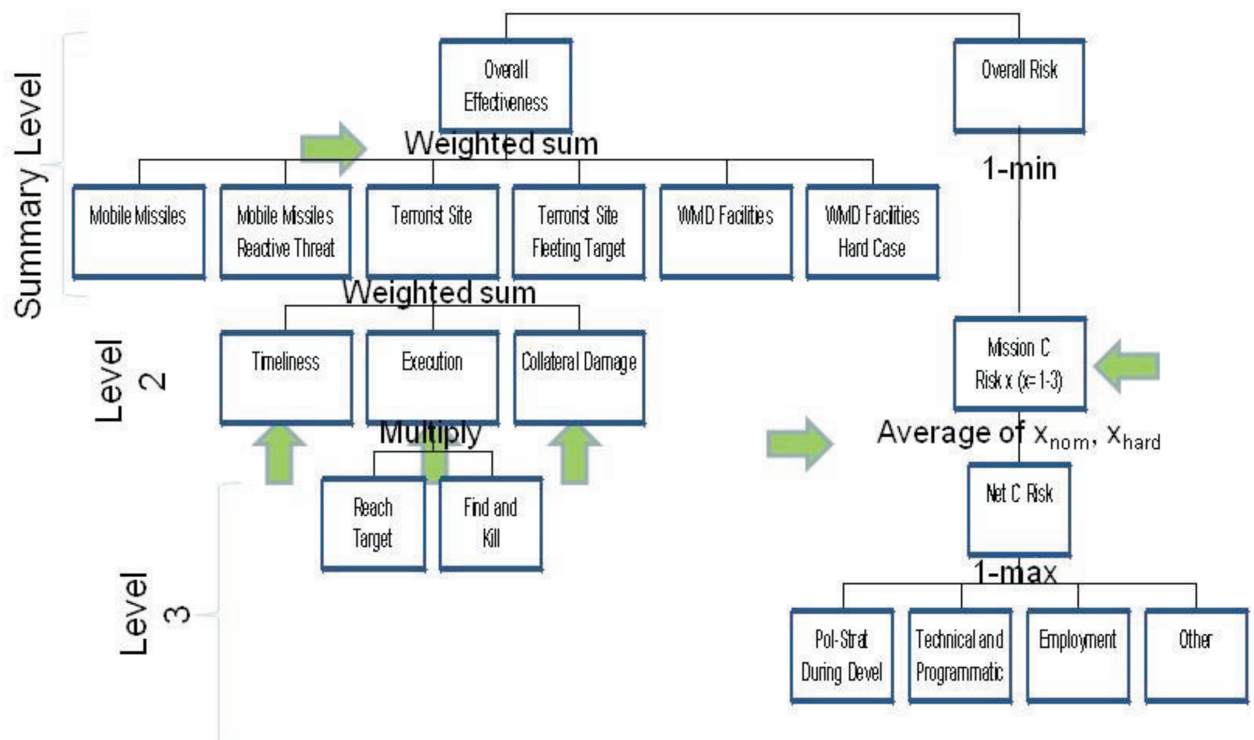

Figure 4.4 - Model Used in CPGS Example with
Arrows Indicating Independent Variables Chosen
for the Computational Experiment

The table below shows this information, arranged by the type of assumption (value, belief, or expectation) made for each parameter.

Assumption	Option	Scenario	Model Parameter	Level	Δ from baseline	Value/ Belief/ Expectation
1) Forward deployed or not	1,2,6	all	Timeliness	Level 2	see (fwd deployed)	belief
2) Execution (reach, find, and kill target)	all	all	Execution	Level 2	+-X %; X programmable	belief
3) Collateral damage	all	2n,2h, 3n,3h	Collateral Damage	Level 2	+-X %; X programmable	expectation
4) Net Mission Risk	all	all	Net Mission Risk	Level 2	+-X %; X programmable	belief
5) Risk aggregation rule	all	all	Aggregation rule	Level 3→2	average vs. worst case	belief
6) OE aggregation Weights for each Scenario	all	all	4 focuses	Level 2→1	see table, below	value

Table 4.3 - Independent Variables Chosen for PGS Illustration

The first column of the table above gives a description of the uncertain assumption. Davis, Shaver, and Beck (2008) treated the question of whether assets were forward deployed or not as two separate options.[41] The approach used here is to treat that indicator variable as an uncertain parameter which affects timeliness. If assets are deployed close to the position of the strike, the parameter Timeliness (defined as the flight time from launch to the target in hours) is higher.[42] Another way timeliness is addressed in this example is by the weight given to that measure in the aggregation to Effectiveness for each scenario; some scenarios place more emphasis on the need for timeliness. For

[41] There are more than one ways to look at the forward-basing question. The first is that it is a separate option, with associated costs. The other way to look at forward basing is as a more random occurrence: at the time of the strike, the U.S. may or may not have forces deployed near the strike. The latter interpretation was chosen for the initial analysis. If forward basing had proven to be a critical factor, the analysis could have been iterated to pull it out as a separate option, take action to increase its probability, and evaluate it against other remaining options.

[42] Note that the parameter Timeliness is another reversed measure: a higher number is bad.

instance, terrorists may be meeting only for a short time and the mobile missiles may be vulnerable briefly.

Continuing to the right in the table, we note that the assumptions do not always relate to all options and scenarios. In the case of forward deployment, this pertains to the aircraft-based options and not to those employing SLBMs. The column labeled "Δ From Baseline" indicates how much each parameter was varied in the computational experiment relative to the baseline case. For the Forward Deployed assumption for Options 1,2, and 6 which employ aircraft, the table below shows the variation of the Timeliness model parameter (in hours to reach target) for each value of the logical variable Forward Deployed and each scenario (S1n is Scenario 1 nominal case, S1h is Scenario 1 hard case, etc.)

	Timeliness for each Scenario for Options 1, 2 & 6					
Forward Deployed	**S1n**	**S1h**	**S2n**	**S2h**	**S3n**	**S3h**
0	24.00	24.00	12.00	12.00	24.00	24.00
1	16.00	16.00	4.00	4.00	16.00	16.00

Table 4.4 - Value of Timeliness as a Function of Logical Variable Forward Deployed and Scenario (Only used for Options 1,2, and 6 which employ aircraft)

As Table 4.3 shows, Execution, Collateral Damage, and Net Mission Risk are varied by plus or minus x percent, with x being programmable in the computational experiment. Two values of x were used: 20% and 40%. By comparing the results for these two excursions, we can see the effects, if any, of nonlinearities such as nonlinear scoring thresholds and aggregation rules.

Continuing down the rows in Table 4.3, the Risk Aggregation Rule from Level 3 to Level 2 was varied between two beliefs of how aggregation should be modeled: As the average of the nominal and hard case for each scenario; and taking the worst case. The next assumption, the aggregation weights used in computing Overall Effectiveness represents different values that the decision makers place on the scenarios. For these weights, sets of parameters were chosen as indicated in the table below.

Focus	Aggregation Weights for each Scenario					
	S1n	S1h	S2n	S2h	S3n	S3h
1	0.17	0.17	0.17	0.17	0.17	0.17
2	0.33	0.00	0.33	0.00	0.33	0.00
3	0.00	0.33	0.00	0.33	0.00	0.33
4	0	0	0.25	0.25	0.25	0.25

Table 4.5 - Sets of Aggregation Weight Focuses in the Computational Experiment

Here, a set of values is called a "focus." Here, focus represents a clustered set of decision-makers' values, as in "I value this scenario highly and that scenario less." This is what Davis Shaver and Beck (2008) called a type of perspective and can be thought of as follows: for Focus 1, the decision maker might believe that the scenarios are equally valid to use for choosing an option. A different decision maker might view the nominal case for each scenario as more valid, since, for instance, the hard case may not be achievable in the time frame being considered. This is represented as Focus 2. Another decision maker may believe that achieving the capability to be effective in the hard case would be an excellent deterrent and therefore should shape the strategy (Focus 3). Focus 3 would also represent the values of a decision maker who believes that the harder case is either more realistic or that the easier case is simply wishful thinking. Still another perspective is that Scenario 1 is not credible, either because it represents too much of a challenge or because the US would not use CPGS capability against mobile missiles and risk retaliation. This is represented by Focus 4. Other focuses are possible, but not represented in this illustrative example. For instance, a decision maker might believe that the third scenario is not credible, in which case it would receive zero weight.

The last column of Table 4.3 which identifies whether each assumption reflects a value, belief, or expectation, deserves a bit more explanation. As described earlier, many values, beliefs, and expectations can be represented as parameters in a mathematical model. For instance assumption 1, whether the assets are forward deployed or not, represents a belief about the likelihood of sustaining this forward-basing capability, or having forces available at the time. One could argue that this is also an expectation about the future, but beliefs are viewed as more complex models about how the world works (or in this case, will work) than expectations. Forward basing is in reality a complex function of many factors such as cost, political support within the US and its allies, the location of the strike, and so on.

Similarly, how well a strike is in reality executed is a very complex function of many variables, some of which may be relatively simple matters of physics (navigation system drift), but others not so simple. For instance, the amount of ground clutter or deceptive tactics used by the adversary to hide mobile missiles is unknown, and can affect the likelihood of finding the target in complex ways. As will be demonstrated later, the approach taken in MPSDM is to represent higher-level parameters as a simple range of variables, use exploratory analysis to see which ones affect relative option superiority, and then drill down in more detail in the model on these parameters that matter. Thus, we can start out with a simple parametric variation to represent a range of complex beliefs.

The design for this experiment was such that all combinations of cases were run. The table below shows the number of levels evaluated for each independent variable.

Assumption	Parameter	# levels
1) Forward deployed or not	Timeliness	2
2) Execution (reach, find, and kill target)	Execution	2
3) Collateral damage	Collateral Damage	2
4) Net Mission Risk	Net Mission Risk	2
5) Risk aggregation rule	Aggregation rule	2
6) OE aggregation Weights for each Scenario	4 focuses	4

Table 4.6 - Number of Levels Used for each Independent Variable in the Computational Experiment

From the table above, we see that in order to cover every combination of parameters for every level, it was necessary to run $2^5 * 4 = 128$ runs in the computational experiment.

Although only 128 runs were required for this illustrative case, it is not uncommon in exploratory analysis to construct tens of thousands of combinations of independent variables. It may be necessary to construct a macro to populate the table of independent variables as model dimensionality increases.

Next, we turn to a discussion of dependent variables. For multiresolution models, it is not entirely obvious which variables are dependent. For instance, is a Level 2 variable a dependent variable of an aggregation from Level 3 variables, or an independent variable of an aggregation to Level 1 variables? The answer is that it depends on the stage of exploratory analysis one is currently considering. For this first stage of EA, where the independent variables are predominantly in Level 2, the Level 1 variables are defined as the dependent variables for the computational experiment. Referring to Figure 4.1, these are: Overall Effectiveness and Overall Risk, and Effectiveness for each scenario. Cost will be included as options are compared. As will be described in more detail later, Relative Option Superiority in returns or risk is the eventual figure of merit.

