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Creating Multi Objective Value Functions from Non-Independent Values

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CREATING MULTI OBJECTIVE
VALUE FUNCTIONS FROM
NON-INDEPENDENT VALUES

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Abstract

Decisions are made every day and by everyone. As these decisions become more important, involve higher costs and affect a broader group of stakeholders it becomes essential to establish a more rigorous strategy than simply intuition or "going with your gut". In the past several decades, the concept of Value Focused Thinking (VFT) has gained much acclaim in assisting Decision Makers (DMs) in this very effort. By identifying and organizing what a DM values VFT is able to decompose the original problem and create a mathematical model to score and rank alternatives to be chosen. But what if the decision should not be *completely* decomposed? What if there are factors that are inextricably linked rather than independent? In the past several years, Improvised Explosive Devices (IEDs) have quickly become the number one killer of American troops overseas. To this end the Joint IED Defeat Organization worked to create a VFT model to solicit and grade countermeasure proposals as candidates for funding. While much time and care was put into soliciting a valid VFT hierarchy from the appropriate DM, it does not represent the only option. With JIEDDO as an example this paper examines a strategy to better reflect a DM's combined values in a way which is understandable to the DM and maintains a level of mathematical rigor.

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To my Wife, without whom this paper would be no more than the ramblings of a crazy person with screaming children.

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Chris D. Richards

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I. Introduction

One of the primary applications of DA has been in initiative selection. Individuals, companies and especially militaries are consistently faced with some sort of ambiguous objective (raise profits, lower costs, defeat the enemy) and must decide which initiatives can be started now which will have the greatest likelihood of accomplishing these goals in the future. In 1998 the Chief of Staff of the US Air Force was faced with just such a situation: What space and air systems should we start now in order to guarantee air and space dominance in 2025? The resultant study by Air University attacked the problem using a classic additive VFT model that graded 40+ notional futuristic systems (in six notional futures) on their ability to support such the desired superiority (Parnell, Conley, Jackson, Lehmkuhl, & Andrew, 1998).

Unsurprisingly the actual DM (in this case Gen Fogleman) was largely unavailable for interview during the study. As a result, researchers were forced to revert to what Kirkwood refers to as the “gold” and “silver” standards of information; official doctrine and the opinions of subject matter experts (SME) (Kirkwood, 1997). In the end, the study relied almost completely on SME’s rather than the gold standard of doctrine due to the fact that, as they explained “It provides a high-level strategic view of national defense policy but does not provide detailed objectives for a value hierarchy" (Parnell, Conley, Jackson, Lehmkuhl, & Andrew, 1998).

Much like the current JIEDDO model, AF 2025 was a step in the right direction but arguably lost valuable insight into ranking initiatives by ignoring "the bigger picture". The "high-level" view that the policy offered could very well have provided a holistic view of alternatives, allowed at least some level of interaction within measures, and have better modeled the effects of future air and space systems. In AFDD 1, Air Force Basic Doctrine, General Jumper clearly states that "… the complex integration required among our fighting elements, the complexity of joint and combined doctrine, and the uncertainty of rapidly developing contingency operations demand that our planning and employment be understood and repeatable" (United States Air Force, 2003). General Jumper's choice of words such as complex, integration and joint all point to a clear recognition that some decisions have at their core, values which are not necessarily simple or the result of only one attribute. This does not mean that these values are impossible to ascertain and quantify.

This thesis proposes strategies for expanding a VFT model to more realistically reflect the combined values and tradeoffs of military leaders. This section specifically looks at a model currently designed for JIEDDO and introduces a framework for improvement.

I.A Background

Due to the growing threat that IEDs posed to soldiers in both Iraq and Afghanistan, in 2003 the US Army created the IED Task Force in order to explore countermeasures. Amid early success it quickly became apparent that the high level of reach out to sister services and interaction was indicative of an initiative which would benefit from attention at the DoD level and not only the Army. As a result, in 2006 DODD 200019.E replaced the task force with JIEDDO (JIEDDO, 2008) as a permanent military body. JIEDDO is charged to "… focus (lead, advocate, coordinate) all Department of Defense actions in support of the Combatant Commanders' and their respective Joint Task Forces' efforts to defeat Improvised Explosive Devices as weapons of strategic influence." Systems to further this goal are divided between defeating the IED (e.g. mitigating effects through armor or disposal), defeating the system (interrupting the chain of IED activities) and training the force (through doctrine, technology, etc.) (Department of Defense, 2006). To that end, JIEDDO solicits proposals for approval and funding through the Joint IED Defeat Capability Approval and Acquisition Management Process. In appropriating such a budget (almost $2B in 2007) (Meigs, 2007) officials, both commercial and governmental, require a high-level of justification and transparency for decisions before any funds can be committed (Government Accountability Office, 2008).

In 2008 Dawley et al. suggested a VFT model for JIEDDO proposal selection. Key JIEDDO decision makers (DMs) as well as other personnel were interviewed and questioned on what aspects were most important to potential IED countermeasures and what measures best reflected these values (Dawley, Lenore, & Long, 2008).

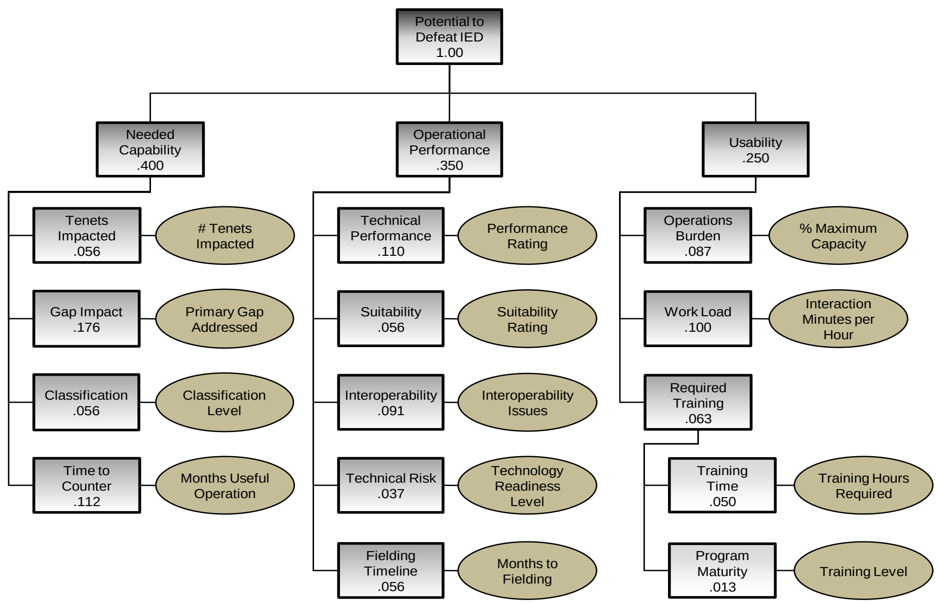


Figure 1: A JIEDDO VFT Hierarchy

As with most value models, there are two immediate advantages to this hierarchy:

1) It defines the “ideal” IED defeat solution. By identifying all desired characteristics and their relative importance, JIEDDO greatly reduces the probability of finding themselves in a situation where they are forced to choose the “best of the worst” from a list of submitted proposals. Instead, proposals are able to be shaped directly by specific JIEDDO requirements.

2) Once defined and weighted, the single dimensional value functions (SDVF) which govern the measures can easily be summed to give an overall “score” or value for a particular alternative allowing it to be ranked against others competing for selection.

As we will discuss later, Kirkwood lays out several desirable properties for a value hierarchy (Kirkwood, 1997). Among these, completeness, non-redundancy, operability and small size all seem to be relatively satisfied by the hierarchy in Figure 1 and support the definition of an ideal solution. Decomposability however, is more complicated. While the decomposition of a complex value may offer sub-values that are simpler to score, this substitution may lose important insight into why the original value was important to the DM.

I.B Problem Statement

The current JIEDDO model claims independence assumptions about values based on DM input. While these assumptions allow for a simple scoring structure and require a minimum of DM input, they may lose important information about interactions and lead to alternatives that may be holistically preferred by a DM to be outranked by alternatives which score well only on individual objectives. How does one create a value model which captures interactions without an unduly lengthy DM solicitation?

I.C Thesis Objective

The objective of this thesis is to introduce an alternate strategy for the analyst to employ during value model solicitation if they or the DM suspect that there exists preferential dependence between one or more values. The hope is to build on the prescribed VFT methodology leaving a process that is clear to a DM with little to no extra explanation as well as maintaining the mathematical foundation which makes the additive model such a desirable and defendable template.

I. D Methodology / Limitations

Although the original JIEDDO VFT model was created over a year ago, it has yet to be implemented by its organization. During this time JIEDDO has continued to receive, evaluate and decide to either accept or reject hundreds of proposals; the current model is understood but not completely accepted. The task will be to use the current VFT model as a foundation for an improved model which can lay to rest to any fears or suspicions of preferential dependence with minimal additional time requirements on the DM. This method should be DM independent and should answer the question of dependence without assuming its existence.

There are two major limitations in this effort: First, while there exists a large archive of accepted and rejected JIEDDO proposals, they have not been scored through the current VFT model. With minimal access to SME's, this task falls upon the researcher and is complicated not only by the number of proposals and measures to be scored, but also due to unclear definitions of desired performance levels. As a result, analysis depends greatly on the previous alternative scoring accomplished by Dawley's team in 2008. The second limitation is access to the relevant DM. Due to the continuous and high-vis nature of JIEDDO, meetings with actual DMs have been short and small in number. To fill this shortfall potential numbers are developed in order to provide an illustrative example as proof of concept of the methodology for future meetings.

I.E Paper Organization

The remainder of this paper is divided into four chapters: Chapter two presents a brief background of decision analysis as well as currently available alternatives for addressing the issue of dependence within value models. Chapter three introduces a new method for handling these issues and proscribes a step-by-step method for its execution with a decision maker. In Chapter four deterministic and sensitivity analysis are applied to the results of the newly established methodology as applied to the JIEDDO model using a sample set of past proposals submitted to the organization. Finally, conclusions as to the value of the presented model as well as recommendations for future research surrounding the topic are offered in Chapter five.

II. Literature Review

II.A Decision Analysis

Whether they realize it or not almost everyone practices some level of decision analysis (DA) every day. Kirkwood argues that any time we are faced with several alternatives which cannot all be chosen and have different consequences, then we are faced with a decision (Kirkwood, 1997). While decisions can range from relatively insignificant (where to go to lunch today?) to life or death (should I launch a nuclear attack?) DA provides a framework for methodically quantifying what is important to the decision maker (DM) and helping to choose the alternative which best accomplishes the overall goals of the DM. After identifying the driving objective, DA works to break the objective into its constituent pieces until they are at a level which is measurable either directly or indirectly. Returning to the question of where to go to lunch, the objective may be to "Eat Lunch" which can be broken down into "Proximity", "Cost", and "Tastiness". The first two can be measured directly by miles and dollars while the last could be based on some constructed scale of past experience. While it is completely plausible that the DM may end up making the same decision that they would have had they simply "gone with their gut", the decomposition has several key advantages. First, it helps the DM to organize their thoughts in making a decision. Second, it allows for transparency and justification of the decision process to others (Why are we going to lunch here? Because the other restaurant may be closer but this one is half the price and twice as good.) Finally, after a decision is made, it can serve to either help figure out where things went wrong (20 miles is too far for lunch) or identify important elements of success (Tastiness is definitely more important than cost).

II.B Value Focused v. Alternative Focused

There are two main camps between which DA techniques divide: the Analytical Hierarchy Process (AHP) and the aforementioned VFT. Developed by Saaty, AHP assumes a list of alternatives already exists and builds measures for scoring the alternatives by assessing a DM's preference between alternatives on particular measures (Given these two cars, which rates higher on dependability?) (Saaty, 1986). While many have argued that AHP suffers from practical problems and inconsistencies which make it undesirable for many DMs (Dyer, 1990), it does help in "…deriving dominance priorities from paired comparisons … with respect to a common criterion" (Saaty, 1994) and may help to prove broader concepts then just making a decision according to Kirkwood (Kirkwood, 1997).

VFT on the other hand attempts to break free of the box to which AHP is confined by developing objectives and measures free of pre-existing alternatives. In practice this forces a DM to consider what is really important to them instead of simply choosing the best of what's available. At its best VFT helps to guide the alternative generation process and innovate new ideas, at its worst it results in a framework for choosing between alternatives and is generally no less effective than AHP. According to Kirkwood "There is no substitute for a good alternative." (Kirkwood, 1997)

While AHP and VFT seek to create objectives and measures differently, they both result in a hierarchy that is used to measure each alternative on a set of individual measures that are then aggregated into a single score that is used to rank overall preference of alternatives

II.C Measure Selection and Construction

Up to this point DA has been described basically as a decomposition of the decision problem into measurable pieces in an attempt to make the analysis more manageable. However, measures are useless without clear definition.

Looking back at our lunch example in II.A, consider the sub-objective of Proximity. While distance seems to be the obvious choice, we could just as easily use time if we know that traffic is an issue. Further, even if distance is chosen, to be complete we may need to define how distance is measured (strict Euclidean distances are rarely an option when driving), as well as what scale (blocks, miles, feet, inches). In developing a measure, all of these concepts must be weighed against their usefulness as well as understandability. For example, measuring our lunch distance in millimeters is probably useless since our data is probably not nearly that accurate. Alternately, a measurement based on the fraction of distance compared to driving to one's house is meaningless to anyone who doesn't know where you live.

After choosing our measure and scale, the last step is to define a method of determining how much value we are willing to assign to different levels of our measure. Looking at our example, suppose that we decide that we are going to define proximity as rectilinear distance on a scale from zero to ten miles. Presumably, given the choice we would prefer to travel zero miles rather than ten miles, but how much more do we prefer it. By assigning a value of zero to our least preferred alternative and one to the most preferred we can develop what decision analysts refer to as a single dimensional value function (SDVF) to model this preference. For example, by looking at the functions in Figure 2 we can see that Person A loses interest at a constant rate the farther we have to go, while

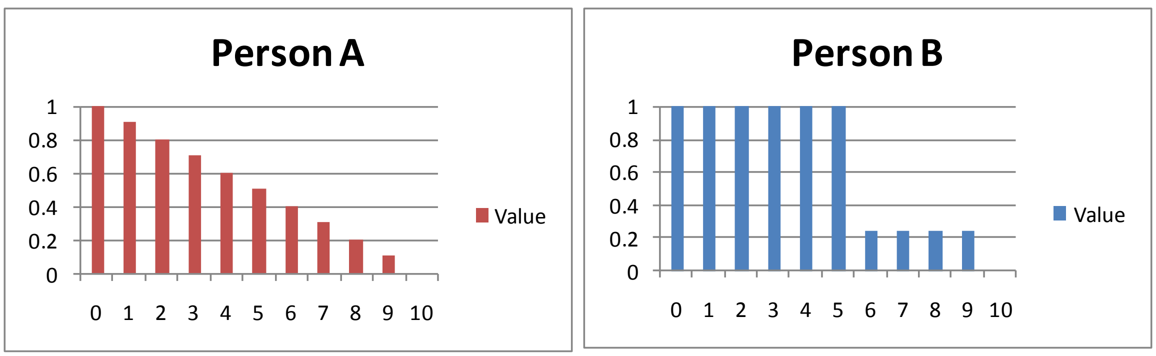


Figure 2: Individual SDVF's

Person B is ambivalent about anything within five miles, but sharply loses interest in having to go any further. Along with many others, Kirkwood describes many different methods to elicit both discrete and continuous SDVFs from a DM (Kirkwood, 1997). Note that while the SDVFs in figure 2 are decreasing, another measure (Tastiness for example) could just as easily be increasing if more of the measure was better. Either way, a key element of the SDVF is its monotonicity.