Exploratory analysis step 2: Run a suite of plausible outcomes

Recall from Figure 4.3 that the second step in EA is to generate a suite of plausible outcomes for the range of independent variables chosen. For the step, the existing PAT model for CPGS required modification. The reason for this is that PAT was designed so that the user specifies some inputs (e.g. choice of aggregation and scoring functions) by selecting from a menu rather than giving a parameter value as required for use with a data table. In addition, to recompute level 2 and 3 worksheets, a "Recompute Level 2 (3) Data Sheet" button must be selected. These menu and recomputing functions were programmed to be executed with Macros. These macros were replaced by explicit equations in Microsoft Excel, hard-wired in for the CPGS example.[43] For instance, parameters were set in the tables of independent variables to define the aggregation and scoring methodology based on IF statements in Microsoft Excel. Duplicate worksheets were created for Level 3, Level2, and Summary level variables which updated the worksheets automatically and incorporated the hard-wired menu functions, and the results checked against the PAT model.

The figure below shows a result of the summary-level calculations done for the CPGS example.

[43] An approach that was not attempted, but which may be useful, is to combine the Microsoft Excel data table function with batch programs in Visual Basic.

Option #	Mobile Missiles (2020)	Mobile Missiles (2020) Reactive Threat	Terrorist Site (2020)	Terrorist Site (2020) Fleeting Target	WMD Facilities (2020)	WMD Facilities (2020) Hard Case	Overall Risk (2020)
1) Base Case	*0.02*	*0.02*	*0.61*	*0.49*	*0.11*	*0.18*	0.00
2) Penaids	*0.02*	*0.02*	*0.77*	*0.57*	*0.49*	*0.46*	0.50
3) SLBM + Penaids	*0.02*	*0.02*	*0.97*	*0.89*	*0.49*	*0.46*	0.50
4) SLBM + Penaids + SOF Vehicle	*0.02*	*0.02*	*0.97*	*0.89*	*0.87*	*0.46*	0.50
5) SLBM + Penaids + Sensors	*0.22*	*0.02*	*0.97*	*0.89*	*0.49*	*0.46*	0.50
6) Adv. Bomber + Sensors + SOF Vehicle	*1.00*	*0.02*	*0.77*	*0.57*	*1.00*	*0.53*	0.50

Figure 4.3 - Summary Scorecard

This compares with Davis, Shaver, and Beck's (2008) Figure S.5, with two exceptions: First, the color scheme is very slightly different. One of the features in Excel for Office 2007 is the ability to automatically generate scorecard colors without the need for a macro.[44] This feature can aid in model transparency and standardization from analyst to analyst of scorecard colors. The second difference between the scorecard above and Davis, Shaver, and Beck's (2008) Figure S.5 pertains to the scores for Options 1, 2, and 6 (the ones that use a bomber) for the Terrorist Site Fleeting Target scenario. Specifically, the scorecard above gives a more positive score (yellow vs. red). This is because of the way the variable Timeliness is aggregated with the variables Execution and Collateral Damage.

Timeliness for this scenario is treated as a more challenging requirement than for the other scenarios because of the time-stressing nature of the scenario: the terrorists are assumed to only be meeting for a limited amount of time. The stricter Timeliness requirement is operationalized in the model in two ways: first, by giving Timeliness more weight in the aggregation; and second, by scoring it more severely than in the other scenarios. The scoring algorithm is illustrated below.

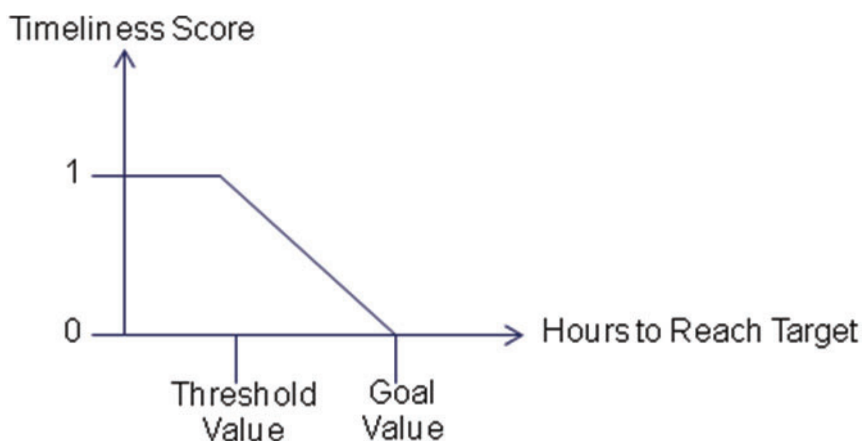

Figure 4.5 - Timeliness Scoring Illustration

[44] A macro is still needed if one wishes to change the scoring thresholds associated with each color, or to insert a letter representing the color (e.g. R for red) for color-blind individuals or black and white copying.

For all the scenarios, the Timeliness Score varies between 0 and 1 as shown above, but the Threshold and Goal Values (in hours) are considerably shorter for the Terrorist Site Fleeting Target scenario as shown in the table below.

Scenario	Threshold Value	Goal Value
Mobile Missiles	16	72
Mobile Missiles Reactive Threat	16	72
Terrorist Site	6	18
Terrorist Site Fleeting Target	0.5	3
WMD Facilities	48	100
WMD Facilities Hard Case	48	100

Table 4.7 - Timeliness Scoring Values for Different Scenarios

As can be seen from the table above, if the time to reach the target exceeds the goal value of 3 hours for the Terrorist Site Fleeting Target scenario, the Timeliness score drops to zero. Other scenarios have less stringent goal values, up to 100 hours because the target is not fleeting.

In addition to the stricter Timeliness Weight and Scoring parameters for the Terrorist Site Fleeting Target scenario, Davis, Shaver, and Beck included a third operationalization of the more stringent timeliness requirement. They assumed separate requirements for timeliness, execution, and minimizing collateral damage (a nonlinear aggregation). Further, they were fairly conservative in estimating the execution time for manned aircraft, even if forward deployed, unless assumed to be on high alert. As a result, manned aircraft failed for the fleeting-target scenario.

Although the model used to illustrate MPSDM included the first two treatments of the stricter Timeliness requirement for the Terrorist Site Fleeting Target scenario (a higher weight for Timeliness and lower goal and threshold values in the scoring algorithm), the third treatment (the nonlinear summary-level aggregation) was not included in the model for two reasons. The first is that the NRC report found that the one hour goal “was not considered as a strict criterion, and some options that would not quite meet the DOD goal were considered in the analysis." In addition, Woolf (2008) included options that would not meet the one-hour goal and posed operational modes to mitigate the longer travel time of manned aircraft (p. 20):

> *How likely is it that the United States would face a sudden, unanticipated conflict, with no time to build up its forces in the region and with the requirement to strike some targets within hours of the start of the conflict? Would a delay of several hours or even days undermine the value of attacking these targets at the start of a conflict? Could other weapons systems provide the United States with the ability to "loiter" near the theater of operations, allowing a prompt attack during the conflict if hidden or concealed targets are revealed? A comparison of the likelihood of those scenarios that may provide the most stressing environments with the likelihood of less stressful scenarios may lead to the conclusion that other weapons systems can respond to many of these requirements in most circumstances.*

Although the NRC study (and Davis-Shaver-Beck) were understandably not sanguine about the ability to achieve short timelines without unusually good strategic warning, it seemed reasonable in this dissertation to soften somewhat the "requirements" for promptness—if only to make comparing options a bit more challenging.

The second reason is that the model used in this research, although retaining many of the salient features of the more detailed model used in Davis, Shaver, and Beck, was simplified in order to more clearly illustrate the MPSM principles and methodology.

Once the independent and dependent variables have been defined, the number and combination of independent variables determined, and nominal analytical results checked out, it was a relatively simple programming task to compute the suite of plausible outcomes using Microsoft Excel's Data Table function.

The suite of plausible inputs and outcomes is a matrix where each row represents a "run" or a different combination of inputs. Each column represents either the input assumption or the outcome score. Since there were 128 possible combinations of inputs chosen in the experimental design, there are 128 rows in the matrix. There were six input assumption as described by Table 4.3, and 48 outcomes: one measure of effectiveness for each of six scenarios along with overall risk for each option (7x6=42 measures); plus Overall Effectiveness for each option (6 measures). The addition of a run number identifier brings the total number of columns to 55 (6 + 42+6+1=55). The table below shows the format of the e128 X 55 matrix of independent and dependent variables.

Run	Independent Variables						Dependent Variables													
							Option 1 ...							Option 6	Overall Effectiveness					
	Forward Deployed?	Execution (1=+X%; 0=-X%)	Collateral Damage	NetMissionRisk (1=+X%; 0=-X%)	Risk Aggregation Rule	Overall Effectiveness Aggregation Weights (Focus)	Effectiveness Scenario 1 Option 1	Effectiveness Scerio 2 Option 1	Effectiveness Scerio 3 Option 1	Effectiveness Scerio 4 Option 1	Effectiveness Scerio 5 Option 1	Effectiveness Scerio 6 Option 1	Overall Risk Option 1	Overall Risk Option 6	Overall Effectiveness Option 1	Overall Effectiveness Option 2	Overall Effectiveness Option 3	Overall Effectiveness Option 4	Overall Effectiveness Option 5	Overall Effectiveness Option 6
1	0	0	0	0	0	1	0.018	0.018	0.715	0.531	0.07	0.107	0	0.6	0.243	0.382	0.468	0.544	0.541	0.64
2	1	0	0	0	0	1	0.02	0.02	0.915	0.531	0.07	0.107	0	0.6	0.277	0.415	0.468	0.544	0.541	0.673
3	0	1	0	0	0	1	0.018	0.018	0.459	0.403	0.07	0.107	0	0.6	0.179	0.298	0.385	0.45	0.385	0.489
⋮																				
128	1	1	1	1	1	4	0.02	0.02	0.699	0.443	0.158	0.25	0	0.56	0.387	0.566	0.646	0.722	0.646	0.683

Table 4.8 - Excerpt from the Results of the Computational Experiment

The first column indicates the Run number, followed by a set of independent variables (Forward Deployed up through Overall Effectiveness Aggregation Weights (Focus)). The dependent variables (Effectiveness for each Option for each Scenario; Risk for each Option; and Overall Effectiveness for each Option) were computed for each set of independent variables.

Exploratory analysis step 3: Explore the results graphically

Now that our matrix of independent variables and dependent variables has been generated, the work of making sense of it all begins. One type of graphic that appears to be particularly useful is a box-and-whisker plot (or box plot) as shown in the figure below.

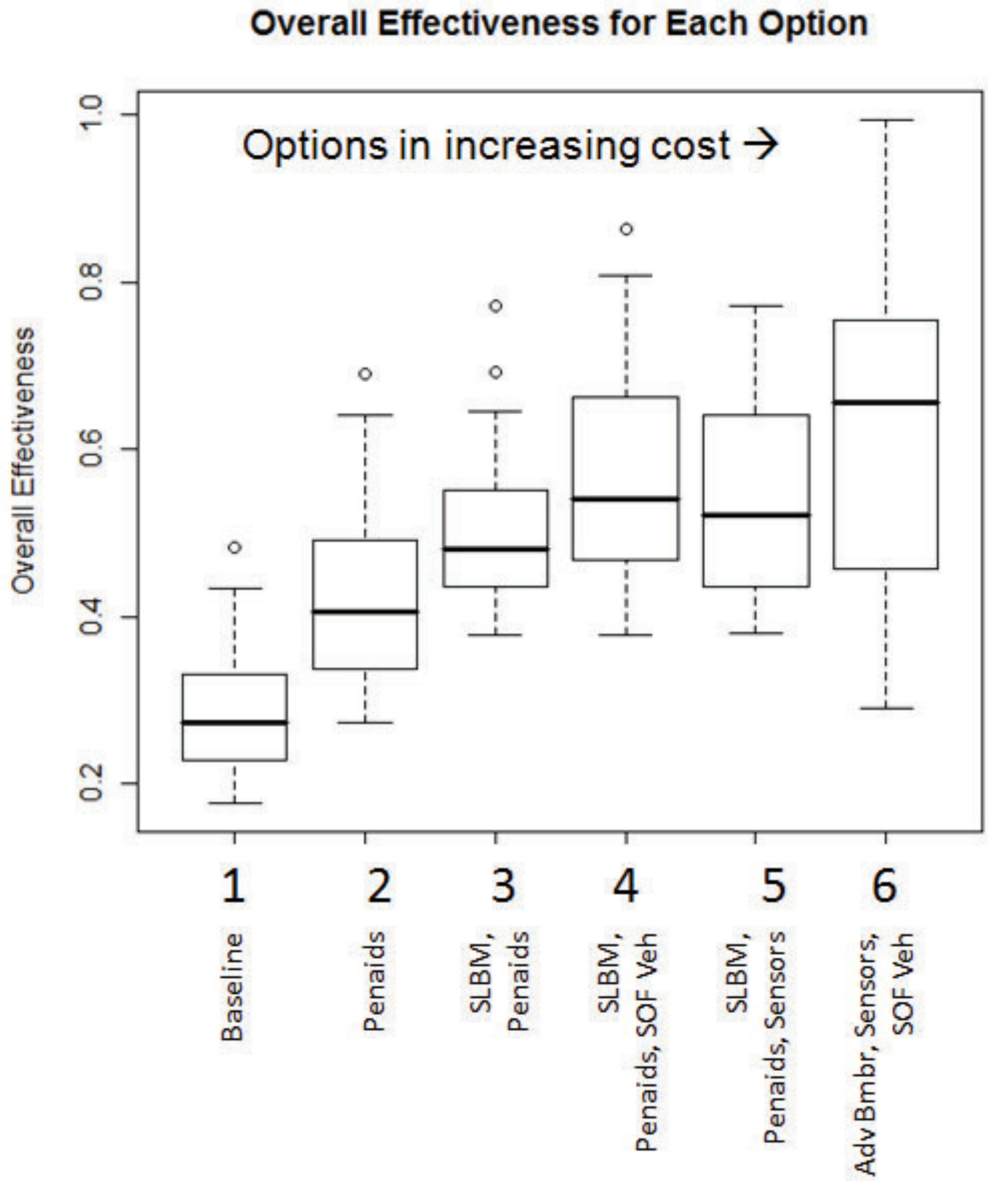

Figure 4.6 - Overall Effectiveness for the CPGS Illustration. ± 20% Parameter Variation

This plot shows the statistical results for the 128 runs of the computational experiment. Overall effectiveness for each option is shown as a box, where the bottom and the top edges of the box indicate the 25th and 75th percentile results, respectively. The difference between the 25th and 75th percentile results is defined as the interquartile range. The heavier horizontal line indicates the median result. The short horizontal bars (the whiskers) represent the value corresponding with 1.5 times the Interquartile Range, with outliers (data lying outside the whiskers) indicated by hollow circles. Options 1-6 are described and listed in order of increased cost.

As discussed earlier, it is not possible to deduce true statistical results for these outcomes because no effort was made to accurately represent the distribution of input parameters, nor are they necessarily independent. Recall that Overall Effectiveness is an aggregate measure of the weighted sum of scenario performance. Some scenarios may lead to low effectiveness, some to high effectiveness. It is difficult to see this bi-modal (or multimodal) result from this aggregated measure. A drill down to the scenario level may give more insight into the options' performance. The figure below shows six box-and-whisker plots: One for each option's Overall Effectiveness by scenario.

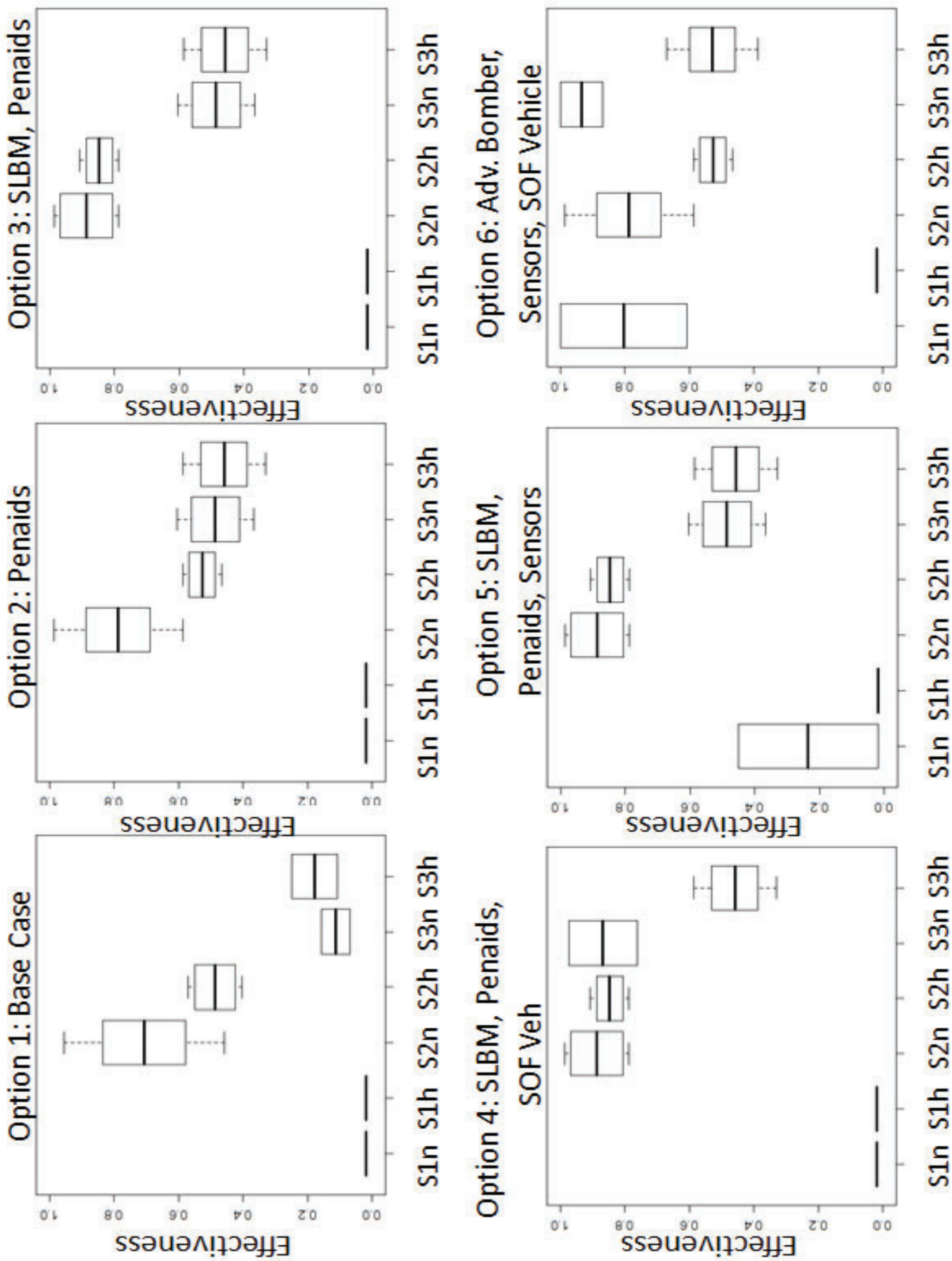

Figure 4.7 - Overall Effectiveness for Each Option
by Scenario in the PGS Illustration: ± 20%
Parameter Variation

The figure below shows the same Overall Effectiveness results, except with a separate plot for each scenario.