II.D Additive Value Functions and Preferential Independence

Once our objective is broken down into measurable pieces, it still means nothing if we have no way to put them back together again. Much in the same way that each individual SDVF graded a particular alternative on one particular measure, an overall value function is needed which grades the alternative as a whole based on all of its constituent SDVF scores. The easiest and most classic method to accomplish this aggregation is the additive value function:

$$v(\vec{x}) = \sum_{i=1}^{i=n} w_i \, v_i(x_i) \tag{2.1}$$

Here $\vec{x}$ is a specific alternative represented by its n measurable attributes, $v_i(x_i)$ are our SDVF for each attribute, and w_i is a scaling constant such that $0 < w_i < 1$. As Keeney points out, the additive value function is only appropriate when $\sum_{i=1}^{i=n} w_i = 1$ (Keeney, 1974). In this sense the w_i's can be seen as weights of importance given to each measure. As a quick result it makes sense that were a particular alternative to max every single SDVF, the above value function would sum to a max score of one as well. Similarly, zeros across the board on SDVFs would result in an overall zero score for the alternative. It should be clear that the selection of different w_i's can have great effects on the final value for an alternative. As such, Kirkwood (Kirkwood, 1997), Keeney (Keeney, 1974), and many others have offered many approaches to accurately elicit these weights from DMs.

An important corollary of the existence of an additive value function is that it directly implies every attribute and attribute pair to be preferentially independent of those remaining in the model. In general, if $\mathbb{X}$= {A_x, B_y} represents an alternative $\mathbb{X}$ with measures partitioned into set A at level x and all remaining measures in set B set at level y, then for A to be preferentially independent of B it must hold true that given $\mathbb{X}$=

$\{A_x, B_y\}$ is preferred over $\mathbb{Y}= \{A_{x'}, B_y\}$, then $\mathbb{X}$ should be preferred to Y for any choice of level y on set B. Consider our notional example of where to go to lunch. Suppose that restaurant $\mathbb{X}$= {10 mi, $10, Delicious} and $\mathbb{Y}$= {5 mi, $10, Moderate}. If our value function is constructed to give higher weight to tastiness, we may very well have that $\mathbb{X}$ is preferred over $\mathbb{Y}$. Now consider that both restaurants decide to cut prices and the alternatives now become $\mathbb{X}$= {10 mi, $5, Delicious} and $\mathbb{Y}$= {5 mi, $5, Moderate}. If Y is now preferred over $\mathbb{X}$ ($5 nearby is too good a deal to pass up even if the food isn't the best), then my model is not preferentially independent.

As an important side note, there exists a similar but stronger independence concept called utility independence. Keeney explains that for a single attribute x_1 to be utility independent of the remaining attributes preference order for lotteries involving only changes in the levels of attributes in x_1 does not depend on the levels at which the remaining attributes are held fixed (Keeney, 1976). However, since utility independence can be seen as the risk dependent analog to preferential independence, in value models which do not consider risk (as is the case with our JIEDDO model), it is admissible to treat any utility independence requirements as preferential independence requirements.

Thorough pair wise proof of preferential independence in the fashion described above can be very hard and tedious to identify and so it is no wonder that Carlsson et al. argues that it is part of the habitual thinking of much of DA to simply assume that all criteria are independent in order to maintain feasible solutions (Carlsson & Fuller, 1995).

The problem with this assumption is that in general most real world applications involve at least some level of interaction between attributes. So the question becomes what options remain if preferential independence appears to be violated in one or more cases between attributes?

II.E Multiplicative Functions

In the case that w_i's are ascertained such that $\sum_{i=1}^{i=n} w_i \neq 1$, then obviously the additive model is incomplete since we are left with the possible situation in which an alternative with maximum SDVF scores is graded overall as either less than one or even possibly greater than one. As with the previous additive model we require that each pair of attributes as well as each single attribute is preferentially independent of the remaining attributes. With this looser weighting requirement we can replace the additive model and obtain the multiplicative:

$$v(\vec{x}) = \sum_{i=1}^{n} w_i\, v_i(x_i) + k \sum_{i=1}^{n} \sum_{j>i}^{n} w_i\, w_j v_i(x_i) v_j(x_j)$$

$$+ k^2 \sum_{i=1}^{n} \sum_{j>i}^{n} \sum_{h>j}^{n} w_i\, w_j w_h v_i(x_i) v_j(x_j) v_h(x_h) + \cdots \tag{2.2}$$

$$+ k^{n-1} w_1 \cdots w_n v_1(x_1) \cdots v_n(x_n)$$

Again, v($\vec{x}$) and $w_i v_i(x_i)$ are defined as before (without the $\sum_{i=1}^{i=n} w_i = 1$ restriction) and we introduce a new scaling constant k such that $-1 < k \neq 0$ (it should be apparent that in the case *k*=0 the model collapses to the additive model previously discussed). With this added constraint on k, 2.2 can be simplified and rewritten:

$$1 + kv(\vec{x}) = \prod_{i=1}^{i=n} [1 + kw_i v_i(x_i)] \tag{2.3}$$

One of the advantages of this model is that it only requires one additional piece of information (namely k) to be solicited from the DM. Looking at the following expansion of the multiplicative form concerning only two attributes it becomes clear that the goal is to account for both the individual contributions of the different attributes as well as some combined multiplicative effect.

$$v(\vec{x}) = w_1 v_1(x_1) + w_2 v_2(x_2) + k[v_1(x_1) v_1(x_1)] \tag{2.4}$$

Keeney suggests a framework for eliciting the new scaling constant (Keeney, 1974) which in essence is adjusting the weights for measures depending on their scores. A look at Figure 3 shows

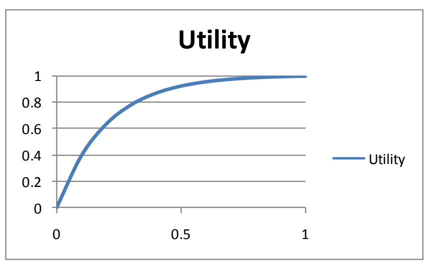


Figure 3: Power Additive Model

an example of how our overall utility score may increase as does our value from our SDVF. The strategy is similar to that of constructing exponential SDVF and thus it is no surprise that Kirkwood actually proves that the multiplicative model is equivalent to the power additive model which has the exponential distribution at its heart (Kirkwood, 1997). It is worth pointing out that this equality also underlines that a multiplicative model assumes the existence of an additive model; the multiplicative model simply allows for a relaxation of the constraint on w_i and stops short of defining value interactions as unique values.

II.F Multilinear Functions

In the case that preferential independence cannot be established for all attribute pairs and instead we are left only with preferential independence of single attributes we can still establish a multilinear value function (Keeney, 1992):

$$
\begin{aligned}
u(\vec{x}) = \sum_{i=1}^{i=n} w_i\, v_i(x_i) + \sum_{i=1}^{i=n}\sum_{j>i}^{i=n} w_{ij}\, v_i(x_i) v_j(x_j) \\
+ \sum_{i=1}^{i=n}\sum_{j>i}^{i=n}\sum_{h>j}^{i=n} w_{ijh}\, v_i(x_i) v_j(x_j) v_h(x_h) \qquad (2.5) \\
+ \cdots + w_{i\cdots n} v_1(x_1) \cdots v_n(x_n)
\end{aligned}
$$

This form is similar to the multiplicative function, but includes a separate scaling constant for each pair of attributes, each triple of attributes and so on up to a constant for the n-tuple of all attributes. The advantage of this approach is that it allows for interactions of every level to be examined and quantified, however the main disadvantage is that it can require a total of 2^n-1 scaling constants to be solicited from the decision maker. While detailed processes for soliciting the constants exist (Keeney, 1980), the length of the process may lead all but the most meticulous DM's to submit contradictory or unrepresentative opinions over time.

II.G Constructed Scales

Direct measures are almost always preferable over a constructed scale in DA. If house prices are to be measured dollars is much more objective and universally understood then a constructed scale of "Cheap, affordable, expensive". Not only does the constructed scale usually give diminished granularity, but it becomes harder to define (cheap means different things to different people). Still, in situations where there is no direct scale available a constructed scale remains a valid option. In this fashion it is possible to combine two separate measures into one single constructed measure either through way of functional transformation or by defining a combined categorical. For example, in their value model for Army base closures Ewing et al creates a weighted sum of square footage based on a quality standard in order to measure the "General Instructional Facilities". While this strategy proved helpful in this particular case, Ewing sites obstacles in general application (Ewing, Tarantino, & Parnell, 2006):

In practice, we found it difficult to find an analogous mathematical transformation for some of our measures. This left us with measures that were not independent in terms of preference and therefore were inconsistent with the application of an additive model.

In the absence of a convenient transformation, a categorical measure can be constructed more simply by enumerating all relevant level combinations of the interacting factors and assigning each one its own category. These categories can then be valued and arranged to form a typical SDVF. Ewing makes strides in accurately soliciting such data by arranging the categories within a matrix to better allow a DM to visualize the changing levels of interactions, but this is at the cost of even more solicitations and value comparisons. Sometimes however the violation of independence may be foggier and require a different approach.

II.H Hidden Objectives

Keeney describes hidden objectives as hidden agendas; "Those that are obscured by the complexity of the decision situation are discovered, and those that are intentionally obscured by a party to the decision are uncovered" (Keeney, 1992). In this case all or some of the DM's true values have not been well identified or defined and results in either mutual exclusivity or preferential independence being violated. This can mean either an examination of terms and definitions or more specifically some dependency requiring the addition of one or more values to the model. A prime example can be seen in the recommendations section of the 2008 JIEDDO VFT thesis by Dawley et al (Dawley, Lenore, & Long, 2008):

After scoring the 30 sample proposals against the decision model in conjunction with reviewing the comments of previous BIDS evaluators, the research team determined that the value of Technical Risk is really the combination of two related values—technical feasibility and technology readiness. Technical feasibility can best be described as the answer to the question "What is the likelihood that this thing will work?" Technology readiness usually assessed by the widely used Technology Readiness

Level (TRL) scale in Appendix A, answers the question "To what fidelity has this system been proven?"

In short, analysts concluded that DM preferences were being violated by the model's scoring because the model was inaccurately attempting to measure a single value which should actually have been decomposed further. Alternatively, the problem may lie with the fact that there is an additional tradeoff between attributes which the DM either does not realize or is unwilling to recognize. This can lead to the afore mentioned multiplicative model in which perhaps two particular attributes may act as partial substitutes for each other which can lead to a negative scaling constant k to represent the value tradeoff (Keeney, 1992). Although difficult to see at times, hidden objectives can usually be reintegrated into the original value model once uncovered.

II.I General Regression

In situations in which a DM is uncomfortable or unable to directly answer questions about the value of particular attributes it may be more constructive to evaluate a set of alternatives instead. As mentioned earlier, for a finite set of alternatives AHP as well as several similar procedures exist which allow the DM to systematically answer comparison questions until all but a certain number of alternatives have been outranked. This concept can be extended to define weighting coefficients for value models that can evaluate an indefinite set in by soliciting a preordering of a smaller sample set of alternatives. One of the main restrictions of this method is that it requires that the overarching value function must be assumed a priori in order to avoid overburdening the DM. Although Stewart offers a methodology for assuming an approximation of Keeney and Raffia's multiplicative function discussed earlier, it still requires the specific SDVFs to be defined separately (Stewart, 1981). Figueira et al actually provide a new method which actually builds a set of additive value functions by looking at not only preferences within a sample set of alternatives, but by rating the intensity of preference (Figueira, Greco, & Slowinski, 2009). At their heart, these methods and those like them allow a model to be constructed by looking at alternatives more holistically in order to uncover the importance of the underlying factors. Stewart agrees that the concept should even extend to allow for nonlinear functions (Stewart, 1984), but to date there has been no extensive practice of these methods and Kleindorfer et al even suggests that such methods should usually be attempted lastly should 'all else fail' (Kleindorfer, Kunreuther, & Schoemaker, 1993).

III. Methodology

III.A Requirements

After reviewing existing strategies for dealing with interdependency within a value model, it was decided that to be a desirable technique, a new method would first need to be transparent. This is to say that not only the process but the finished product would be both understandable and defendable by the DM without the assistance of the analyst. As seen in Chapter 2, there already exists many procedures for creating mathematically robust yet complex models for interdependency, but these models are useless if the DM does not feel a sense of ownership of the process. The new model should be one which the DM can explain, not a magic black-box function which they must trust spits out their values on the other side.

Second, the new method must be repeatable. While the goal is to examine the effect of measuring interactions within the JIEDDO model, the methodology should be general enough to apply to any value model in which possible interactions have been detected. Even the JIEDDO model itself is only as static as the DM and their opinions and may require partial or complete reevaluation as the DM or JIEDDO's priorities rearrange; "*…different individuals may look at the problem from different perspectives, or they may disagree on the uncertainty or value of the various outcomes.*" (Clemen & Reilly, 2001).

Lastly, the new function should fit within the current structure of an additive VFT hierarchy. The reasoning for this is twofold: First, with an existing VFT model like

JIEDDO, it is desirable to confront the issue of dependency without scrapping the considerable amount of time and effort that went into its creation. This will allow for a model to be corrected, over time if necessary, with less risk of DM solicitation burnout. Second, like it or not the additive VFT model has rapidly become increasingly popular as the choice for both business and military DM's when faced with difficult decisions. Whether it is Gen Fogleman facing the future military challenges of the Air Force (Parnell, Conley, Jackson, Lehmkuhl, & Andrew, 1998) or oil companies trying to capitalize on the increasing flood of available data and statistics (Coopersmith, Dean, McVean, & Storaune, 2001), VFT has a considerable foothold of acceptance and by working within its framework rather than outside, the chances of high ranking buy-in increase considerably.

III.B Assumptions

In an attempt to maintain the requirement of transparency, the new method will be limited to at most two-way interactions of factors. Intuitively it becomes increasingly burdensome for a DM to consider the impact of three or more factors all changing levels at once. Statistically most models are dominated by single factors and low-level interactions; according to the sparsity of effects principle most higher-order interactions become negligible anyway (Montgomery, 2005).

In examining these two-way interactions, we will also make the assumption that interaction between two factors effectively precludes both from being considered in any other interaction. This restriction stems not from an inability to model such interactions but from the fact that such a situation would point to a more fundamental problem with the original VFT model. Take for example the situation in which it has been identified that Factor A interacts with Factor B. Further, now consider that Factor A also interacts with Factor C. The more factors that Factor A is linked to, the more likely it becomes that perhaps the model would be better represented multiplicatively rather than additively. As mentioned earlier there exist several methods for creating such a model which could provide a better representation of the apparently sweeping importance of Factor A as either a substitute for other factors or a scaling factor by which all others must be subject to.