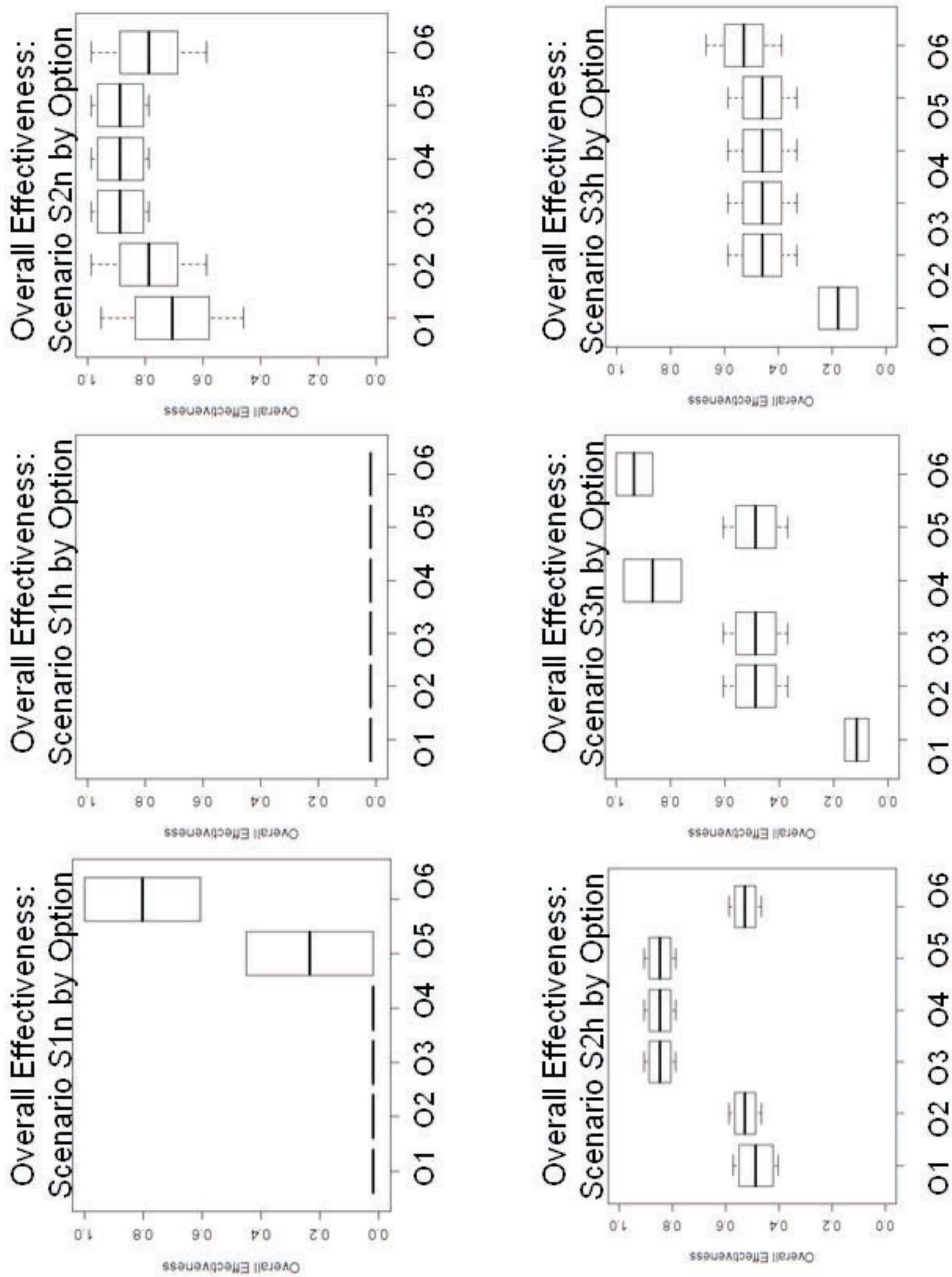

Figure 4.8 - Overall Effectiveness for Each Scenario by Option in the PGS Illustration: ± 20% Parameter Variation

Recall that the figure of merit is Relative Option Superiority, and we are not drawing conclusions about absolute effectiveness. The aim is to identify which options should be retained for further analysis. From the figure above, we can see that:

- Scenario 1n (Mobile missiles case) is performed best by Options 5 and 6, but it remains to be seen whether Option 6 is worth the extra cost.
- Scenario 1h (Mobile missiles hard case) is not performed well by any option, showing no difference from the worst performing option to the best performing option.
- Scenario 2n (Terrorist site case) performs reasonably well by all options, but shows little difference from the worst performing option to the best performing option. Although one cannot interpret the statistical results literally because all cases are not equally likely, the top whisker is almost identical from one option to the next, the 75th percentiles are within 0.1 and the median varies by less than 0.2 units of Overall Effectiveness.[45]
- Scenario 2h (Terrorist site fleeting target) shows some variation between Options. Options 3-5 perform well, compared with Options 1,2, and 6.
- Scenario 3n (WMD facilities) shows a large variation between Options. Options 4 and 6 perform better than Options 2, 3, and 5, which perform better than Option 1.
- Scenario 3h (WMD facilities hard case) is performed moderately well by all but the first Option.

Thus, scenarios 1n, 2h and 3n show some difference in performance between options, and are identified as “option differentiators” since they help us choose between options. The other scenarios, 1h, 2n, and 3h show essentially no difference from the worst performing option to the best performing option, and therefore do not help us differentiate the options. We will focus on the option differentiator scenarios, eliminating the others for this iteration of the EA process.

[45] Overall Effectiveness is normalized from 0 (not effective) to 1 (fully effective).

Just as scenarios which are not option differentiators can be eliminated from consideration, options that *always* perform worse than others—those that are dominated--can be eliminated. Recall that Relative Option Superiority for Overall Effectiveness for option I over option j is defined as.

$$R_{OE,I,j} = \text{Overall Effectiveness}_{i\ (i=1\text{-}6)} - \text{Overall Effectiveness}_{j\ (i=1\text{-}6)}$$

For each of the 128 runs, $R_{OE,I,j}$ was computed for each pair of options. It was determined that Options 1-3 are dominated in Overall Effectiveness by Options 4 and 5; the difference in Overall Effectiveness was positive for all 128 runs. Option 6 was not dominated in effectiveness. Before we eliminate Options 1-3 from further consideration, let's take a look at Overall Risk.

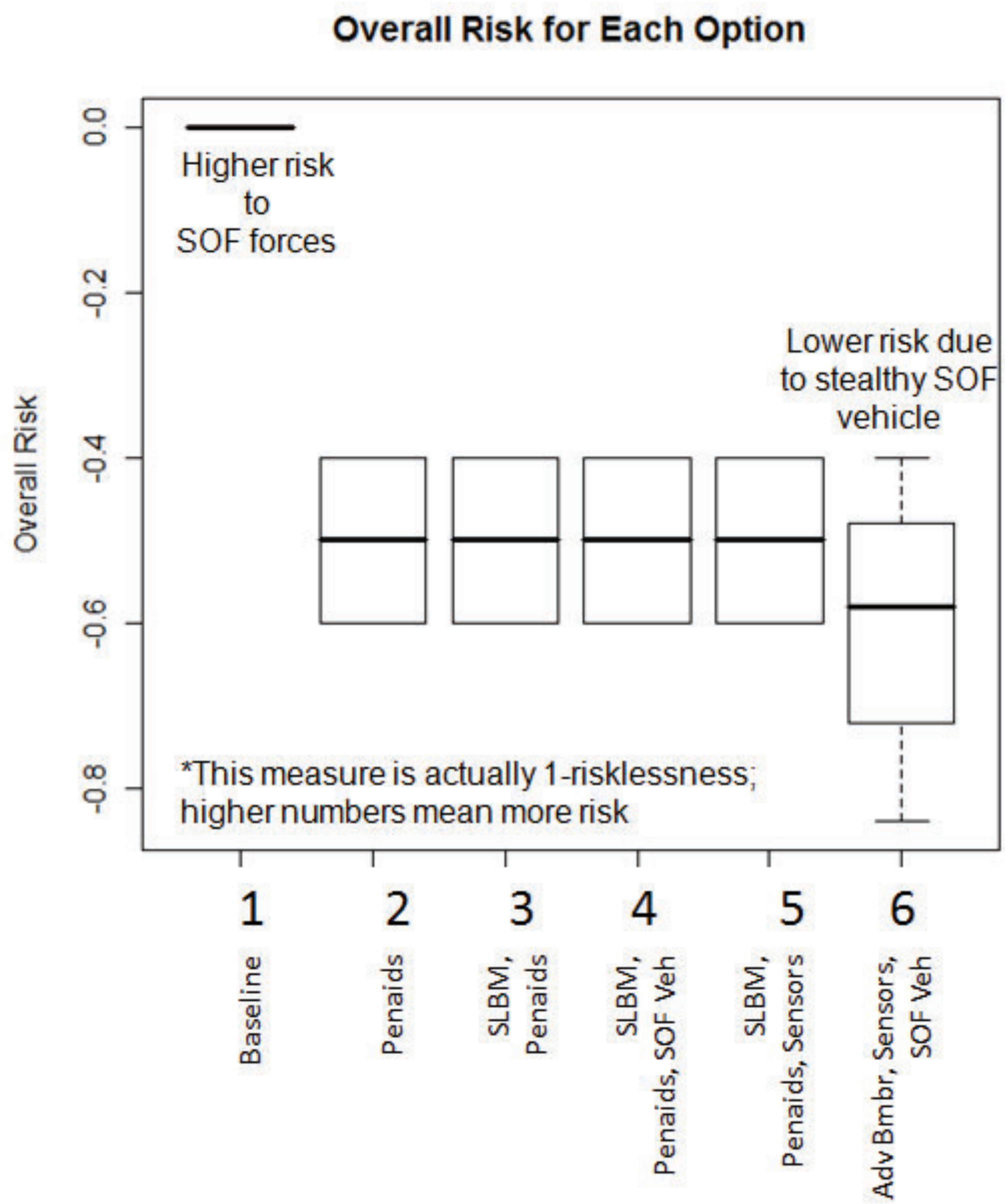

Figure 4.9 - Overall Risk for Each Option
(± 20% Parameter Variation)

From the figure above, we can see that Option 1 has a higher Overall Risk than the other options (for two reasons: SOF are required for this option in order to identify the precise target, and also because the manned aircraft's ingress/egress is risky) and that Option 6 has some cases of lower risk than the others (it includes a stealthy SOF vehicle and an advanced bomber with increased stealth). Options 3-5 include an SLBM which carries with it the perceived risk of misinterpretation. This will be discussed in more detail later. For now, nothing in the Overall Risk results indicates that Options 1-3, which are dominated in Effectiveness, should not be eliminated from consideration.

Recall that options are numbered in terms of increasing relative cost, and that Options 4 through 6 are higher cost than Options 1 through 3. Is this a reason to retain Options 1 through 3? It is a judgment call whether cost is a significant driver and options that otherwise perform poorly should be retained because they are less costly. In this example, two considerations went into the judgment to drop Options 1 through 3, which are dominated in return, and not worse in risk. First, it was assumed that all options are feasibly affordable and that the wide range of return and risk would more influence the choice of options than cost. Secondly, cost of the remaining options is included in the discussion aids used to elicit decision makers' value of cost relative to risk and return.

Thus, scenario S1h, S2n, and S3h can be eliminated from further consideration for this set of options because they are not option differentiators, and Options 1-3 can be eliminated because they are dominated by Options 4,5, or 6. The figure below shows the Scenario Effectiveness for the remaining options and criteria.