The model will also only consider interactions between those factors which share both the same tier and objective within a hierarchy. Looking at Figure 4 we can see the inherent issues involved with allowing interaction between any factors:

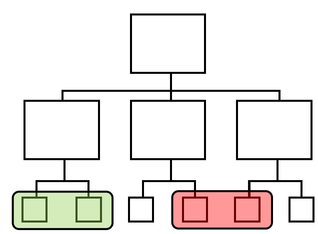


Figure 4: Allowed Interactions

The second interaction would effectively link two objectives on the above tier and thus violate the rules of an additive VFT model. This does not mean that such an interaction cannot exist nor does it mean that it is incapable of being modeled; the point is simply that in such a case the two factors in question must ultimately share both tier and parent objective. Once reorganized all that is left is to recalculate top tier weights to coincide with the new lower tier global weight sums.

It should further be assumed that preferential independence as defined earlier will already have been established between all factors except those which are the focus of investigation. In these cases we can then make the assumption that while the two specific factors interact, when considered jointly the pair remains independent from all remaining factors.

Lastly, regardless of whether or not individual SDVFs have yet been established for each factor, a suitable scale for each measure must exist for any modeling scheme and thus we will assume that respective maximum and minimum values have been set. Further, we will assume that two-way monotonicity is a desirable quality of the new value function. This means that if Factor A and Factor B are to be combined and both have measures which have been defined on a more-is-better scale, then it should follow that as both increase the value of the new function should also increase or remain constant. While there do exist unique situations in which overall value may actually decrease as one or both factors increase (e.g. eating more ice cream is preferable up to one bowl and eating more cookies is preferable up to four cookies, but when combined I will get sick after eating half a bowl of ice cream and four cookies), but these situations are not the norm and can usually be dealt with by reevaluating scales or objectives.

III.C Solicitation

A standard additive VFT model is made up of a group of SDVFs that in turn are weighted and added together to score feasible alternatives. The goal of this process is to create a new value function that would replace two SDVFs and bear their combined weight. This new function will consider both constituent values and their interactions, but will output a single value which can be aggregated normally back into the model.

The first step of this process is to identify which factors to investigate for interactions. An advantage of the process is that once an initial hierarchy has been created, an interactive function can be created before or after individual SDVFs have been defined. This allows for hierarchies such as JIEDDO's to be adjusted, but also saves the time of soliciting SDVFs at all if a DM is convinced that the factors must be considered together from the start. While any number of interactions can be tested, it depends on the motivation and patience of the DM. It should also be explained to the DM that after creation the new function can easily be tested for independence to determine their advantage in place of SDVFs. Thus, time permitting, there is no harm in investigating pairs in which suspicion of interaction is weaker should the DM desire.

Looking at the JIEDDO model once again, there are several specific areas of possible interaction; consider for example Gap Impact and Time to counter.

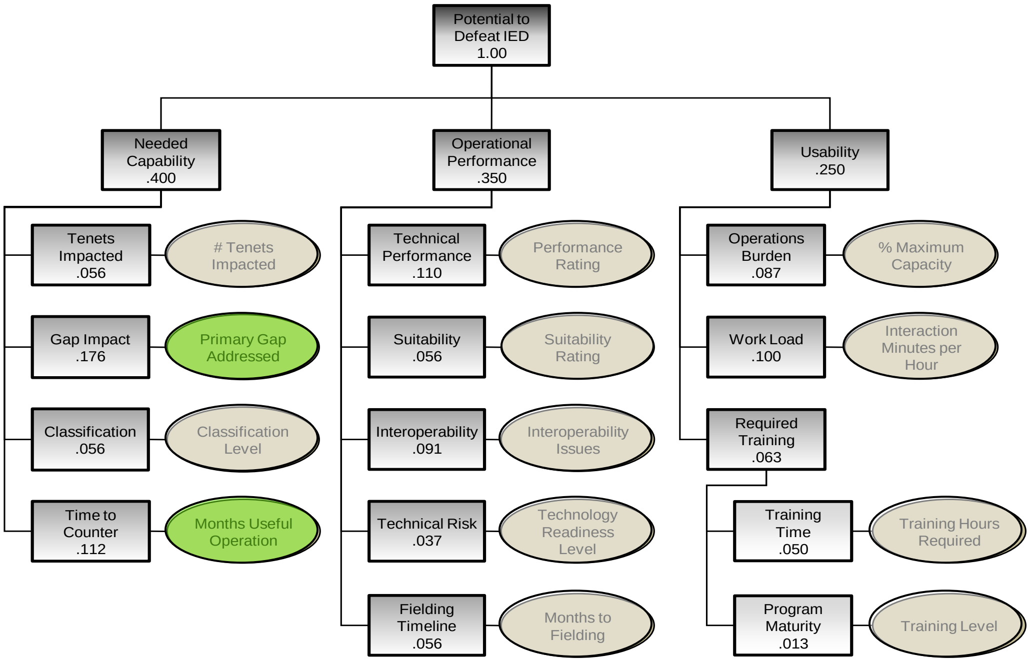


Figure 5: Identified Interactions

After the factors have been chosen, the next step is to choose appropriate breakpoints for continuous as well as large categorical measures. These points ultimately will define the accuracy and granularity of the new function. Every additional breakpoint will constitute extra solicitation on the part of the DM and it is therefore recommended that the total number remain manageable. Likewise, it is best to choose points along the scale which the DM feel represent tangible change (i.e. given a ten year warranty is the best, it's difficult to gauge how much six months is worth, but a year is definitely 20% value). Due to the finite nature of categorical measures it is recommended that as long the total number of categories remains reasonable that all categories be evaluated as breakpoints to increase accuracy. In the continuous case should the DM have no strong feeling about any particular points, the de facto strategy will be to simply divide the scale into equal increments. Applying this to the two chosen factors achieves the breaks in Figure 6.

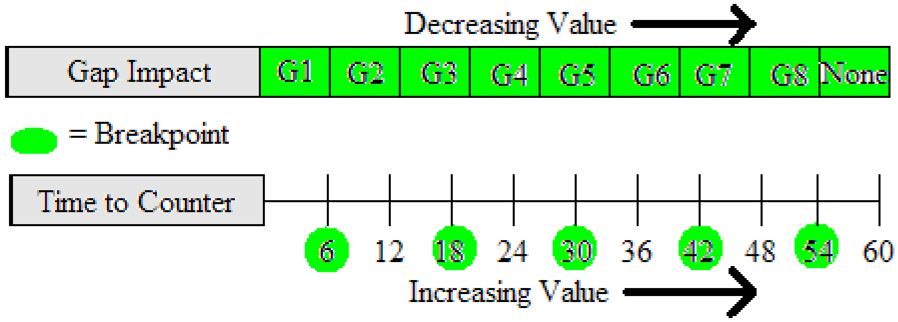


Figure 6: Breakpoints

It should be noted that Time to Counter is a continuous scale and as such could have been broken at any point. Further, while the endpoints of the continuous scale could easily be used if desired by the DM, they are avoided here in an attempt to force the DM to think about specific values rather than being influenced by the fact that they are at the extreme of one scale and overvalue their estimate. This follows well known DA research which showed that not only was it difficult to extract accurate values very near endpoints but that 5%, 50% and 95% values worked surprisingly well in defining a wide range of distributions (Keefer & Bodily, 1983). Depending on the DM it may be advisable to extend this strategy to categorical scales as well if the analyst feels there is undue bias (i.e. solicited values are too tightly clustered). As stated earlier the granularity to which the scales are divided is completely up to the DM and only depends on the amount of time they are willing to commit to the process.

Once the breakpoints have been established, the next step is to solicit values from the DM for each factor. This is done in a similar fashion to soliciting traditional

SDVFs, except for the main distinction that the DM will be valuing the different breakpoints of one factor *given* the highest (or possibly second highest categorical if bias is identified as mentioned above) breakpoint of the other factor. In the example, since Gap Impact is a decreasing scale the task for the DM would be to assign decreasing values between one and zero to G1 through G8 under the assumption that they are guaranteed a Time to Counter of 54 months. The task is then repeated for Time to Counter; given they are guaranteed a Gap Impact of G2 what value does the DM assign to Time to Counter levels of 6, 18, 30, 42 and 54 months (again between zero and one, but this time in increasing value). The results are shown in Tables 1 and 2. Once the

Gap Impact Value Given 54 Month Time to Counter	
Level	**Value**
G1	0.95
G2	0.90
G3	0.70
G4	0.35
G5	0.30
G6	0.20
G7	0.15
G8	0.10
None	0.05

Table 1: Categorical Values

Time to Counter Value Given Gap Impact of G1	
Level	**Value**
6	0.10
18	0.25
30	0.35
42	0.60
54	0.85

Table 2: Continuous Break Values

tables have been solicited, a consistency and validation check must be completed.

First, based on their construction both tables will overlap at a single value. Looking at Tables 1 and 2 this happens at G1 and 54 months. In order to consistently represent the interactive value of the two factors this value must be the same in each solicitation. If as in the example it does not, the DM must decide whether one or both of their solicitations must be adjusted so that these interactions are ultimately equivalent. Let us assume that our categorical values are deemed accurate but the continuous scale must be adjusted resulting in the new values shown in Table 3.

Next, look at the jumps in value along the solicited scale. The new multi-objective function will depend on linear interpolations between the solicited values in Table 3. As such, larger jumps in value represent a larger chance of inaccurately capturing intermediate values. Exponential functions have been shown to be robust in modeling DM values (Kirkwood & Sarin, 1980). Furthermore, in examining realistic situations we see that the defining rho-value for such functions is rarely less than one tenth of the overall range of possible factor levels (Kirkwood C. W., 1997).

Time to Counter Value Given Gap Impact of G1	
Level	**Value**
6	0.10
18	0.25
30	0.50
42	0.80
54	0.95

Table 3: Adjusted Values

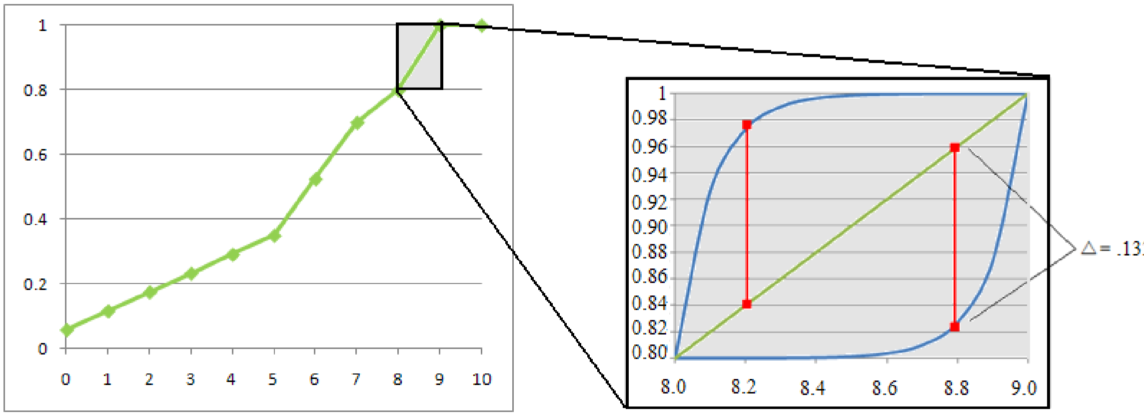


Figure 7: Piecewise linear v. exponential w/ rho=0.1

Based on these results and Figure 7 it is clear that in comparing any linear section of a piecewise interpretation to an exponential representation of that same section that the highest possible error is 66% of the original range. Thus, looking at the values solicited in Table 3, for any adjacent values which differ by more than 0.15, we will interpolate exponentially rather than linearly. This will ensure that any possible discrepancies between interpolated values and those of the DM should be held to less than 0.1. It should be noted that if this error margin is unacceptable to the DM, lower tolerances are easily substituted at the cost of further solicitations as each exponential interpolation requires one additional data point from the DM. Looking at Table 3, our example requires two extra solicitations to account from the jump between 18 and 30 months as well as from 30 to 42. Kirkwood explains that the midvalue (i.e. what factor level achieves mean value between the two endpoints) provides a convenient method for calculating the function(Kirkwood C. W., 1997). Looking at Table 3 this amounts to asking the question "If guaranteed a Gap Impact of G1, how much Time to Counter would you require before reaching a value of 0.375?" Similarly, the jump from 30 to 42 months would be addressed by assessing the level to reach a value of 0.65. Tables 4 and 5 now show our complete data set.

Gap Impact Value Given 54 Month Time to Counter	
Level	**Value**
G1	0.95
G2	0.90
G3	0.70
G4	0.35
G5	0.30
G6	0.20
G7	0.15
G8	0.10
None	0.05

Table 4: Categorical Values

Time to Counter Value Given Gap Impact of G1	
Level	**Value**
6	0.10
18	0.25
20*	0.38
30	0.50
40*	0.65
42	0.80
54	0.95

* Exponential Midvalues

Table 5: Updated Continuous w/ Midvalues

III.D Processing

After completing solicitation with the DM, the data can now be processed into the combined value function. As alluded to earlier, this is done by interpolating the data in Tables 4 and 5 to fully define values to all possible ordered pairs of levels of our two chosen factors. To this end, our two tables of solicited data can more appropriately be seen in Table 6 as two dimensions of a common function.

Gap Impact									
G1		0.10	0.25	0.38	0.50	0.65	0.80	0.95	1.00
G2								0.90	
G3								0.70	
G4								0.35	
G5								0.30	
G6								0.20	
G7								0.15	
G8								0.10	
None	0.00							0.05	
	0	**6**	**18**	**20**	**30**	**40**	**42**	**54**	**60**
	Time to Counter								

Table 6: Two-Dimensional Value Matrix

It is important to note the addition of values to the far corners of Table 6. In the same way that an ordinary SDVF must range from zero to one in value, so must our new two-dimensional function. Thus it is logical that (60, G1) should represent a value of one and (0, None) should represent a value of zero since they respectively represent the combined best and worst of each measure.

Not only is this matrix largely sparse, but it does not account for an infinite number of continuous points. Thus, a three step process is applied which will both fill our matrix and provide functions for all intervening unaccounted continuous values.