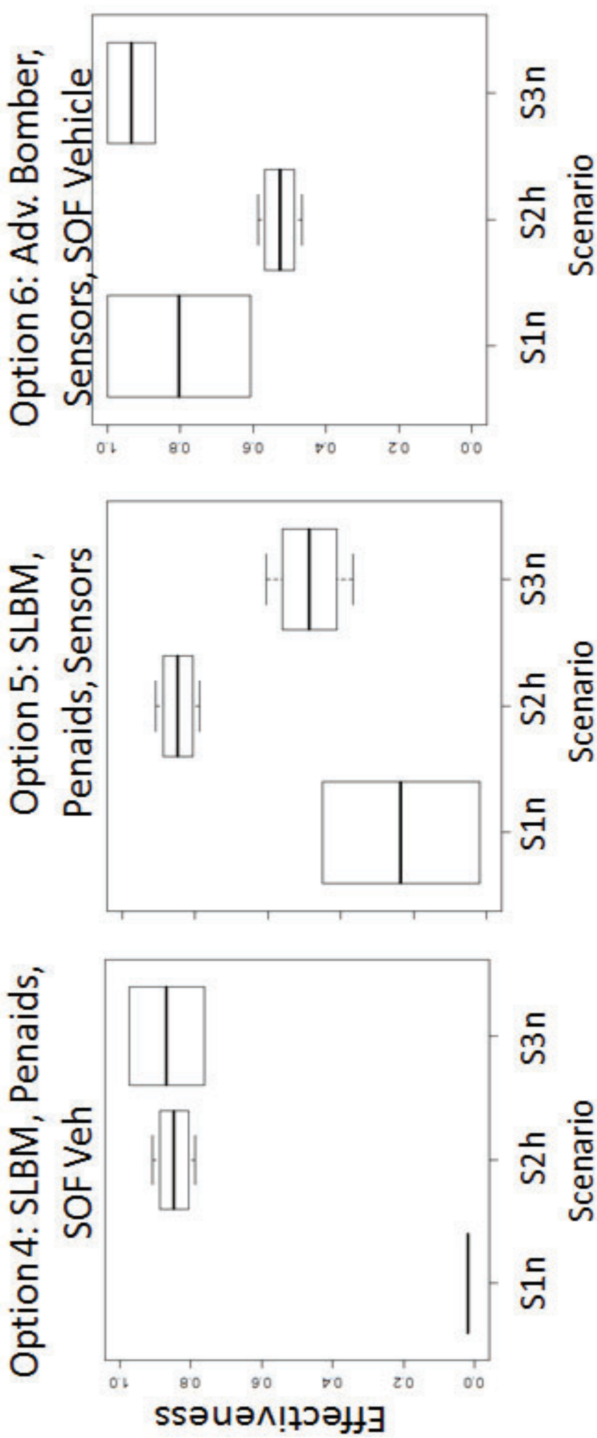

Figure 4.10 - Effectiveness for Each Non-Dominated Option for Each Differentiating Scenario

Of course it will not always be the case that options and criteria can be eliminated. For instance, some criteria may differentiate some of the options. It is possible that, once the preliminary scenarios are developed, one or more option may be created to deal with the particular challenges or opportunities suggested by some of the scenarios. Similarly, options won't always be dominated in every case that is run in the computational experiment; some cases may emphasize a relative strength of an option compared to the others, some may point out a relative weakness. The approach advocated here is to look for simplifications. If the number of options and criteria can be reduced, so much the better. If they can't, the remaining methodology remains the same.

Recall that the relative value for each scenario was defined as a set of four "focuses", each representing a set of scenario weights corresponding to a particular perspective. Since some of those scenarios have been eliminated, it makes sense to go back and revisit these focuses for the three existing scenarios. The table below shows the new formulation of sets of aggregation weights for each focus.

	Aggregation Weights for each Scenario		
Focus	S1n	S2h	S3n
1	.33	0.33	0.33
2	.33+X	.33-X/2	.33-X/2
3	.33-X/2	.33+X	.33-X/2
4	.33-X/2	.3-X/2	.33+X

Table 4.9 - Reformulation of Aggregation Weight Sets for Each Focus of the Differentiating Scenarios

From the table above, the first focus represents the perspective that the remaining scenarios are equally valuable in choosing an option. The next three rows include a variable X, which corresponds to the relative preference for one scenario over the other two. When X=0.67, Focus 2 puts all the weight on Scenario S1n and none on the other two scenarios. This corresponds to a strong belief that Scenario S1n be the most valuable scenario to consider when choosing options. Focus 3 puts all the value on Scenario S2h, and Focus 4 puts all the emphasis on Scenario S3n. Thus, by varying X between 0 and 0.67, the relative preference of one scenario over another can be explored.

The figure below shows Overall Effectiveness for the extreme values of X.

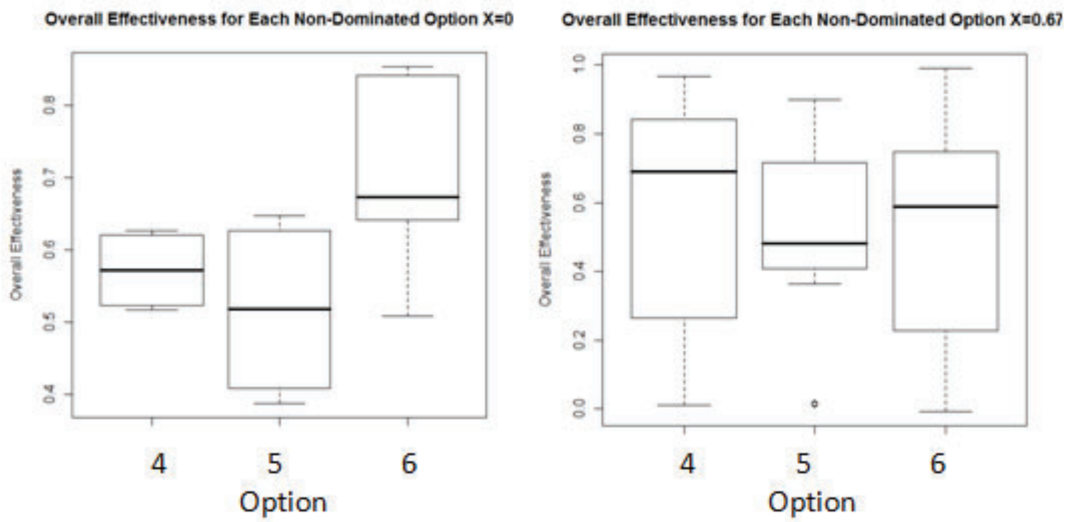

Figure 4.11 - Overall Effectiveness for Each Non-Dominated Option For Different Values of Focus Variable X (± 20% Parameter Variation)

Because decision makers may have strong preferences for one scenario vs. another, the value X=0.667 was chosen for further consideration. The effect of choosing this over X=0 can be seen from the figure above; the range of Overall Effectiveness was increased for each option, and Option 4's median result increased somewhat.

Exploratory analysis step 4: Mine the data to determine driving forces

The previous section described graphical exploration of the data. Often, the analyst can gain useful insights about the system from bridging the gap from data table to data mining with graphical exploration. In addition, high-level decision makers may find graphs and plots more intuitively satisfying and explainable than data mining results. The next section describes the method to perform statistical data mining in order to determine the factors that drive one option to be superior to another, or drive an option to have low effectiveness. Let us begin by determining the factors that predict when Option 4 will be superior to Option 5.

Recall that PRIM defines parameter space using the dimensions of the independent variables, and tries to identify regions of multidimensional parameter space of predominantly “good” outcomes. MPSDM defines Relative Option Superiority for measure Y of Option i over j as the difference

$R_{yij} = Y_{i(i=1\text{-}6)} - Y_{j(i=1\text{-}6,\, i\neq j)}$ where Y is an outcome of interest and i,j are options

For this exploration, we wish to find factors that drive Option 4’s superiority to Option 5 in Overall Effectiveness. Thus, in the equation above, i is set to Option 4 and j is set to Option 5 and Y is Overall Effectiveness. A positive value for Relative Option Superiority (R_{y45}) indicates that for that particular run, Option 4 is superior to Option 5 in Overall Effectiveness. “Good” cases for this exploration are defined as cases where R is positive, “bad” where R is negative. Thus, the PRIM algorithm searches for areas in multidimensional parameter space where Option 4’s Overall Effectiveness is superior to that of Option 5.

The results of running the PRIM algorithm showed that the predominant factor driving Option 4’s relative superiority to Option 5 was when the variable Focus was equal to 4. Referring to Table 4.8, above, this means that Option 4 is Superior to Option 5 when decision makers value Scenario S3n more than the other two differentiating scenarios. Recalling Figure 4.7, an excerpt of which is shown below, this PRIM result is consistent with the graphical observations: Option 4 is superior to Option 5 when decision makers value scenario S3n highly.

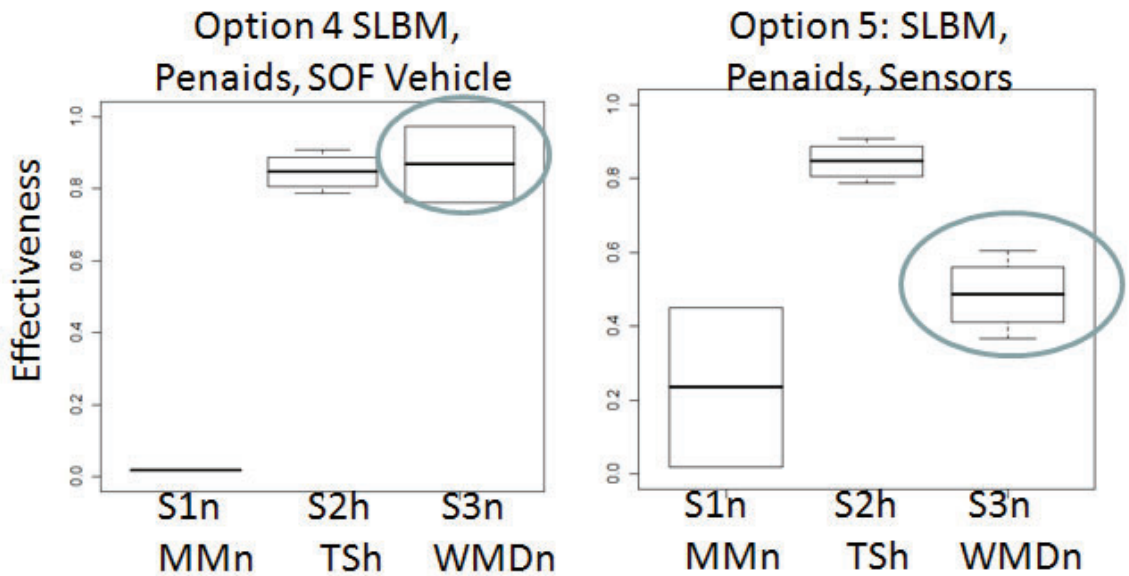

Figure 4.12 - Graphical Result Supporting PRIM
Conclusion on Relative Option Superiority

Next we turn to finding the forces that drive Option 4 to perform poorly. As we will see later, identifying these factors may be useful if an option is picked for further consideration, because there may be a strategy to address its vulnerabilities. What is meant by vulnerability? Although a number of measures could be used, the idea is to explore the "worst performing" cases using some threshold. The threshold that separated "good" cases from "bad" cases in PRIM was defined here for all options as the 25th percentile Overall Effectiveness.[46] PRIM found that the factors driving Option 4's poor performance were:

- Focus = 2 (emphasis on Scenario S1n) which is consistent with the low effectiveness score for S1n from the left side of the figure above
- Execution being low in Scenario S1n.