Step 1. Looking at Table 6, it is useful to think of each row and each column in terms of a SDVF, the main difference being that unlike a traditional value function, we allow a different SDVF for every level each individual factor (e.g. a complete SDVF *given* a Gap Impact of G2). SDVFs for remaining levels of each factor can now be determined by examining and extending the relationship between adjacent cells. Consider the point (42, G2); based on comparing values in the adjacent column we see that the DM's value for a Gap Impact of G2 given 54 months usefulness is approximately $\left(\frac{0.9}{0.95}\right)$ or 97.4% the value of G1 given the same number of months. Using this information we could infer that the DM would similarly assign (42, G2) a value equal to 97.4% of (42, G1). Since (42, G1) has previously been solicited at 0.80 we are able to assign (42, G2) a value of 0.76. Two direct advantages follow from this process:

First, value calculations are consistent regardless of whether they are calculated horizontally or vertically. Consider Table 7 where values have been solicited for *a, x,* and *y*:

Factor A	…	*a*	*x*
	…	*b*	*y*
	…	…	…
	Factor B		

Table 7: Value Matrix

Looking at the equations below it is clear that *b* remains unchanged if calculated based on the relationship between *a* and *b* instead of between *x* and *y*:

$$b = a\left(\frac{y}{x}\right) = \frac{ay}{x} \tag{3.1}$$

$$b = y\left(\frac{a}{x}\right) = \frac{ay}{x} \tag{3.2}$$

Second, extracting values in this manner explicitly maintains the two-way monotonicity which was defined earlier. Original solicitation already requires that $a \leq x$ and that $y \leq x$, thus by solving for *a* and *y* in the preceding equations we can show that

$$a \leq x \quad \Rightarrow \quad \frac{bx}{y} \leq x \quad \Rightarrow \quad b \leq y \tag{3.3}$$

$$y \leq x \quad \Rightarrow \quad \frac{bx}{a} \leq x \quad \Rightarrow \quad b \leq a \tag{3.4}$$

By extending the process to the interior of Table 6 these relationships continue to hold and yield the new collection of values in Table 8. Note that although (0, None) has been fixed at zero as previously stated, the respective column remains unevaluated (larger values cannot be constructed by scaling zero).

Gap Impact									
G1		0.10	0.25	0.38	0.50	0.65	0.80	0.95	1.00
G2		0.09	0.24	0.36	0.47	0.62	0.76	0.90	0.95
G3		0.07	0.18	0.28	0.37	0.48	0.59	0.70	0.74
G4		0.04	0.09	0.14	0.18	0.24	0.29	0.35	0.37
G5		0.03	0.08	0.12	0.16	0.21	0.25	0.30	0.32
G6		0.02	0.05	0.08	0.11	0.14	0.17	0.20	0.21
G7		0.02	0.04	0.06	0.08	0.10	0.13	0.15	0.16
G8		0.01	0.03	0.04	0.05	0.07	0.08	0.10	0.11
None	0.00	0.01	0.01	0.02	0.03	0.03	0.04	0.05	0.05
Time to Counter	**0**	**6**	**18**	**20**	**30**	**40**	**42**	**54**	**60**

Table 8: Matrix w/ Calculated Values

Step 2. Table 8 represents a considerable sample of possible ordered pairs, but since one of the factors is continuous, functions must be defined in order to calculate all possible intervening points (e.g. the value of (25, G6)). Between adjacent cells when neither has been solicited as a midvalue, this function is simply the line connecting the two values. In this manner the function for calculating values of a Gap Impact of G4 and a Time to Counter between 42 and 54 months would be:

$$\begin{aligned} f(x) &= m(x - x_1) + y_1 \\ &= \left(\frac{0.70 - 0.59}{54 - 42}\right)(x - 42) + 0.59 \qquad (3.5) \\ &= 0.2416\,x - 0.425 \end{aligned}$$

Likewise, where midvalues are concerned values on either side are calculated via an exponential function. Thus values of a Gap Impact of G4 and a Time to Counter between 30 and 42 would be represented by:

$$v(x) = \frac{1 - e^{\left(\frac{-(x_2 - x)}{\rho}\right)}}{1 - e^{\left(\frac{-(x_2 - x_1)}{\rho}\right)}}$$

$$= \frac{1 - e^{\left(\frac{-(42 - x)}{-2.93}\right)}}{1 - e^{\left(\frac{-(12)}{-2.93}\right)}} \tag{3.6}$$

While the equation form differs slightly based on the solicited midvalue, the general concept remains the same with the specific rho constant available in lookup tables in many texts (Kirkwood C. W., 1997, p. 69). It is worth noting that while it is not the case in this example, it is possible to have a situation in which both factors are continuous. In these cases, values without adjacent values can be interpolated by first interpolating the missing adjacent values and then interpolating based upon these new numbers. It can be shown that given a situation such as Table 9 where the highlighted cells have been interpolated, the center cell evaluates the same regardless of whether it is interpolated horizontally between values of 3.6 or vertically.

5	**0.3**	*0.92*	**1**
3.6	*0.15*	*0.68*	*0.75*
0	**0**	*0.44*	**0.5**
	1	3	4

Table 9: Two-Way Interpolation

Step 3. In situations where endpoints have not been solicited, values cannot be calculated as in step 1. Unlike *b* in Table 7, end columns and rows may not have the required solicited adjacent values in order to be calculated. Without two adjacent values to interpolate between, these values are extrapolated by simply extending the adjacent function (either linear or exponential) established in step 2. However, since the new two-dimensional function must only range between zero and one, when extrapolating a maximizing row or column, we take the minimum between the extrapolation and one. Similarly when extrapolating a minimizing row or column, we must take the maximum between the extrapolation and zero. The only remaining possible situation exists when an adjoining end row and end column both must be extrapolated which implies two possible values for the corner of their intersection. In these cases the difference is usually negligible and it is left to the DM to choose between the larger or smaller estimate. In the absence of DM input it is suggested to err on the side of caution and opt for the larger of the two values as it is generally preferable by a DM to slightly overvalue an alternative rather than to slightly undervalue it.

Combining these three steps together the process not only fully populates the initially sparse Table 6 into the now robust Table 10 but also provides definition of all functions required for any possible ordered pair of levels from the original two factors. It should be clear that once presented with the final functions, if the DM expresses concern for any inaccuracy, any of the original levels may be re-solicited in addition to intermediate levels for increased granularity. Once defined, the three step process described above is automatic and instant and can be rerun as many times as necessary without any extra burden on the DM.

Gap Impact									
G1	0.03	0.10	0.25	0.38	0.50	0.65	0.80	0.95	1.00
G2	0.02	0.09	0.24	0.36	0.47	0.62	0.76	0.90	0.95
G3	0.02	0.07	0.18	0.28	0.37	0.48	0.59	0.70	0.74
G4	0.01	0.04	0.09	0.14	0.18	0.24	0.29	0.35	0.37
G5	0.01	0.03	0.08	0.12	0.16	0.21	0.25	0.30	0.32
G6	0.01	0.02	0.05	0.08	0.11	0.14	0.17	0.20	0.21
G7	0.00	0.02	0.04	0.06	0.08	0.10	0.13	0.15	0.16
G8	0.00	0.01	0.03	0.04	0.05	0.07	0.08	0.10	0.11
None	0.00	0.01	0.01	0.02	0.03	0.03	0.04	0.05	0.05
	0	6	18	20	30	40	42	54	60
	Time to Counter								

Table 10: Two-Dimensional Value Matrix

By considering each ordered pair as input to this family of functions, the original two weighted contributions to the model's overall value function can now be replaced with the single output of our new function scaled by the sum of the weights of the two factors.

$$V(X) = .056\, v(Tenets) + .176\, v(Gap) + .056\, v(Class) + .112\, v(TimeToCounter) + .11\, v(TechPerf) + .056\, v(Suit) + .091\, v(Interop) + .037\, v(TechRisk) + .056\, v(FieldTime) + .087\, v(OpsBurden) + .1\, v(Workload) + .05\, v(TrngTime) + .013\, v(TrngMaturity)$$

The original JIEDDO value function is simply edited by replacing the two highlighted contributions with *+.288 v(TimeToCounterGap)*, where v(TimeTo CounterGap) represents the new combined value function. The weights of the new value function still sum to one, and based on the assumptions now (given all suspected interactions within the model have been explored) meet the preferential independence requirement between factors necessary to accurately score alternatives.

IV. Results & Analysis

IV.A Overview

This chapter starts with the original JIEDDO value model and builds two additional models; an illustrative example created by the researcher and results solicited from a recently deployed Marine Engineering Commander. Both models are created by expanding on the original model to allow for interactions using the proscribed methodology from chapter three. Additionally, two-dimensional value functions are created by directly soliciting *all* possible interaction values (e.g. all 81 values found in Table 10). By using thirty JIEDDO proposals (each of whose factors were scored by the original JIEDDO model team of Dawley et al) deterministic analysis is performed on all three models to determine the credibility of the value function interpolation methodology. Main results are addressed within the illustrative example while the second model closes the chapter by identifying several areas of possible concern in practical implementation.

IV.B Measure Creation

Throughout the proceeding four sections, the researcher takes on the role of the DM in analyzing the JIEDDO model. This provides a surrogate for the purpose of demonstrating the methodology. Further, as this model is intended to be applicable to other scenarios including future JIEDDO DM changes, validation of the model depends not on the depth of C-IED knowledge on the part of the DM but rather on the consistency between the alternative rank structures resulting from both methods.

After reviewing the current hierarchy, three areas were identified in Figure 8 as candidates for suspected interdependency:

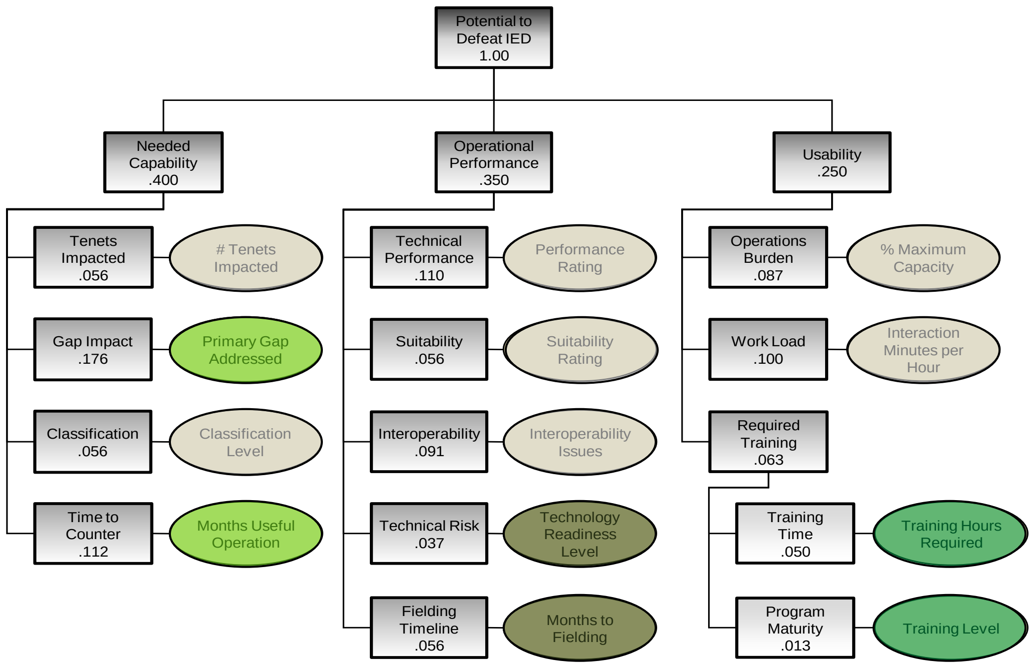


Figure 8: Interactions

Gap Impact & Time to Counter: Together these factors largely represent the counter IED fight; what needs fixing and how long will that fix hold? After consideration they were nominated for combination because due to the fast paced dynamic world of IEDs the value of Time to counter can vary greatly depending on what capability is being addressed. High level needs are killing soldiers *now* and while a long-term solution is invaluable, even a six month stop-gap can be very helpful. Solutions to low level needs on the other hand are important but their lesser urgency should allow more patience in waiting for more robust solutions, passing on those which are easily countered.

Technical Risk & Fielding Timeline: War fighters understand that new technology can take time to make it to the field, but that patience is linked to the ultimate effectiveness of the technology once it reaches the field. A solution with very low risk maintains its value much more easily as its fielding time is pushed forward whereas high risk proposals with long timelines quickly become difficult to defend.

Training Time & Program Maturity: A training time for a program which has not been developed yet is an estimate at best. As the maturity of such programs is better established the value of training time estimates should increase as well.

Tables 11 through 16 show the solicited breakpoints and associated values for each interaction defined above. While inspection of the tables reveals seven instances of value jumps above 0.15, once midvalues were solicited it became clear that in this particular case there was no difference between using linear or exponential interpolation (i.e. the two shared the same midpoint). Using the methods from Chapter three these six tables were used to generate the full two dimensional range of values for each of the three newly combined measures which are available in Appendix A. Solicitation of each table took less than five minutes and, while the researcher is conversant in such tasks, test solicitations with several other non-DA participants proved that each table took at most ten minutes to explain and solicit keeping the entire process under one hour.

Three additional direct solicitations were then accomplished for each interaction to test the validity of the mathematically interpolated and extrapolated values. As shown in Table 17, each of these solicitations was a complete enumeration of the two-dimensional space as defined by the breakpoints. It should be immediately clear that this requires not only many more inputs by the DM but also many more comparisons to ensure that two-way monotonicity is maintained. Assuming n breakpoints for each individual measure the original method requires only $2n$ inputs and a minimum of $2(n\text{-}1)$ comparisons to ensure monotonicity. By contrast, the completely enumerated solicitation requires n^2 inputs from the DM and at least $2n^2\text{-}2n$ comparisons to ensure monotonicity. In our particular example of Gap Impact and Time to counter this means that our required inputs jump from 18 to 99 and our comparisons from 16 to 180. Time wise this amounted to nearly two hours of work when accomplished solely by the researcher. In comparison the only outside subject willing to devote the time to complete solicitation took four one hour sessions over four days and resulted in a table which still contained several instances of decreasing values. This underlines one of the main difficulties associated with constructed scales such as those put forth by Ewing et al in Chapter 2. Even though a visual representation such as Table 17 aids in soliciting the data more accurately, what Ewing and his team gain in visual simplicity they quickly lose to the sheer number of comparisons demanded from the DM. In addition to the $2n^2\text{-}2n$ monotonicity comparisons, Ewing et al require up to an additional $\binom{n^2}{2}$ or $\frac{n^2!}{2([n^2-2]!)}$ comparisons to ensure consistency of the DM. Again, in this particular example this amounts to requesting over 4,000 additional value judgments from the DM, a task unlikely to be accomplished.