[46] Note again that the 25th percentile cases do not represent actual probabilities since no effort was made to model the distributions of input parameters, and they are not all independent. Another alternative would be to define the threshold as an absolute level, or the lowest 10th percentile cases, This lower relative threshold was also used for some of the options, and no difference was found in the driving factors.

This last finding is consistent with the graphical results in the figure above but additional insights require more analysis: what drives Execution for Scenario S1n to be low?

Recall from Figure 4.1 that Execution itself is an aggregate measure. It is the product of variables Reach Target and Find and Kill Target. There are two paths for exploring deeper from Execution:

1. Run the exploratory analysis procedure, using Execution as the *dependent* variable and lower-level variables as the independent variables
2. Drill down in the multiresolution model to see what drives Option 4's Execution in Scenario S1n.

The first path has three attractive features: it effectively increases the dimensional capabilities of PRIM. Instead of starting the exploratory analysis with all possible lower-level variables, taking this step-wise approach—exploring one level at a time and then exploring from the driving forces found at each level—affords a methodical "walk" through multidimensional parameter space, using fewer PRIM variables. Secondly, this lower-level exploration may be necessary for extraordinarily large models where a drill down in the multiresolution model is not as simple. Third, PRIM would be most useful when answering more discriminating questions, such as "at what value of this driving force, or with what combinations of values for multiple driving forces would relative option superiority switch signs?

The second path, drilling down in the model, was chosen for this demonstration because it was quicker, and demonstrates another value of the multiresolution modeling technique: real-time drill-downs to gain quick insight into lower-level factors that drive results of interest. A quick inspection of the results of the computational experiment showed that the variable Find Target drove Option 4's Execution in Scenario S1n. For this Mobile Missiles scenario, sensors are required to find the target.

Thus far Option 4 has been explored in terms of its superiority to Option 5, and also in terms of its poor performance. Next, the PRIM procedure is repeated, comparing each nondominated option pair. The table below shows the results of these explorations:

	Option 4 Superior	Option 5 Superior	Option 6 Superior
To Option 4: • **SLBM** • **Penaids** • **SOF Vehicle**	-	• Scenario S1n (striking mobile missiles) valued most strongly	• Scenario S1n (striking mobile missiles) valued most strongly • Scenario S1n Execution is low (need Sensors)
To Option 5: • **SLBM** • **Penaids** • **Sensors**	Scenario S3n (striking weapons of mass destruction) valued most strongly	-	Scenario S3n (striking weapons of mass destruction) valued most strongly
To Option 6: • **Adv. Bomber** • **Sensors** • **SOF Vehicle**	Scenario S2h (Striking Terrorist Site-Fleeting Target) valued most strongly	Scenario S2h (Striking Terrorist Site-Fleeting Target) valued most strongly	-

Table 4.10 - Summary of Relative Option Superiority: ± 20% Parameter Variation

The off-diagonal terms show conditions where one option is superior to another. Many of the cells are somewhat obvious from the box plots, but a drill down helps give insight into what lower-level factors are driving the results at the scenario level. As before, there are two drill-down approaches: One using PRIM and the one used for this illustrative model: Inspecting the results of the MRM. Some of the drill down results are worthy of discussion. Option 5 incorporates on-board sensors, which reduces the maximum weight of the warhead that can be used, compared with Option 4. WMDs in this scenario are assumed to be more challenging to destroy, because they may be somewhat hardened or buried. This also explains why Option 4 is superior to Option 5 when this scenario is valued most strongly. Similarly, Option 6 is superior to Option 5 when scenario S3n (destroying a WMD site) is valued most strongly. This is because

Option 6, which utilizes an advanced bomber, has the highest payload weight capability of all options, increasing the likelihood of destroying a WMD.

Continuing to the bottom row of the table above, Options 4 and 5 are superior to Option 6 when Scenario S2h is most emphasized. This is because the SLBM of Option 4 is timelier than the advanced bomber of Option 6, and this scenario stresses timeliness.

Next we explore what drives an option's vulnerabilities—the factors that are associated with particularly low effectiveness. The table below shows the results of this analysis.

	Option's Vulnerability
Option 4: • **SLBM** • **Penaids** • **SOF Vehicle**	Option 4's effectiveness is particularly low when • Scenario S1n (striking mobile missiles) valued most strongly • Scenario S1n Execution is low (need Sensors)
Option 5: • **SLBM** • **Penaids** • **Sensors**	Option 5's Effectiveness is particularly low when: • Execution in Scenario S3n is low (larger warhead needed) • Collateral Damage in Scenario S3n high
Option 6: • **Adv. Bomber** • **Sensors** • **SOF Vehicle**	Option 6's Effectiveness is particularly low when all scenarios are valued the same

Table 4.11 - Summary of Option Vulnerability: $\pm$ 20% Parameter Variation

Option 4's vulnerabilities are evident when Scenario S1n is valued most strongly by the decision makers. This option has particularly poor performance for this scenario because it does not include advanced sensors to find the target. Option 5 has particularly low effectiveness when execution is low and collateral damage in scenario S3n (striking Weapons of Mass Destruction) is high. Option 6's effectiveness is particularly low when all scenarios are valued the same: this is because Option 6 performs one scenario (S1n) better than the other two options, and one scenario (S2h) worse than the other two options.

These tabular results give a complete picture of relative option superiority and conditions of poor option performance, but another representation of the results might be more useful. The figure below shows the box-and-whisker plot with highlights from the tabular results, along with annotation describing the factors that drive an option to be more or less effective than others for a given scenario.

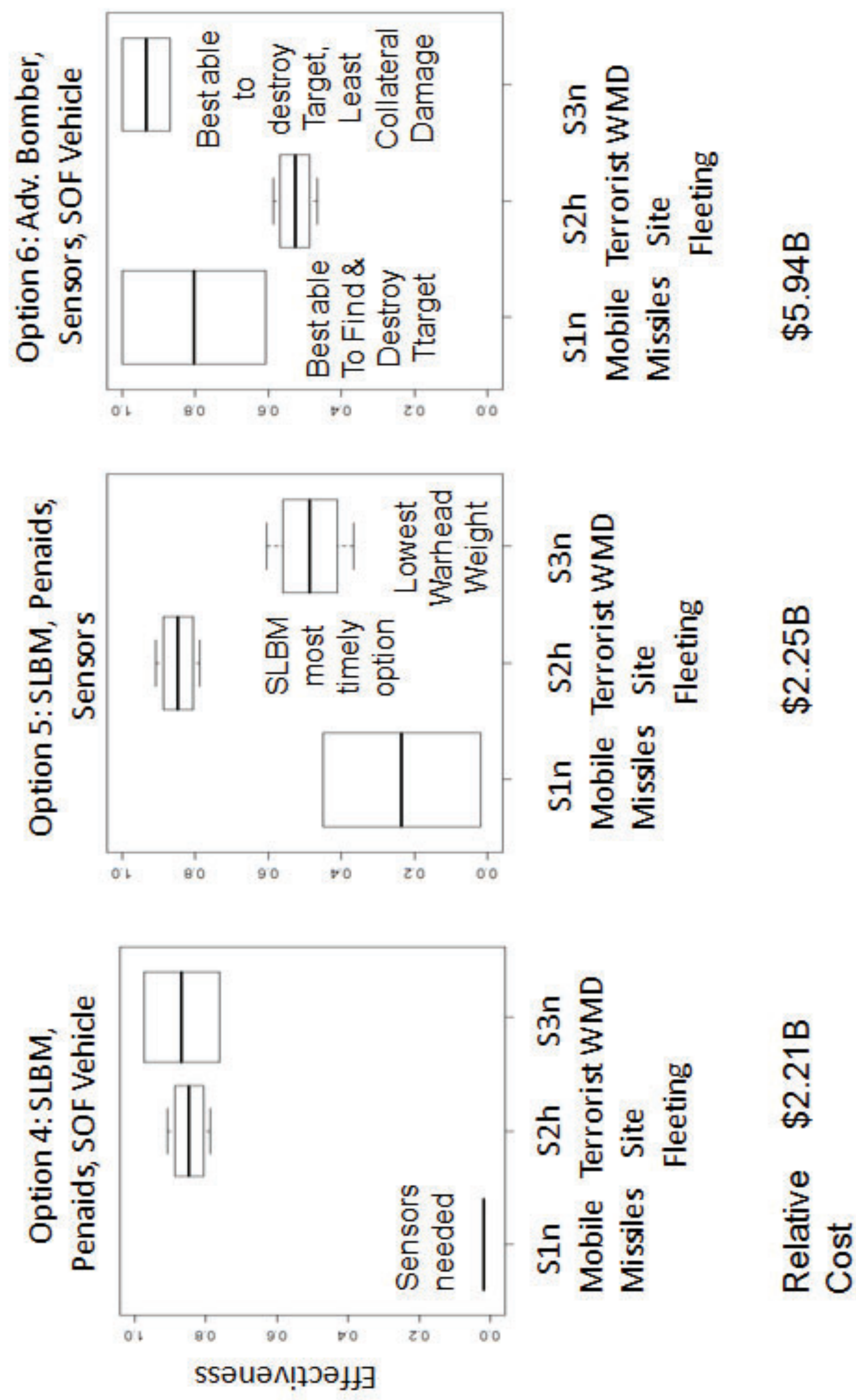

Figure 4.13 - Annotated Box Plot. ± 20% Parameter Variation

MPSDM proposes that the annotated box-and-whisker plot be used as a discussion aid with decision makers. Scorecards, which are often used, have their advantages:

- They are more familiar to many decision makers, particularly in business and defense applications
- They are less abstract and may be more cognitively effective for a diverse audience
- They are more complete, giving results for all options and criteria
- Scorecards, especially as created by the PAT model, allow instantaneous drill-downs to lower-level factors that may be affecting higher-level results.

However, the annotated box-and-whisker plot has some advantages over scorecards:

- They show the results of full parameter space exploration
- They indicate the range and some distributional data
- They give an indication of the "corners" of parameter space for further analysis of the feasibility of particular cases. Often the vulnerabilities are areas the adversary will seek to exploit
- A box plot simplifies the problem, showing differentiating scenarios' relative effectiveness for nondominated options along with cost

The most complete way to represent the analyst's understanding of the system may to use both a scorecard and an annotated box-and-whisker plot. The scorecard can be used to give a more complete "big picture" and aid real-time drill down exploration. The box-and-whisker plots provide some explicit analytical results that might otherwise have to be done in the decision maker's head, and provide an analytic distillation of complex understandings.