Value Solicitations (Illustrative Model)

Given 54 Months Use		
Primary Gap Addressed	G1	0.95
	G2	0.8
	G3	0.5
	G4	0.35
	G5	0.3
	G6	0.2
	G7	0.15
	G8	0.05
	None	0

Table 11: Gap Given Time to Counter

Given Gap Impact of G1		
Time To Counter	54	0.95
	48	0.9
	42	0.8
	36	0.65
	30	0.5
	24	0.4
	18	0.3
	12	0.2
	6	0.05

Table 12: Time to Counter Given Gap

Given 6 Months to Fielding		
Technology Readiness Level	9	1
	8	0.95
	7	0.9
	6	0.85
	5	0.65
	4	0.4
	3	0.2
	2	0.1
	1	0.05

Table 13: TRL Given Months to Fielding

Given TRL of 9		
Time To Fielding	6	1
	12	0.9
	18	0.8
	24	0.7
	30	0.6
	36	0.4
	42	0.3
	48	0.2
	54	0.1

Table 14: Months to Fielding Given TRL

Given Maturity of 5		
Training Hours Required	5	0.9
	10	0.6
	15	0.45
	20	0.4
	25	0.35
	30	0.3
	35	0.25

Table 15: Training Time Given Maturity

Given 5 Hours Required		
Training Maturity	5	0.9
	4	0.8
	3	0.4
	2	0.2
	1	0.1

Table 16: Maturity Given Training Time

Primary Gap Addressed	0	6	12	18	24	30	36	42	48	54	60
G1	0	0.1	0.2	0.3	0.45	0.6	0.8	0.85	0.9	0.95	1
G2	0	0.05	0.1	0.2	0.3	0.45	0.6	0.75	0.9	0.95	0.95
G3	0	0.05	0.05	0.1	0.2	0.3	0.4	0.5	0.65	0.75	0.8
G4	0	0.05	0.05	0.05	0.1	0.2	0.2	0.3	0.45	0.6	0.6
G5	0	0	0.01	0.05	0.05	0.1	0.1	0.2	0.2	0.3	0.4
G6	0	0	0	0	0.01	0.05	0.05	0.1	0.15	0.2	0.2
G7	0	0	0	0	0	0	0.05	0.05	0.1	0.15	0.15
G8	0	0	0	0	0	0	0	0	0.05	0.1	0.1
None	0	0	0	0	0	0	0	0	0	0	0.05
	Months Useful Operaton										

Table 17: Complete Solicitation of Primary Gap & Time to Counter

IV.C Value Function Comparison

It should be noted at this point that a two-way value solicitation such as the one shown in Table 17 neither implies nor requires the two factors to be dependent or interact in any meaningful way. In fact, using the originally solicited SDVF's and the weights of their respective factors we can easily recreate a similar table of values under the original assumption of independence. Using this idea Table 18 (other value tables can be found in Appendix E) gives an idea of what a complete solicitation might look like were the factors indeed independent.

Primary Gap Addressed	0	6	12	18	24	30	36	42	48	54	60
G1	0.61	0.61	0.62	0.63	0.64	0.66	0.68	0.72	0.78	0.87	1.00
G2	0.54	0.55	0.55	0.56	0.57	0.59	0.61	0.65	0.71	0.80	0.93
G3	0.48	0.48	0.48	0.49	0.50	0.52	0.55	0.59	0.64	0.73	0.86
G4	0.41	0.41	0.42	0.42	0.44	0.45	0.48	0.52	0.58	0.66	0.80
G5	0.34	0.34	0.35	0.36	0.37	0.38	0.41	0.45	0.51	0.60	0.73
G6	0.27	0.28	0.28	0.29	0.30	0.32	0.34	0.38	0.44	0.53	0.66
G7	0.20	0.21	0.21	0.22	0.23	0.25	0.28	0.31	0.37	0.46	0.59
G8	0.14	0.14	0.14	0.15	0.16	0.18	0.21	0.25	0.30	0.39	0.52
None	0.00	0.00	0.01	0.02	0.03	0.05	0.07	0.11	0.17	0.26	0.39
	Months Useful Operaton										

Table 18: Independent Value Calculation

Similarly, Figure 9 takes a look at what such a combined but independent value function would look like. In this case it should be clear that the graph is a combination of the exponential SDVF for Time to Counter and the roughly linear categorical scale for Gap Impact. By investigating interactions with the matrix solicitation we are simply allowing for the possibility that the values interact in a non-independent fashion.

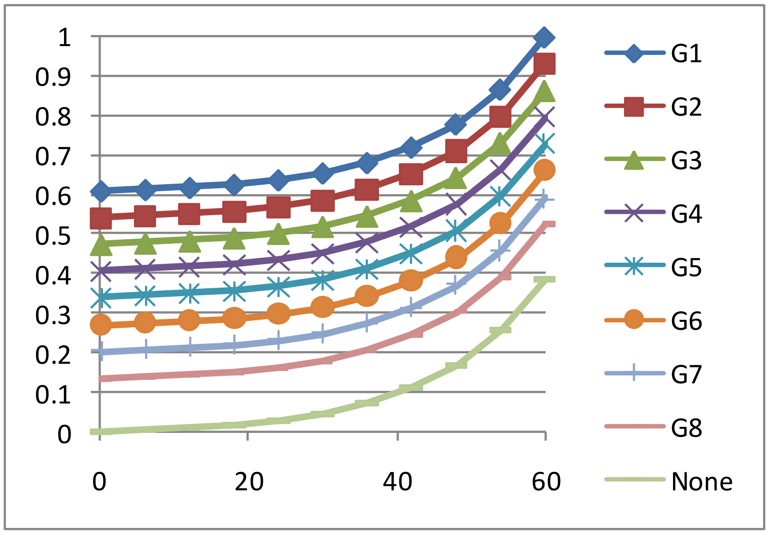


Figure 9: Independent Additive Value Function (Value v. Time to Counter)

As an immediate example, Figure 10 gives the graphical representation of the values directly solicited in Table 17. Visually the graph points to function similarities between the different series, but it is also clear that there are specific perturbations present in each that would be lost under the assumption of independence. Research supports the indications seen in Figure 11, that this uniqueness is more accurately and easily retained under the new interpolating methodology.

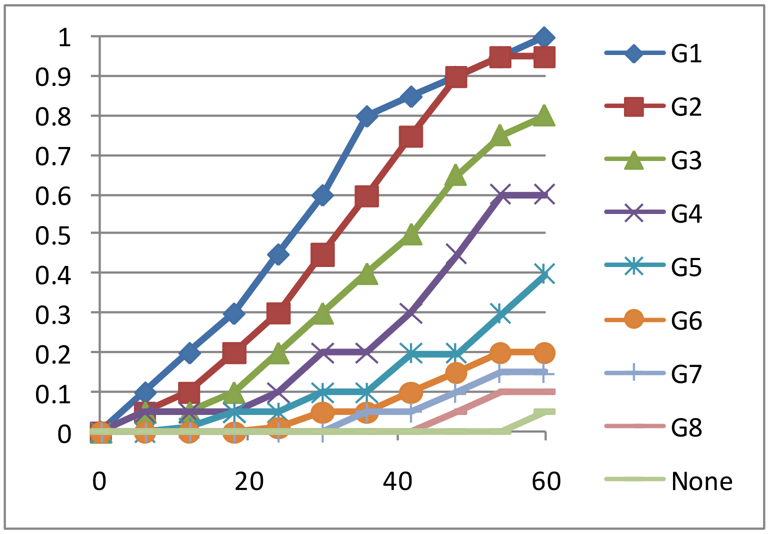


Figure 10: Directly Solicited Combined Value Functions (Value v. Time to Counter)

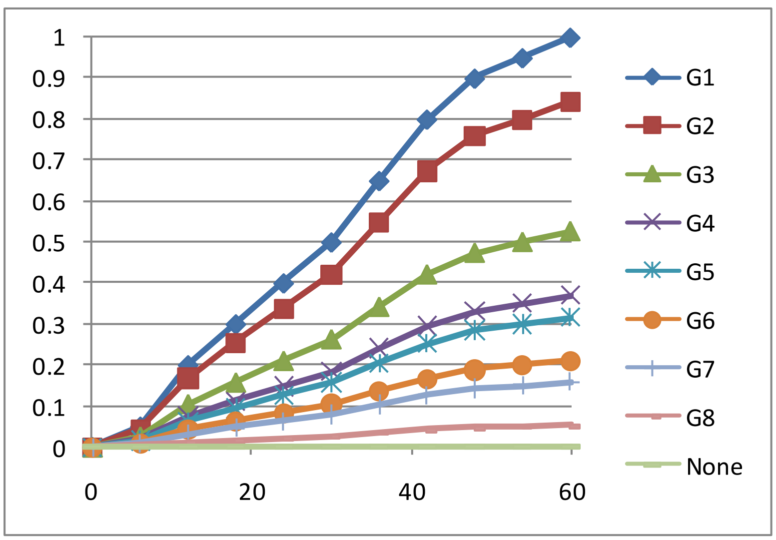


Figure 11: Interpolated Combined Value Functions (Value v. Time to Counter)

IV.D Alternative Scoring & Ranking

Appendix B lists 30 counter IED proposals submitted to JIEDDO in 2007. Each of the original 13 factors was scored by Dawley et al for each proposal (proposal titles have been removed for classification reasons). The first column of Table 19 provides the final score for each proposal based on the model in equation 4.1 which integrates all three direct complete combined solicitations. Column two represents the same model but replaces each combined value function with interpolation according to the proscribed methodology.

$$\begin{aligned} \boldsymbol{V(X)} = \; & .056\, v(Tenets) + \boldsymbol{.288\, v(Gap\&Counter)} + .056\, v(Class) \\ & + .11\, v(TechPerf) + .056 v(Suit) + .091\, v(Interop) \\ & \boldsymbol{+ .093\, v(TechRisk\&Fielding)} + .087\, v(OpsBurden) \\ & + .1\, v(Workload) \boldsymbol{+ .063\, v(TrngTime\&Maturity)} \end{aligned} \tag{4.1}$$

While certain changes in score are immediately evident, the data in Table 19 is purely ordinal meaning that the scores themselves have meaning only in the ranking which they provide to the data set. These ranks are given in Table 20 and are ordered based on the “Complete Solicitation” scores for later analysis. Two important observations of Table 20 can be made simply by inspection even before any type of statistical analysis. While not identical in rank, complete and partial solicitation with interpolation both yield the same top ten alternatives and the same bottom ten. This is specifically important to an organization such as JIEDDO where the model is intended as a tool to filter alternatives rather than to choose a single winner. This would mean that a DM would receive the same reduced set of alternatives to examine between these newly solicited models. These conjectures can be better quantified with nonparametric rank testing.

	Complete Solicitation	Solicitation w/ Interpolation
A	0.2755	0.2700
B	0.4374	0.4362
C	0.3815	0.3959
D	0.5181	0.5344
E	0.4931	0.4959
F	0.5024	0.5349
G	0.3562	0.3853
H	0.1202	0.1273
I	0.4475	0.4447
J	0.4359	0.4224
K	0.3319	0.3386
L	0.4245	0.4466
M	0.2316	0.2230
N	0.3588	0.3612
O	0.2664	0.2736
P	0.4209	0.4236
Q	0.4445	0.4526
R	0.5775	0.5552
S	0.5662	0.5864
T	0.5551	0.5764
U	0.4940	0.5021
V	0.3203	0.3400
W	0.4109	0.4149
X	0.4854	0.5077
Y	0.5718	0.5484
Z	0.4320	0.4239
AA	0.5980	0.5234
BB	0.5764	0.5774
CC	0.6192	0.5529
DD	0.7840	0.7951

Table 19: JIEDDO Alternative Scores

	Complete Solicitation	Solicitation w/ Interpolation
DD	1	1
CC	2	6
AA	3	10
R	4	5
BB	5	3
Y	6	7
S	7	2
T	8	4
D	9	9
F	10	8
U	11	12
E	12	13
X	13	11
I	14	16
Q	15	14
BB	16	17
J	17	20
Z	18	18
L	19	15
P	20	19
W	21	21
C	22	22
N	23	24
G	24	23
K	25	26
V	26	25
A	27	28
O	28	27
M	29	29
H	30	30

Table 20: JIEDDO Alternative Rankings

IV.E Rank Testing

Due to the afore mentioned ordinal nature of our data, we are unable to make any assumptions as to the distributions from which they are pulled and cannot use typical parametric tests in examining the data. Fortunately, there exist many nonparametric tests which are distribution free making up in robustness what they may lose in simplicity. While many nonparametric tests seek to give specific information about the distribution from which the data is pulled, we are interested instead in the correlation between rankings. Kendall’s Tau and Spearman’s Rho are both widely accepted as methods to this end. While other measures exist, these two statistics are uniquely appropriate in measuring the correlation of ranking pairs and both rest on relatively simple assumptions. The two tests are considered to be equivalent and only differ in their interpretation of results (Bolboaca & Jantschi, 2006). Spearman’s Rho yields a correlation coefficient while Kendall’s gives a slightly more simple interpretation of the correlation as a probability. For these reasons we will use Kendall’s Tau in our analysis.

$$\tau = \frac{C - D}{\frac{1}{2}n(n-1)} \tag{4.2}$$

where:

C = # of *Y* pairs in natural order

D = # of *Y* pairs in reverse order

n = # of total (*X,Y*) observations

Like most nonparametric statistics, Kendall's Tau has very few critical assumptions (Pett, 1997):

1. *The randomly selected data are sets of paired observations (X, Y) that have been collected from the same subjects.*
2. *The two continuous variables, X and Y, are measured on at least an ordinal scale.*

Using the alternative scores as our *X* and *Y*, it should be clear that these assumptions are well met and Kendall's Tau is calculated based on the information in Table 20. Since the rankings achieved from complete solicitation simply permit rather than require that factors interact, it represents our ideal ranking. The remaining ranking represents a way in which to estimate this ideal, through interpolation of data. Thus by defining the complete solicitation scores as our *X* variables the remaining ranking is used as *Y's* to measure the level of correlation with the ideal set.

To calculate Kendall's Tau we must first count both the number of concordant and discordant pairs. Looking again at Table 19, this entails identifying all possible score pairs in our non-ordered column and counting how many of those pairs are in natural order (i.e. increasing) and how many are in reverse order (i.e. decreasing). These concordances, calculated in Appendix C, are then fed into equation 4.2:

Complete Solicitation v. Partial Solicitation:

$$\tau = \frac{C - D}{\frac{1}{2}n(n-1)}$$

$$= \frac{405 - 30}{\frac{1}{2}30(30-1)}$$

$$= 0.862$$

Kendall's Tau represents the difference between the probability that two rankings are correlated and the probability that they are not (Chalmer & Whitmore, 1986). A value of one represents perfect correlation (i.e. they are the same), a value of zero represents no correlation (i.e. random) and a correlation of negative one represents perfect inverse correlation (i.e. they are exactly opposite). Accordingly, the hypotheses to be tested become:

$$H_0\text{: } The\ two\ rankings\ are\ unrelated\ (\tau = 0)$$

$$H_A\text{: } The\ two\ rankings\ are\ positively\ related\ (\tau > 0)$$

Using a one-tailed test (due to the emphasis on positive correlation), statistical tables compiled by Rohlf and Sokal identify the 5% critical value for significance for a ranking of 30 alternatives as 0.218 (Rohlf & Sokal, 1995). Clearly we can safely reject the null hypothesis that the ranking is unrelated to the complete solicitation. This means that not only is it safe to assume that the partial solicitation adequately represents the complete solicitation but that it does so with very reliable probability.

A final finding worth noting is the correlation behavior of separate measures when the alternatives are looked at in groups rather than alternatively. Recall the similarity within the top ten choices that was recognized earlier on. This is important to JIEDDO and similar organizations in which rather than picking a single winner the model is intended to provide a refined group for the DM to choose from. In these situations the DM may take the top ten model-provided alternatives and choose five from that group. In this manner a DM can look at successive groupings in order to compare alternatives without looking at the entire set.

Group Size	Complete v. Partial	Critical Values		
	τ	α=.05	α=.025	α=.005
1 (n-30)	0.862	0.218	0.255	0.333
3 (n=10)	0.887	0.467	0.511	0.644
5 (n=6)	1	0.733	0.867	1

Table 21: Group Ranking Comparisons

Table 21 underlines another strength of the partial solicitation model by comparing the average rankings of successively larger groupings found in Appendix D. The partial solicitation continues to remain strongly correlated, maintaining significance to an alpha of .005 up to a group size of five.

IV.F Sensitivity Analysis

After a value model has been created and weights assigned to all objectives, sensitivity analysis allows the DM to see how sensitive the alternative ranking is to changes in individual weights. As the purpose of this paper is to introduce an alternate measure construction and not question the particular weights chosen it is useful to compare the respective sensitivity analyses of the two methods. For the sake of simplicity we examine only the top tier weights. Figures 12 and 13 represent each alternative as a different line.

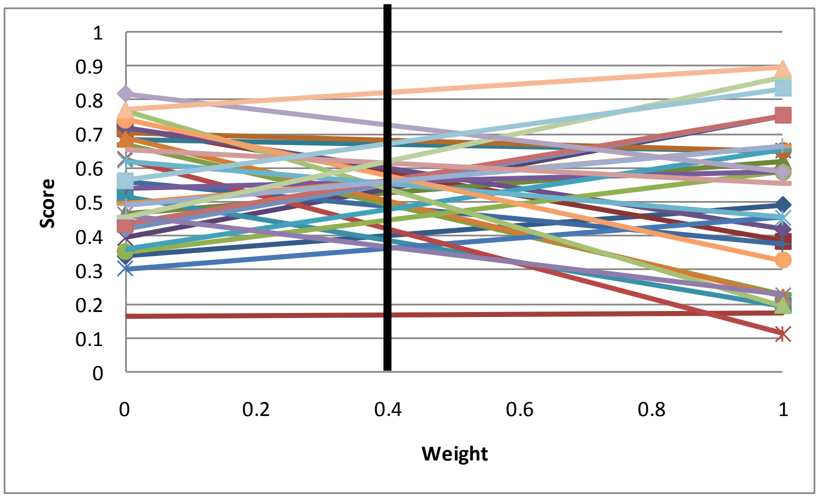


Figure 12: Needed Capability Sensitivity Analysis (Original Model)

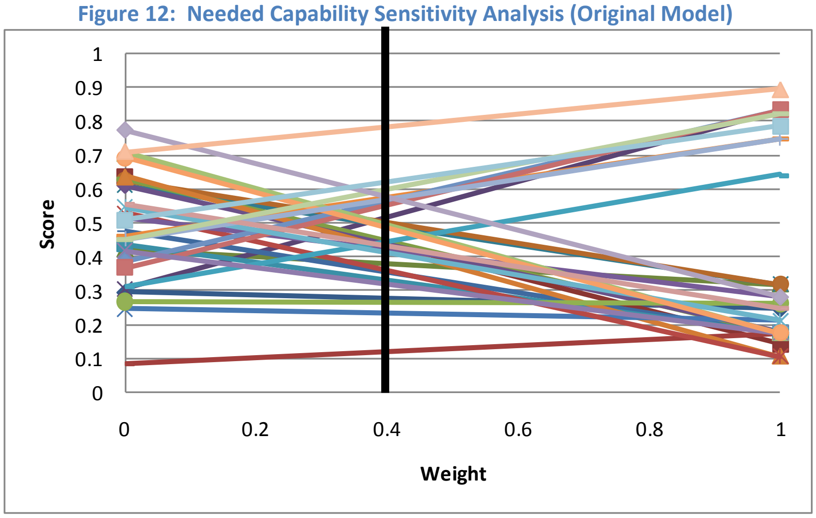


Figure 13: Needed Capability Sensitivity Analysis (Complete Solicitation)

While it seems that neither model is completely insensitive to weight change, the breakpoints in weight at which alternatives switch rank appear to be more tightly clustered and fewer in number in the combined model over the original. Further, by combining factors the new model has reduced the overall number of measures and likewise reduced the number of sensitivities which require analysis. Not only does this make sense but it supports two of the chief tenets of a VFT hierarchy; small size and operability (Kirkwood C. W., 1997).

The clustering result may owe more to chance than construction as the remaining sensitivity charts in Appendix F fail to show as stark a difference, but it does offer further proof that the combined model may have additional specific advantages as a filtering tool. Eight out of ten of the top alternatives in the combined model are very closely related in their sensitivity (average slope difference of 0.13) represented in Figure 12. This means that as weights change the alternative rankings shuffle mostly within specific groupings rather than spontaneously from first to last.

IV.F Marine Model and Additional Findings

After creating and analyzing the previous illustrative model, the methodology was ultimately reapplied to an actual acting Marine Commander with extensive C-IED experience recently returned from deployment to Iraq. The corresponding data and rank analysis can be found along with the first solicitation in the attached appendices. Three specific points stand out in comparison to the previous implementation of the methodology.

First and most importantly, the methodology continues to exhibit a strong ability to correctly model a DM's explicit combined values. Recalculating Kendall's Tau for our new rank comparisons we see a statistic of 0.908 between the full and partial solicitation of the commander. The model also remains strongly correlated as alternative group size is increased; group sizes of three and five yielded increasing and consistently significant Tau's of 0.977 and 1.

Second is the case of proposal X. Looking at an abbreviated comparison of the completely and partially solicited rankings in Figure 14 X appears as a clear outlier.

Proposal	Complete (Score)	Partial (Score)	Complete (Rank)	Partial (Rank)
DD	0.961	0.959	1	1
BB	0.900	0.872	2	2
Z	0.840	0.800	3	6
F	0.837	0.823	4	3
.	.	.	.	.
.	.	.	.	.
.	.	.	.	.
S	0.696	0.719	13	12
X	**0.694**	**0.792**	**14**	**7**
C	0.673	0.669	15	15
.	.	.	.	.
.	.	.	.	.
.	.	.	.	.
A	0.343	0.348	28	28
M	0.320	0.325	29	29
H	0.313	0.306	30	30

Figure 14: Marine Model Alternative Ranking

Rank difference between the models averages at barely 1 and with the exception of X is never more than 3. By being 7 ranks out of place Alternative X raises possible concerns about using the model as a filter. Closer inspection of the solicited values provides some explanation:

Gap Impact	**G1**	0.3	0.7	0.85	1	1	1	1
	G2	0.3	0.6	0.7	0.9	1	1	1
	G3	0.2	0.5	0.6	0.8	0.9	1	1
	G4	0.1	0.4	0.6	0.7	0.8	0.9	1
	G5	0.1	0.3	0.5	0.7	0.8	0.8	0.9
	G6	0.1	0.2	0.4	0.7	0.7	0.8	0.9
	G7	0.1	0.2	0.3	0.6	0.7	0.8	0.9
	G8	0.1	0.2	0.3	0.6	0.7	0.8	0.9
	None	0	0	0	0	0	0	0
		0	**10**	**20**	**30**	**40**	**50**	**60**
		Time to Counter (months)						

Figure 15: Directly Solicited Values

Gap Impact	G1	0.3	0.7	0.85	1	1	1	1
	G2	0.3	0.7	0.85	1	1	1	1
	G3	0.3	0.7	0.85	1	1	1	1
	G4	0.25	0.63	0.765	0.9	0.9	0.9	0.9
	G5	0.2	0.56	0.68	0.8	0.8	0.8	0.8
	G6	0.2	0.56	0.68	0.8	0.8	0.8	0.8
	G7	0.2	0.56	0.68	0.8	0.8	0.8	0.8
	G8	0.2	0.56	0.68	0.8	0.8	0.8	0.8
	None	0	0	0	0	0	0	0
		0	**10**	**20**	**30**	**40**	**50**	**60**
		Time to Counter (months)						

Figure 16: Partially Solicited Values w/ Interpolation

While the blue solicited row and column in Figure 16 perfectly matches their counterparts in Table 15, the values are very tightly clustered near the high end and give very little differentiation between levels to interpolate upon. As many of the alternatives scored high on one or both of the measures this did not prove to be a problem in general. Alternative X however possessed a Gap Impact of G7 and a Time to Counter of only 12. As the interpolation breaks down near zero this leads to a difference in value of 0.364 between the complete and partial model and an overall score difference of 0.105. This disparity is singularly responsible for the misplacement of X and significantly lowers the overall Kendall's Tau. As discussed in future research this would appear to be an issue of choosing at which level to solicit values on which to interpolate those remaining and merits further investigation.

Lastly, while sensitivity analysis charts in Appendix F for the Needed Capability still exhibit a certain level of the clustering phenomenon mentioned earlier, the remaining charts seem to support the supposition that this is more likely a coincidence of these particular measures and not a general result of the methodology.

V. Conclusions and Recommendations

This chapter provides a summary of the research presented, outlines key contributions to JIEDDO and the field of decision analysis and submits several suggestions for future research in the area.

V.A Research Review

VFT models have always depended on assumptions which require little work to understand but much more to empirically prove. Not least amongst these is the assumption of preferential independence. This research has investigated past methods for creating robust decision models not bound by the assumption of preferential independence and has developed a simple understandable process for creating such a model.

As a case study JIEDDO provided a key example of a decision process modeled through VFT but plagued by suspicions of independence violations. Building on the original additive model, scored alternative set and accompanying research accomplished by Dawley et al it was possible to create and validate the new methodology with minimal interaction from JIEDDO representatives. By applying mathematical interpolation a model which closely matched an exhaustive enumeration of DM values was created which greatly reduced the number of required inputs from the DM and fit within the established VFT hierarchy. This has the added advantage of developing a method which is neither DM nor decision dependent. The new model was validated not against how accurately it represented the specific JIEDDO decision process, but rather how consistently and accurately it was able to capture the interactive values of a DM in comparison to the more robust but lengthy enumeration process. This validation was accomplished through the application of non-parametric rank tests.

V.B Contributions

Parallel research into the validity of the current JIEDDO value model has been pursued by measuring its correlation to proposals approved by the organization without the aid of the model. The research presents evidence which strongly suggests the accuracy of the additive model in reflecting actual JIEDDO decisions (Willy, 2009). The final results of this research not withstanding; this does not diminish the importance or contribution of the presented research to JIEDDO. JIEDDO is unique among military organizations in its ability and necessity to quickly adjust its mission to the ever changing battle presented by IEDs. While the independent additive model currently meets JIEDDO's needs, it would be naïve to assume that this will always be the case. The current model is only as accurate as the current doctrine and leadership, both of which have changed over the years. Our methodology allows for reevaluation of the model without complete re-accomplishment.

As a high-profile, high-budget joint organization JIEDDO is the target of intense governmental oversight from many directions. As a result any decision model implemented by JIEDDO will more than likely be the immediate target of scrutiny as to its value to the program and taxpayers. By considering interactions our methodology sidesteps the difficulty in explaining and proving preferential independence and instead offers an immediate and simple answer for any with questions about synergistic effects of certain factors; better to answer a question than attempt to explain its irrelevancy.

As stated earlier, a key characteristic of our methodology is its applicability beyond JIEDDO. The methodology was purposefully created as a tool to work in cooperation with established VFT methods. Since the methodology is based on independent solicitation and not established SDVFs it is equally capable of both creating combined functions from scratch during the initial model construction if the DM insists on factors with known interdependence or creating combined functions after SDVFs have been created if interdependency becomes suspected and must be tested.

V.C Future Research

Throughout the course of this research there have been several avenues for improvement upon or extensions of the current methodology which were unable to be pursued due to time and resource restrictions:

1. Reevaluation of the JIEDDO model: As mentioned earlier, the purpose of this research was to develop a new methodology for capturing interactive values, not to specifically "fix" the JIEDDO model. As the original model developed by Dawley et al has yet to be implemented it would be interesting to work with the actual JIEDDO DM and attempt to modify the current model through application

of our methodology and measure the effects of the new model both on alternative ranking and DM and SME acceptance.

2. Higher dimension interaction consideration: This research has limited itself to two-dimensional interactions of factors for previously discussed reasons. In theory however the same solicitation concepts could be extended to any level of interaction. The question would seem to be to find at what point do the number and difficulty of solicitations outweigh the advantages of the more specifically defined holistic model.
3. Independent determination of value functions: Prior research has been done on comparing the VFT models and decisions made by a group working together versus individually (Gezeravci, 2008). Many decisions (including JIEDDO to a degree) are less the result of a single DM and more the culmination of a group of SME's. Determining the combined values required for the new methodology can be increasingly difficult depending on the technical level of the measure. How would the model and its accuracy be affected if after interaction pairs were identified by the DM, specific SME's were responsible for providing the required value inputs?
4. Further validation of the methodology with a more robust sample set: The current set of 30 alternatives used to test the methodology represents a relatively small number in comparison to the total alternatives received by an organization such as JIEDDO. Furthermore, the individual factor scoring for the alternatives was accomplished by AFIT researchers rather than actual JIEDDO

SME's. In order to provide more useful results to JIEDDO it is suggested to solve these inadequacies as well as factoring in additional information about proposals such as selection status and ultimate field effectiveness.

5. Comparison of methodology across several separate decisions: Research would seem to support the extension of our methodology beyond JIEDDO but would be considerably reinforced by the explicit application to several different hierarchies and at different points within the process (e.g. before and after the creation of SDVFs).
6. Effects of breakpoint selection on value solicitation: In Chapter 3 breakpoints were chosen evenly and were solicited at either the highest or near highest level of factors. There may be advantages to be gained by a varying the number and distribution of breakpoints. Further, would the model be improved or degraded if solicitations were based on midrange or lower values rather than higher.

V.D Summary

Violation of preferential independence within decision models is nothing new nor is it something for which there does not exist a list of solutions. Unfortunately the difficulty of most of these solutions either in understanding or implementation has often led some DMs to ignore such violations in an attempt to embrace simpler models. The methodology presented within this research greatly reduces the need for such a tradeoff by offering both robustness and simplicity with mathematical techniques no more complex than those already associated with simple VFT decision models.