The next step is to evaluate the effects of nonlinear parameter space. Nonlinearity comes into the model, for instance, when nonlinear aggregation rules and scoring thresholds are used, or when elements are modeled as nonlinear functions of other parameters. Recall from Table 4.3 that some of the parameters (Execution, Collateral Damage, and Net Mission Risk) were varied $\pm$ 20% in this last exploration. Next, variations of $\pm$ 40% are explored, and the results compared. The figure below repeats the previous figure, and adds the plots of $\pm$ 40% parameter variation for comparison.

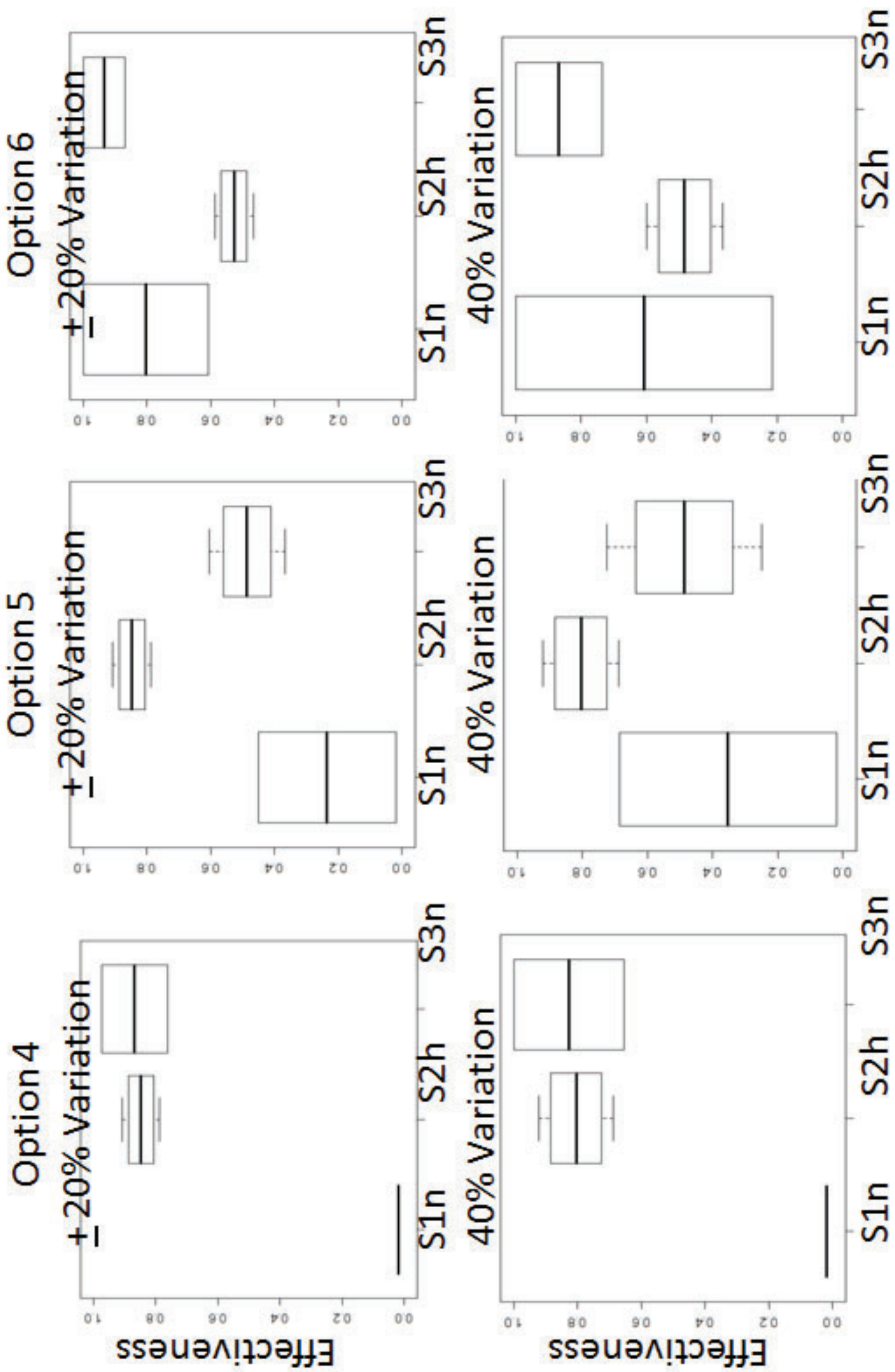

Figure 4.14 - Comparison of ± 20% and ± 40% Parameter Variation on Overall Option Effectiveness

The figure above shows that the spread of results, as expected, is larger for the $\pm$ 40% variation than the $\pm$ 20% variation. For the most part, the results are unchanged. The exception is for Scenario S1n: Options 5's median is very slightly higher for the $\pm$ 40% variation, and Option 6's median is somewhat lower. This may be due to a "floor effect" for option 5, where Effectiveness is often quite low, and a "ceiling effect" for Option 6 where Effectiveness is sometimes quite high. Note that the relative option superiority for the $\pm$ 20% and $\pm$ 40% variation are fundamentally the same. The important result is that nonlinear effects are not significant for our chosen figure of merit, relative option superiority.

So far, the first two steps of the MPSDM methodology have been completed: The problem has been framed as a set of initial options and criteria, with perspective parameters evaluated explicitly along with more objective factors; and the problem has been simplified by eliminating dominated options and non-differentiating criteria and performing exploratory analysis to find the factors driving relative option superiority.

MPSDM methodological step #3: Derive the strategy

Recall from Figure 3.1 that the third step in the MPSDM methodology is to derive the strategy by using the driving forces' time frame and controllability to determine type of strategy to employ, and then modifying the options and criteria, iterating as required.

Let us imagine that decision makers used the annotated box plot of Figure 4.13 as an aid to discuss the relative value of the options, including their relative cost. Let us further assume that they chose Option 5 as a relatively cost-effective choice for further consideration. It is the timeliest option, with somewhat more capability in Scenario S1n than Option 4. Although it does not perform Scenario S3n as well as Option 6, it is less than half the relative cost. Although the next step in the MPSDM process could be performed using all three options, the methodology is illustrated by proceeding with Option 5 as the most cost-effective choice.

Recall from the middle row of Table 4.9 that the factors driving Option 5's relative option inferiority were low Warhead Weight and high Collateral Damage in Scenario S3n (Destroying WMDs). Can we improve these factors, thereby improving Option 5?

Warhead Weight is somewhat controllable in the long term, as is Collateral Damage The figure below shows the MPSDM controllability/time frame heuristic, with the factor driving Option 5's relative inferiority to Option 4 in Return (warhead weight and collateral damage) placed in the "controllable" quadrant in the long term.

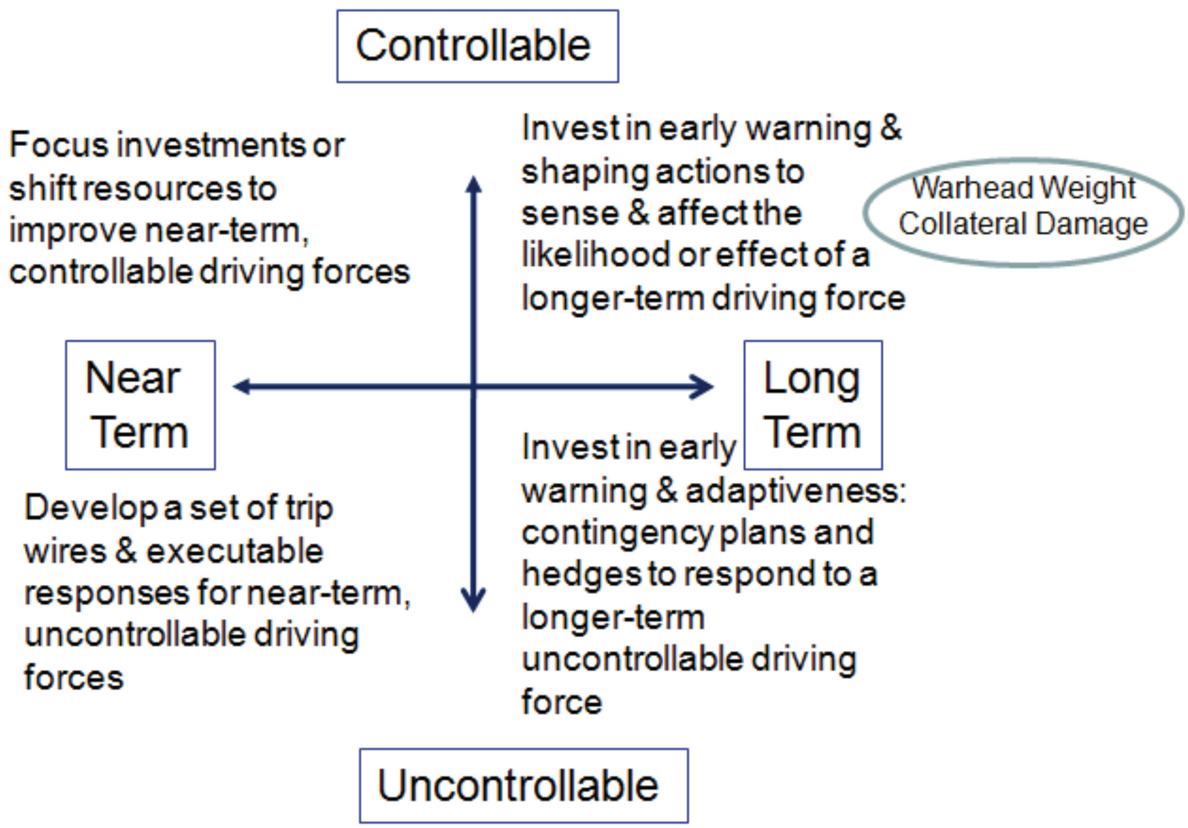

Figure 4.15 - Time Frame/Controllability Heuristic
with Driving Force in Most Appropriate Quadrant

Thus, from the upper right hand quadrant of the figure above, Option 5's Effectiveness could be improved in the long term by shaping actions to affect 1) the likelihood of destroying the WMD site and 2) causing unacceptable collateral damage. Item 1 can be accomplished by removing the third stage of the Conventional Trident Missile used in Option 5, and replacing it with a new payload. This allows the SLBM to carry a biconic re-entry vehicle with a payload that more accurately aims a heavier warhead to strike at a given angle. This modification has several advantages of the CTM third stage:

1. the heavier payload increases the likelihood of “killing” the target
2. the biconic re-entry vehicle enables the warhead to hit the target at a normal angle, increasing the likelihood of “killing” the target
3. the improved aim increases the likelihood of finding the target
4. the steerable re-entry vehicle has more range than other re-entry vehicles.
5. this increased payload weight capability could also be used to carry an unmanned aerial vehicle (UAV) that could be developed for longer-term use. The UAV would be very helpful in Scenario 1 since it could carry sensors to locate the mobile missiles

In addition to increasing warhead weight, this modification would also improve the other driving force, Collateral Damage. Items 2 and 3, above, would also reduce collateral damage.