Appendix A

A.1: Directly Solicited Value Matrices (Researcher)

Primary Gap Addressed	0	6	12	18	24	30	36	42	48	54	60
G1	0	0.1	0.2	0.3	0.45	0.6	0.8	0.85	0.9	0.95	1
G2	0	0.05	0.1	0.2	0.3	0.45	0.6	0.75	0.9	0.95	0.95
G3	0	0.05	0.05	0.1	0.2	0.3	0.4	0.5	0.65	0.75	0.8
G4	0	0.05	0.05	0.05	0.1	0.2	0.2	0.3	0.45	0.6	0.6
G5	0	0	0.01	0.05	0.05	0.1	0.1	0.2	0.2	0.3	0.4
G6	0	0	0	0	0.01	0.05	0.05	0.1	0.15	0.2	0.2
G7	0	0	0	0	0	0	0.05	0.05	0.1	0.15	0.15
G8	0	0	0	0	0	0	0	0	0.05	0.1	0.1
None	0	0	0	0	0	0	0	0	0	0	0.05

Months Useful Operaton

Technology Readiness Level	60	54	48	42	36	30	24	18	12	6	0
9	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.95	1	1
8	0.05	0.1	0.2	0.3	0.4	0.55	0.7	0.8	0.9	0.95	1
7	0	0.05	0.1	0.2	0.3	0.3	0.6	0.7	0.85	0.9	0.9
6	0	0	0.05	0.1	0.2	0.2	0.4	0.5	0.6	0.7	0.8
5	0	0	0	0	0	0	0.1	0.3	0.4	0.5	0.6
4	0	0	0	0	0	0	0.05	0.1	0.2	0.3	0.4
3	0	0	0	0	0	0	0	0	0.05	0.1	0.2
2	0	0	0	0	0	0	0	0	0	0.05	0.1
1	0	0	0	0	0	0	0	0	0	0	0.05

Months to Fielding

Training Hours Required	1	2	3	4	5
0	0.1	0.2	0.5	0.9	1
5	0.05	1	0.4	0.6	0.95
10	0	0.05	0.2	0.5	0.8
15	0	0	0.1	0.35	0.6
20	0	0	0.1	0.3	0.5
25	0	0	0.05	0.25	0.4
30	0	0	0.05	0.2	0.3
35	0	0	0.05	0.1	0.2
40	0	0	0.05	0.1	0.1

Training Level

A.2: Directly Solicited Value Matrices (Marine Commander)

Gap Impact	0	10	20	30	40	50	60
G1	0.3	0.7	0.85	1	1	1	1
G2	0.3	0.6	0.7	0.9	1	1	1
G3	0.2	0.5	0.6	0.8	0.9	1	1
G4	0.1	0.4	0.6	0.7	0.8	0.9	1
G5	0.1	0.3	0.5	0.7	0.8	0.8	0.9
G6	0.1	0.2	0.4	0.7	0.7	0.8	0.9
G7	0.1	0.2	0.3	0.6	0.7	0.8	0.9
G8	0.1	0.2	0.3	0.6	0.7	0.8	0.9
None	0	0	0	0	0	0	0
	Time to Counter (months)						

Tenets Addressed	Above TS	TS	SEC/ NONFORN	SEC/REL	CONFI- DENTIAL	FOUO	UNCLASS
3	0.2	0.5	0.8	1	1	1	1
2	0.1	0.5	0.7	1	1	1	1
1	0.1	0.3	0.5	0.8	1	1	1
0	0	0	0	0	0	0	0
	Classification						

Technical Performance	60	50	40	30	20	10	0
5	0.3	0.3	0.3	0.4	0.7	0.9	1
4	0.2	0.2	0.2	0.3	0.7	0.8	1
3	0.1	0.1	0.1	0.2	0.6	0.8	1
2	0	0.1	0.1	0.2	0.6	0.8	1
1	0	0.1	0.1	0.2	0.5	0.8	1
	Time to Fielding (months)						

A.3: Mathematically Interpolated Value Matrices (Researcher)

Primary Gap Addressed											
G1	0.00	0.05	0.20	0.30	0.40	0.50	0.65	0.80	0.90	0.95	1.00
G2	0.00	0.04	0.17	0.25	0.34	0.42	0.55	0.67	0.76	0.80	0.84
G3	0.00	0.03	0.11	0.16	0.21	0.26	0.34	0.42	0.47	0.50	0.53
G4	0.00	0.02	0.07	0.11	0.15	0.18	0.24	0.29	0.33	0.35	0.37
G5	0.00	0.02	0.06	0.09	0.13	0.16	0.21	0.25	0.28	0.30	0.32
G6	0.00	0.01	0.04	0.06	0.08	0.11	0.14	0.17	0.19	0.20	0.21
G7	0.00	0.01	0.03	0.05	0.06	0.08	0.10	0.13	0.14	0.15	0.16
G8	0.00	0.00	0.01	0.02	0.02	0.03	0.03	0.04	0.05	0.05	0.05
None	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	0	6	12	18	24	30	36	42	48	54	60
	Months Useful Operaton										

Technology Readiness Level											
9	0.05	0.10	0.20	0.30	0.40	0.60	0.70	0.80	0.90	1.00	1.00
8	0.05	0.10	0.19	0.29	0.38	0.57	0.67	0.76	0.86	0.95	0.95
7	0.05	0.09	0.18	0.27	0.36	0.54	0.63	0.72	0.81	0.90	0.90
6	0.04	0.09	0.17	0.26	0.34	0.51	0.60	0.68	0.77	0.85	0.85
5	0.03	0.07	0.13	0.20	0.26	0.39	0.46	0.52	0.59	0.65	0.65
4	0.02	0.04	0.08	0.12	0.16	0.24	0.28	0.32	0.36	0.40	0.40
3	0.01	0.02	0.04	0.06	0.08	0.12	0.14	0.16	0.18	0.20	0.20
2	0.01	0.01	0.02	0.03	0.04	0.06	0.07	0.08	0.09	0.10	0.10
1	0.00	0.01	0.01	0.02	0.02	0.03	0.04	0.04	0.05	0.05	0.05
	60	54	48	42	36	30	24	18	12	6	0
	Months to Fielding										

Training Hours Required					
0	0.11	0.22	0.44	0.89	1.00
5	0.10	0.20	0.40	0.80	0.90
10	0.07	0.13	0.27	0.53	0.60
15	0.05	0.10	0.20	0.40	0.45
20	0.04	0.09	0.18	0.36	0.40
25	0.04	0.08	0.16	0.31	0.35
30	0.03	0.07	0.13	0.27	0.30
35	0.03	0.06	0.11	0.22	0.25
40	0.02	0.04	0.09	0.18	0.20
	1	2	3	4	5
	Training Level				

A.4: Mathematically Interpolated Value Matrix (Marine Commander)

Gap Impact								
	G1	0.3	0.7	0.85	1	1	1	1
	G2	0.3	0.7	0.85	1	1	1	1
	G3	0.3	0.7	0.85	1	1	1	1
	G4	0.25	0.63	0.765	0.9	0.9	0.9	0.9
	G5	0.2	0.56	0.68	0.8	0.8	0.8	0.8
	G6	0.2	0.56	0.68	0.8	0.8	0.8	0.8
	G7	0.2	0.56	0.68	0.8	0.8	0.8	0.8
	G8	0.2	0.56	0.68	0.8	0.8	0.8	0.8
	None	0	0	0	0	0	0	0
		0	**10**	**20**	**30**	**40**	**50**	**60**
		Time to Counter (months)						

Tenets Addressed								
	3	0.2	0.5	0.8	1	1	1	1
	2	0.2	0.5	0.8	1	1	1	1
	1	0.2	0.5	0.8	1	1	1	1
	0	0	0	0	0	0	0	0
		Above TS	**TS**	**SEC/ NONFORN**	**SEC/REL**	**CONFI-DENTIAL**	**FOUO**	**UNCLASS**
		Classification						

Technical Performance								
	5	0.3	0.3	0.3	0.4	0.7	0.9	1
	4	0.27	0.27	0.27	0.36	0.62	0.8	0.89
	3	0.27	0.27	0.27	0.36	0.62	0.8	0.89
	2	0.27	0.27	0.27	0.36	0.62	0.8	0.89
	1	0	0.27	0.27	0.36	0.62	0.8	0.89
		60	**50**	**40**	**30**	**20**	**10**	**0**
		Time to Fielding (months)						

** Large jumps in value led to extra solicitation of Gap Impact at 5 and 25 months Time to Counter and Technical Performance at 55 and 25 months Time to Fielding. The resulting interpolation included adding an additional piecewise linear break at 5 and 55 months and exponentially interpolating between 20 and 30 months with rho values of 3.58 and 7.08 for Time to Counter and Time to Fielding respectively.*

Appendix B

B.1: Alternative Factor Levels

Proposal	Tenets	Gap	Classification	Time to Counter	Performance Rating	Suitability	Interoperability	TRL	Time to Fielding	% Max Capacity	Interaction Min/Hr	Training Hrs	Training Maturity
A	2	None	FOUO	60	2	4	Significant	2	24	20	2-5	40	3
B	0	None	FOUO	60	1	5	None	4	14	0	0-1	0	3
C	1	G1	FOUO	12	2	4	Minor	5	8	5	>30	4	3
D	1	G1	FOUO	50	2	3	Minor	3	8	5	>30	16	3
E	1	G6	FOUO	60	1	5	None	1	24	0	0-1	0	3
F	1	G6	FOUO	60	1	5	None	5	24	0	0-1	0	3
G	1	G6	FOUO	12	3	5	Significant	4	18	20	0-1	0	3
H	1	None	FOUO	1	1	4	Significant	1	6	100	16-30	40	3
I	1	None	FOUO	36	4	3	Significant	7	4	1	2-5	1	3
J	1	None	SEC/REL	60	1	5	None	1	9	0	0-1	0	3
K	1	None	FOUO	24	2	3	Minor	2	18	20	0-1	4	3
L	0	G8	FOUO	24	3	5	Minor	6	18	1	2-5	4	3
M	1	None	FOUO	60	2	3	Significant	1	24	5	16-30	8	3
N	0	None	FOUO	12	4	1	None	3	2	80	0-1	4	3
O	3	G3	FOUO	3	2	3	Significant	2	14	1	16-30	8	3
P	2	G8	FOUO	60	2	4	Minor	6	6	10	2-5	40	3
Q	2	G2	FOUO	36	2	4	Significant	4	20	2	6-15	40	3
R	1	G1	FOUO	36	3	3	Minor	6	9	2	16-30	24	3
S	1	G1	FOUO	50	2	3	Minor	6	12	5	>30	20	3
T	1	G1	FOUO	50	2	3	Minor	4	18	1	16-30	6	3
U	1	None	FOUO	24	3	5	Minor	6	4	5	0-1	1	3
V	1	None	FOUO	36	3	5	Minor	5	18	20	16-30	4	3
W	1	None	FOUO	60	3	4	Minor	4	18	3	2-5	2	3
X	2	G7	SEC/REL	12	2	5	None	6	6	2	2-5	4	3
Y	1	G1	FOUO	36	3	4	Minor	5	12	5	16-30	8	3
Z	1	G8	FOUO	60	2	4	Minor	3	4	2	0-1	4	3
AA	3	G3	FOUO	60	2	3	Minor	7	7	2	>30	20	3
BB	2	G8	FOUO	60	3	5	None	6	12	2	0-1	4	3
CC	2	G3	FOUO	60	2	4	Minor	6	12	3	6-15	1	3
DD	1	G1	FOUO	60	1	5	None	6	9	0	0-1	0	3

B.2: Factor Scoring

Proposal	Tenets	Gap	Classification	Time to Counter	Performance	Suitability	Interoperability	TRL	Time to Fielding	% Max Capacity	Interaction Min/Hr	Training Hrs	Training Maturity	Total
A	0.042	0.000	0.042	0.112	0.028	0.042	0.000	0.004	0.020	0.034	0.070	0.000	0.008	0.401
B	0.000	0.000	0.042	0.112	0.000	0.056	0.091	0.007	0.031	0.087	0.100	0.050	0.008	0.584
C	0.028	0.176	0.042	0.002	0.028	0.042	0.046	0.011	0.041	0.069	0.000	0.035	0.008	0.528
D	0.028	0.176	0.042	0.056	0.028	0.028	0.046	0.006	0.041	0.069	0.000	0.012	0.008	0.539
E	0.028	0.078	0.042	0.112	0.000	0.056	0.091	0.000	0.020	0.087	0.100	0.050	0.008	0.672
F	0.028	0.078	0.042	0.112	0.000	0.056	0.091	0.011	0.020	0.087	0.100	0.050	0.008	0.683
G	0.028	0.078	0.042	0.002	0.055	0.056	0.000	0.007	0.027	0.034	0.100	0.050	0.008	0.488
H	0.028	0.000	0.042	0.000	0.000	0.042	0.000	0.000	0.045	0.000	0.005	0.000	0.008	0.170
I	0.028	0.000	0.042	0.021	0.083	0.028	0.000	0.034	0.049	0.083	0.070	0.046	0.008	0.491
J	0.028	0.000	0.028	0.112	0.000	0.056	0.091	0.000	0.039	0.087	0.100	0.050	0.008	0.599
K	0.028	0.000	0.042	0.008	0.028	0.028	0.046	0.004	0.027	0.034	0.100	0.035	0.008	0.387
L	0.000	0.039	0.042	0.008	0.055	0.056	0.046	0.033	0.027	0.083	0.070	0.035	0.008	0.502
M	0.028	0.000	0.042	0.112	0.028	0.028	0.000	0.000	0.020	0.069	0.005	0.025	0.008	0.364
N	0.000	0.000	0.042	0.002	0.083	0.000	0.091	0.006	0.052	0.001	0.100	0.035	0.008	0.420
O	0.056	0.137	0.042	0.000	0.028	0.028	0.000	0.004	0.031	0.083	0.005	0.025	0.008	0.447
P	0.042	0.039	0.042	0.112	0.028	0.042	0.046	0.033	0.045	0.055	0.070	0.000	0.008	0.561
Q	0.042	0.156	0.042	0.021	0.028	0.042	0.000	0.007	0.024	0.079	0.028	0.000	0.008	0.477
R	0.028	0.176	0.042	0.021	0.055	0.028	0.046	0.033	0.039	0.079	0.005	0.005	0.008	0.565
S	0.028	0.176	0.042	0.056	0.028	0.028	0.046	0.033	0.034	0.069	0.000	0.008	0.008	0.555
T	0.028	0.176	0.042	0.056	0.028	0.028	0.046	0.007	0.027	0.083	0.005	0.030	0.008	0.563
U	0.028	0.000	0.042	0.008	0.055	0.056	0.046	0.033	0.049	0.069	0.100	0.046	0.008	0.539
V	0.028	0.000	0.042	0.021	0.055	0.056	0.046	0.011	0.027	0.034	0.005	0.035	0.008	0.367
W	0.028	0.000	0.042	0.112	0.055	0.042	0.046	0.007	0.027	0.076	0.070	0.042	0.008	0.554
X	0.042	0.059	0.028	0.002	0.028	0.056	0.091	0.033	0.045	0.079	0.070	0.035	0.008	0.576
Y	0.028	0.176	0.042	0.021	0.055	0.042	0.046	0.011	0.034	0.069	0.005	0.025	0.008	0.561
Z	0.028	0.039	0.042	0.112	0.028	0.042	0.046	0.006	0.049	0.079	0.100	0.035	0.008	0.613
AA	0.056	0.137	0.042	0.112	0.028	0.028	0.046	0.034	0.043	0.079	0.000	0.008	0.008	0.620
BB	0.042	0.039	0.042	0.112	0.055	0.056	0.091	0.033	0.034	0.079	0.100	0.035	0.008	0.727
CC	0.042	0.137	0.042	0.112	0.028	0.042	0.046	0.033	0.034	0.076	0.028	0.046	0.008	0.672
DD	0.028	0.176	0.042	0.112	0.000	0.056	0.091	0.033	0.039	0.087	0.100	0.050	0.008	0.822

Appendix C

C.1: Concordance Calculations (Researcher)