Noteworthy is the fact that this option was created by the NRC as the so-called CTM-2. Their expert opinion converged to the same solution as the MPSDM approach.

In addition to these shaping actions, Figure 4.15 recommends that resources be applied to developing early warning of the effect of the adversary developing WMD capabilities. Early warning in general is beneficial to enable a wider variety of responses, but in the case of WMD, detailed intelligence about facility characteristics and vulnerabilities is especially valuable to reduce actual collateral damage. Enrolling allies early in the need to get this intelligence, or to destroy the WMD facilities early may reduce the *effect* of collateral damage, especially if the facilities can be destroyed before toxic materials are produced.

A final note: This “controllifying” activity, or figuring out if any aspect of the driving forces can be brought under the control of the decision makers is not to be underestimated. Often, when a factor seems completely outside the decision makers’ control, influences from other domains can be brought to bear. An agreement with a third party, a game-changing breakthrough, or even an unforeseen circumstance my bring the factor into indirect control. Sometimes the group, especially when stakeholders are included, has resources far beyond what any individual decision maker may recognize.

What about Option 5's risk? Recall from Figure 4.9 That Option 5's Overall Risk is driven by the ambiguity issues of a conventional warhead being launched from the same submarine as a nuclear warhead. Although ambiguity is the most often-raised concern about CTM options, and Congress has expressed reservations about funding CTM for this reason[47], the NRC (2008) committee and Woolf (2008) offer several observations on the ambiguity issue. First, that any CPGS option could carry nuclear weapons, making the launch platform criterion less of an option differentiator than previously considered. Second, the risk could be mitigated by a number of methods:

- Notifying other countries, in particular China and Russia, prior to launch
- Enacting transparency arrangements to inform other countries about the CPGS system, its operation, and its doctrine for use
- Sharing early warning data at a joint facility
- Inspection of U.S. facilities
- A continuous visual monitoring system to ensure that conventional warheads have not been replaced by nuclear ones

The NRC committee made the following conclusion

> *The risk of a CPGS attack being misinterpreted and leading to a nuclear attack on the United States could be mitigated and managed through readily available mechanisms. The benefits of possessing a limited CPGS capability, such as that provided by CTM, outweigh the risks associated with nuclear ambiguity.*

Now that the driving forces have been found and Time Frame/Controllability heuristic has been used to identify strategies to modify Option 5, the criteria themselves

[47] NRC (2008) Appendix B presents a letter from Senators Daniel K. Inouye and Ted Stevens, Chairman and Ranking Members of the Senate Committee on Appropriations, Subcommittee on Defense. The letter states that "there was widespread, but not universal, agreement [in the Senate] that the Congress should not proceed with the conventional Trident program [and that] critical to the opposition was a belief that the Trident option proposed the most difficult challenge of ambiguity." The NRC disagreed with Congress' decision to not support testing of conventional Trident missiles in 2008.

can be evaluated in light of the insights gained so far. In reviewing the results of exploratory analysis and seeing a simpler view of a complex problem, decision makers may wish to modify the initial criteria: Is ambiguity as much of an option differentiator as originally thought? From the discussion of the relative value of different scenarios, are the values of the decision makers converging?

As indicated in Figure 3.1, the last step in the MPSDM methodology is to modify the options and criteria and iterate the process. Using the modifications to Option 5 discussed above, and any updates to the criteria that the decision makers have come to understand, a new set of options and criteria can be used as the starting point for another round of exploratory analysis. A new suite of plausible outcomes can be generated, a new set of driving forces can be identified, and the options modified according to the insights gained from both the analysis and from the discussion of decision makers' perspectives elicited in each iteration. This iterative process can continue as long as resources are available, or until decision makers find shaping actions and hedges to address the driving forces associated with the option chosen, or they reach consensus.

Reports from the NRC (2008) indicates that the committee started with highly diverse views amongst themselves.[48] This group of scientists, engineers, retired flag officers, policy analysts, political scientists, and retired senior officials was sought by NRC organizers for their expertise in the different fields. Some members were very sensitive to foreign relations issues, including arms control. Some were more technology-focused. There were debates about all significant issues, often with disagreements. Members pointedly did not purport to reach agreement, for example, on the relative importance of the scenarios or the desirability of more far-reaching deployments.

Nevertheless, the committee came to consensus about the final recommendations and the relative superiority of the option they created as a result of the insights gained during their discussion. At the end of the day, the committee had many recommendations, but they focused on facts, analysis, and on what should be done.

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[48] Unpublished communication with Paul Davis, NRC Committee member.

Chapter 5 – Implementing MPSDM

Practical considerations

In this work, strategic decision making considers longer time frames and shapes the course of an organization more than tactical, or operational decision making. The topic of multi-perspective strategic decision making (MPSDM) is of interest to a variety of US and global organizations who are finding that the decision-making group includes, or must consider, a wider set of perspectives--values, beliefs, and expectations--than ever before. This research draws from literatures in policy analysis, economics and decision science, financial analysis, psychology, and system thinking. It extends the concept of exploratory analysis to explicitly include parameters representing perspectives (including those used to score and aggregate factors in a multiresolution model) in parallel with more objective factors. This dissertation contributes to the state of the art by providing and illustrating the principles, methods and tools to explicitly consider diverse perspectives of stakeholders and decision makers in creating strategy upon which they can agree.

The MPSDM approach is envisioned to fit into a high-level decision-making process that involves multiple contributors to a decision who attempt to achieve a significant degree of consensus. The approach also would fit in organizations in which decisions are made by votes. It would be applicable to a group that seeks consensus but—if need be—proceeds with the decision of a single leader. Much of the approach could be adapted for use by a single decision maker who aims to get input from others, or who wishes to communicate a rationale for the decision in order to gain alignment. In particular, the iterative nature of the process could be of use when individuals identify issues that affect their support.

The MPSDM approach presupposes that analytical support resources are available to evaluate options. This support could come from a staff organization, a consulting arrangement, or perhaps a group of analysts representing the different decision-making constituencies or areas of expertise. The decision makers are envisioned to meet as a group at least twice. The first session would cover the approach, Relative Option Superiority as it relates to the evaluation of the initial criteria, and would develop strategies and option modifications using the time frame/controllability heuristic. The subsequent session(s) would finalize the strategy after at least one iteration of the MPSDM methodology. More group discussions may be needed, and that many communications occur outside the strategic planning sessions, in chance meetings or via informal means.

It is recognized that some organizations do not have a strong tradition of analysis-based strategic planning. A scorecard is a relatively simple thing to construct, perhaps even real time if needed, and it is conceivable that criteria and forces driving the system could be elicited from expert judgment. However, to be truly effective, a strategy should consider a broad set of options in a wide parameter space, which is difficult to do systematically without analytical support. One of the aims of the MPSDM approach is that the simplified depictions of the problem in scorecards, box-and-whisker plots or the time frame/controllability heuristic will appeal to a variety of organizational cultures.

Finally, an effective strategic decision-making methodology takes into account the fact that decision makers are often not the final judges of their strategy. Executives have boards, elected officials have voters, and almost everyone has constituencies and bill payers. One of the most important results from the qualitative portion of RDM research is that strategic decision-makers must be able to communicate the reasons for the group's decisions to their constituencies. Typically, the constituents have narrower views of the system than the decision makers, so the graphical aids in the MPSDM toolset may be useful outside of the group.

The frequency of strategic planning exercises varies by organization; it is not uncommon to have a five-year strategy which is revisited every few years, although some organizations evaluate strategy yearly. It is hoped that the more straightforward the process, the less cumbersome it will become and the more likely organizations will be to perform strategic planning on a regular basis. One of the biggest challenges of the MPSDM process is creating the model of the system. Using a multiresolution model may encourage re-use of important elements rather than "starting from scratch" every time.

How does MPSDM help decision makers agree on strategy despite diverse perspectives?

MPSDM offers several ways to explicitly address different values, beliefs, and expectations without requiring the individuals in the group to agree on them. First, the framework chosen is an analytical one, based on a multiresolution model that includes representations of many different types of perspectives and uncertain factors. Second, options are chosen to be action oriented, as in "invest here," "watch for that sign post," etc. Third, so-called perspective parameters are explored simultaneously with more objective factors. This allows the effect of different perspectives to be determined. Fourth, the recommended figure of merit is relative option superiority for specific criteria. Although the group may never agree on the absolute expected return or risk of an option, or which score deserves a "red" rating, agreement is more likely when this more qualitative concept is discussed using an annotated box-and-whisker plot. In addition, this decision aid can elicit discussion of the relative importance of the different criteria in the face of computational experimental results.

Fifth, exploratory analysis identifies the most important values, beliefs, and expectations that drive the outcomes of interest. This is not to say that an individual's perspectives are not important to the individual—in fact the judgment of high-level decision makers is an important asset they bring to the table. However, not all values, beliefs, and expectations affect the return, risk, or cost by the same magnitude. The MPSDM analytical methodology and discussion aids help groups glean and share insights about the system and each other: return/risk/cost performance, which criteria differentiate the options, which options may be relatively inferior or superior to others, and which values are of highest priority. MPSDM proposes discussion aids such as annotated box-and-whisker plots to focus the discussion on factors which the exploratory analysis determines are the ones driving the outcomes of interest.

In addition, the time frame/controllability heuristic guides the strategy discussion to address those driving factors, suggesting circumstances where it is wise to invest in shifting resources, sign posts, shaping actions, or adaptiveness.

Finally, there may always be minority opinions on expectations of the future or beliefs about adversary's capability. As decision-making groups grow more heterogeneous, it is reasonable to imagine that the group's range of views of the future may be very wide. Traditional management literature prescribes coming to agreement on expected futures, or defining some average among the group that may represent the group's expectation. MPSDM, on the other hand, views these minority views as one way to identify a broad array of possible futures. Another tool to explore the extreme corners of outcome space is the computational experiment, wherein assumptions are varied simultaneously, with the resulting outcomes covering the plausible futures. If one of these combinations of assumptions, or some minority view of the future, proves prescient, it is better to plan for it early while the option set is relatively broad. Thus, a difference in perspectives doesn't have to be associated with a clash in consensus, but rather an opportunity to plan for some force that may drive outcomes in the most favorable way. Minority opinions, rather than being a barrier to agreement, can be an opportunity to plan hedges "just in case" the opinion is prescient.

The preceding discussion is supported by the following principle:

Principle #6: Groups can agree on strategic actions without agreeing on values, beliefs, and expectations.

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