	Rank			Partial Solict Pairs	
Proposal	Complete Solicit	Partial Solicit		Concordant (C)	Discordant (D)
DD	1	1		29	0
CC	2	6		24	4
AA	3	10		20	7
R	4	5		23	3
BB	5	3		24	1
Y	6	7		22	2
S	7	2		23	0
T	8	4		22	0
D	9	9		20	1
F	10	8		20	0
U	11	12		18	1
E	12	13		17	1
X	13	11		17	0
I	14	16		14	2
Q	15	14		15	0
B	16	17		13	1
J	17	20		10	3
Z	18	18		11	1
L	19	15		11	0
P	20	19		10	0
W	21	21		9	0
C	22	22		8	0
N	23	24		6	1
G	24	23		6	0
K	25	26		4	1
V	26	25		4	0
A	27	28		2	1
O	28	27		2	0
M	29	29		1	0
H	30	30		0	0
			Total	405	30

C.2 Concordance Calculations (Marine Commander):

	Rank		Partial Solict Pairs	
Proposal	Complete Solicit	Partial Solicit	Concordant (C)	Discordant (D)
DD	1	1	29	0
BB	2	2	28	0
Z	3	6	24	3
F	4	3	26	0
E	5	4	25	0
CC	6	5	24	0
P	7	10	20	3
AA	8	8	21	1
R	9	9	20	1
Y	10	11	19	1
T	11	13	17	2
D	12	14	16	2
S	13	12	16	1
X	14	7	16	0
C	15	15	15	0
Q	16	16	14	0
U	17	20	10	3
J	18	19	10	2
L	19	17	11	0
G	20	18	10	0
I	21	21	9	0
B	22	22	8	0
W	23	23	7	0
K	24	25	5	1
O	25	24	5	0
V	26	26	4	0
N	27	27	3	0
A	28	28	2	0
M	29	29	1	0
H	30	30	0	0
		Total	415	20

Appendix D:

D.1: Group Rankings (5 Alternative / n=6) - Researcher

		Group Ranks	
Proposal		Complete Solicit	Partial Solicit
DD		1	1
CC		2	6
AA		3	10
R		4	5
BB		5	3
Rank	Average	**3**	**5**
	Ordinal	**1**	**1**
Y		6	7
S		7	2
T		8	4
D		9	9
F		10	8
Rank	Average	**8**	**6**
	Ordinal	**2**	**2**
U		11	12
E		12	13
X		13	11
I		14	16
Q		15	14
Rank	Average	**13**	**13.2**
	Ordinal	**3**	**3**
B		16	17
J		17	20
Z		18	18
L		19	15
P		20	19
Rank	Average	**18**	**17.8**
	Ordinal	**4**	**4**
W		21	21
C		22	22
N		23	24
G		24	23
K		25	26
Rank	Average	**23**	**23.2**
	Ordinal	**5**	**5**
V		26	25
A		27	28
O		28	27
M		29	29
H		30	30
Rank	Average	**28**	**27.8**
	Ordinal	**6**	**6**

D.2: Group Rankings (5 Alternatives / n=6) – Marine Commander

Proposal		Complete Solicit	Partial Solicit
DD		1	1
BB		2	2
Z		3	6
F		4	3
E		5	4
Rank	Average	3	3.2
	Ordinal	1	1
CC		6	5
P		7	10
AA		8	8
R		9	9
Y		10	11
Rank	Average	8	8.6
	Ordinal	2	2
T		11	13
D		12	14
S		13	12
X		14	7
C		15	15
Rank	Average	13	12.2
	Ordinal	3	3
Q		16	16
U		17	20
J		18	19
L		19	17
G		20	18
Rank	Average	18	18
	Ordinal	4	4
I		21	21
B		22	22
W		23	23
K		24	25
O		25	24
Rank	Average	23	23
	Ordinal	5	5
V		26	26
N		27	27
A		28	28
M		29	29
H		30	30
Rank	Average	28	28
	Ordinal	6	6

D.3: Group Rankings (3 Alternatives / n=10)

Proposal		Rank: Complete Solicit	Rank: Partial Solicit
DD		1	1
CC		2	6
AA		3	10
Rank	**Average**	**2**	**5.666667**
	Ordinal	**1**	**2**
R		4	5
BB		5	3
Y		6	7
Rank	**Average**	**5**	**5**
	Ordinal	**2**	**1**
S		7	2
T		8	4
D		9	9
Rank	**Average**	**8**	**5**
	Ordinal	**3**	**1**
F		10	8
U		11	12
E		12	13
Rank	**Average**	**11**	**11**
	Ordinal	**4**	**3**
X		13	11
I		14	16
Q		15	14
Rank	**Average**	**14**	**13.66667**
	Ordinal	**5**	**4**
B		16	17
J		17	20
Z		18	18
Rank	**Average**	**17**	**18.33333**
	Ordinal	**6**	**5**
L		19	15
P		20	19
W		21	21
Rank	**Average**	**20**	**18.33333**
	Ordinal	**7**	**5**
C		22	22
N		23	24
G		24	23
Rank	**Average**	**23**	**23**
	Ordinal	**8**	**6**
K		25	26
V		26	25
A		27	28
Rank	**Average**	**26**	**26.33333**
	Ordinal	**9**	**7**
O		28	27
M		29	29
H		30	30
Rank	**Average**	**29**	**28.66667**
	Ordinal	**10**	**8**

D.4: Group Rankings (3 Alternatives / n=10) – Marine Commander

Proposal		Complete Solicit	Partial Solicit
DD		1	1
BB		2	2
Z		3	6
Rank	Average	2	3
	Ordinal	1	1
F		4	3
E		5	4
CC		6	5
Rank	Average	5	4
	Ordinal	2	2
P		7	10
AA		8	8
R		9	9
Rank	Average	8	9
	Ordinal	3	3
Y		10	11
T		11	13
D		12	14
Rank	Average	11	12.66667
	Ordinal	4	5
S		13	12
X		14	7
C		15	15
Rank	Average	14	11.33333
	Ordinal	5	4
Q		16	16
U		17	20
J		18	19
Rank	Average	17	18.33333
	Ordinal	6	6
L		19	17
G		20	18
I		21	21
Rank	Average	20	18.66667
	Ordinal	7	7
B		22	22
W		23	23
K		24	25
Rank	Average	23	23.33333
	Ordinal	8	8
O		25	24
V		26	26
N		27	27
Rank	Average	26	25.66667
	Ordinal	9	9
A		28	28
M		29	29
H		30	30
Rank	Average	29	29
	Ordinal	10	10

Appendix E

E.1: Matrix Representation of Independent Value Pairs

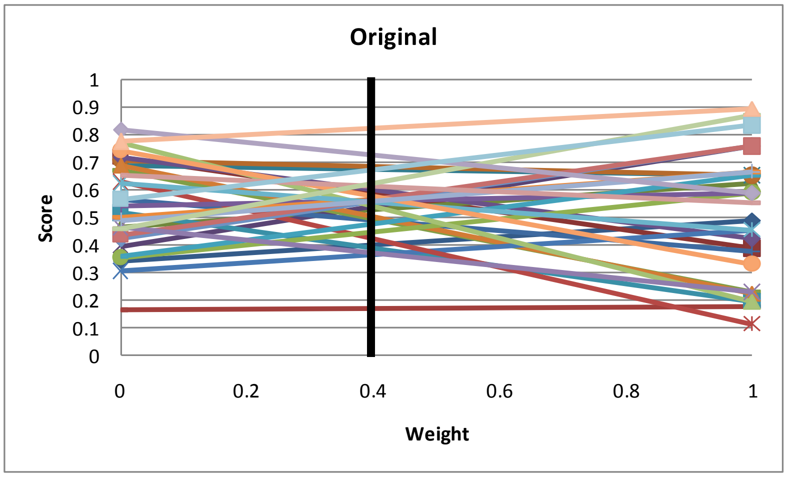
Primary Gap Addressed											
G1	0.61	0.61	0.62	0.63	0.64	0.66	0.68	0.72	0.78	0.87	1.00
G2	0.54	0.55	0.55	0.56	0.57	0.59	0.61	0.65	0.71	0.80	0.93
G3	0.48	0.48	0.48	0.49	0.50	0.52	0.55	0.59	0.64	0.73	0.86
G4	0.41	0.41	0.42	0.42	0.44	0.45	0.48	0.52	0.58	0.66	0.80
G5	0.34	0.34	0.35	0.36	0.37	0.38	0.41	0.45	0.51	0.60	0.73
G6	0.27	0.28	0.28	0.29	0.30	0.32	0.34	0.38	0.44	0.53	0.66
G7	0.20	0.21	0.21	0.22	0.23	0.25	0.28	0.31	0.37	0.46	0.59
G8	0.14	0.14	0.14	0.15	0.16	0.18	0.21	0.25	0.30	0.39	0.52
None	0.00	0.00	0.01	0.02	0.03	0.05	0.07	0.11	0.17	0.26	0.39
	0	**6**	**12**	**18**	**24**	**30**	**36**	**42**	**48**	**54**	**60**
	Months Useful Operaton										

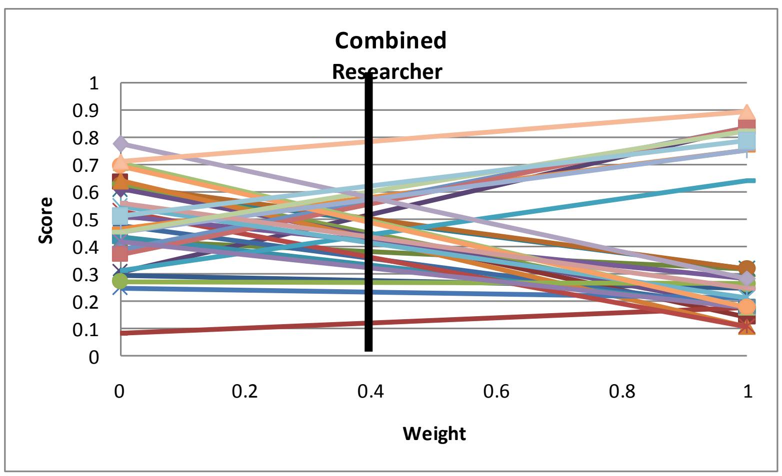
Technology Readiness Level											
9	0.40	0.41	0.43	0.44	0.46	0.53	0.61	0.68	0.76	0.88	1.00
8	0.39	0.40	0.42	0.43	0.45	0.52	0.60	0.67	0.75	0.87	0.99
7	0.37	0.39	0.40	0.42	0.43	0.51	0.58	0.66	0.73	0.85	0.97
6	0.36	0.37	0.39	0.40	0.42	0.49	0.57	0.64	0.72	0.84	0.96
5	0.12	0.13	0.15	0.16	0.18	0.25	0.33	0.41	0.48	0.60	0.72
4	0.08	0.09	0.11	0.12	0.14	0.22	0.29	0.37	0.44	0.56	0.68
3	0.06	0.07	0.09	0.10	0.12	0.20	0.27	0.35	0.42	0.54	0.66
2	0.04	0.05	0.07	0.08	0.10	0.18	0.25	0.33	0.40	0.52	0.64
1	0.00	0.02	0.03	0.05	0.06	0.14	0.21	0.29	0.36	0.48	0.60
	60	**54**	**48**	**42**	**36**	**30**	**24**	**18**	**12**	**6**	**0**
	Months to Fielding										

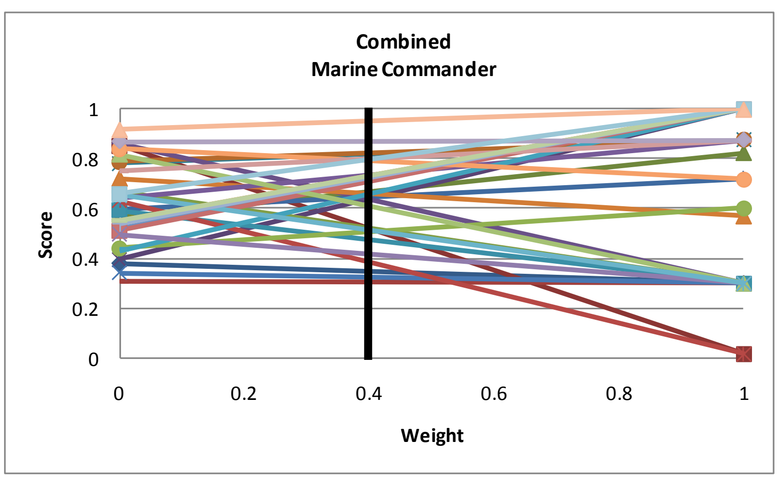
Training Hours Required					
0	0.79	0.82	0.92	0.96	1.00
5	0.52	0.55	0.64	0.68	0.72
10	0.33	0.36	0.46	0.50	0.54
15	0.21	0.24	0.33	0.38	0.42
20	0.13	0.16	0.25	0.29	0.34
25	0.08	0.11	0.20	0.24	0.28
30	0.04	0.07	0.16	0.20	0.25
35	0.02	0.05	0.14	0.18	0.22
40	0.00	0.03	0.12	0.17	0.21
	1	**2**	**3**	**4**	**5**
	Training Level				

Appendix F

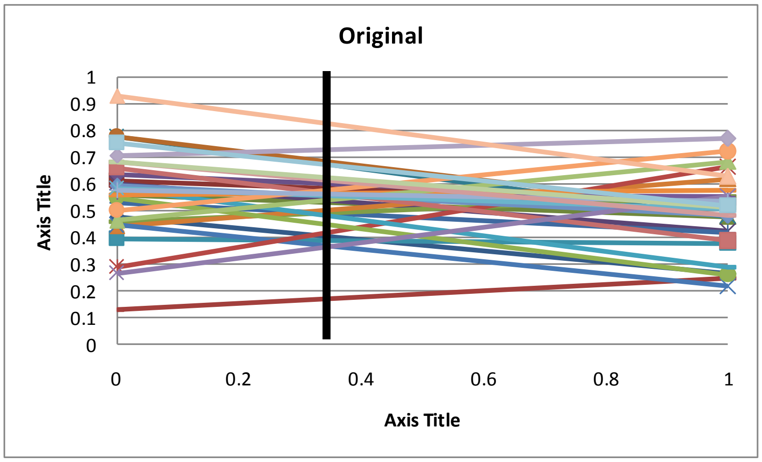
F.1: Sensitivity Analysis (Needed Capability)

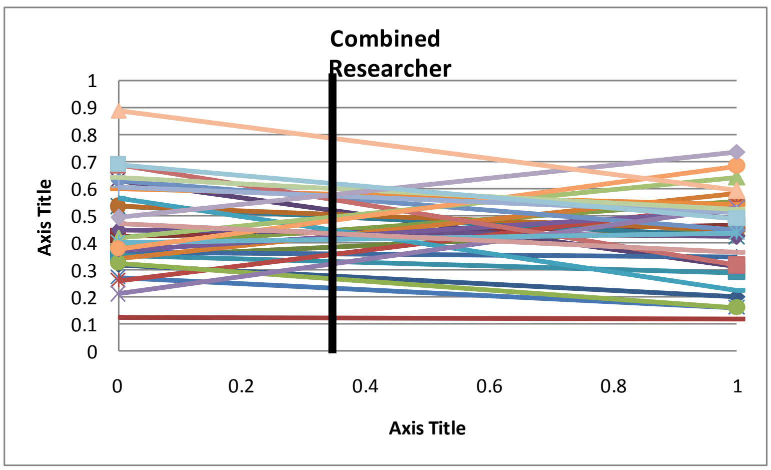


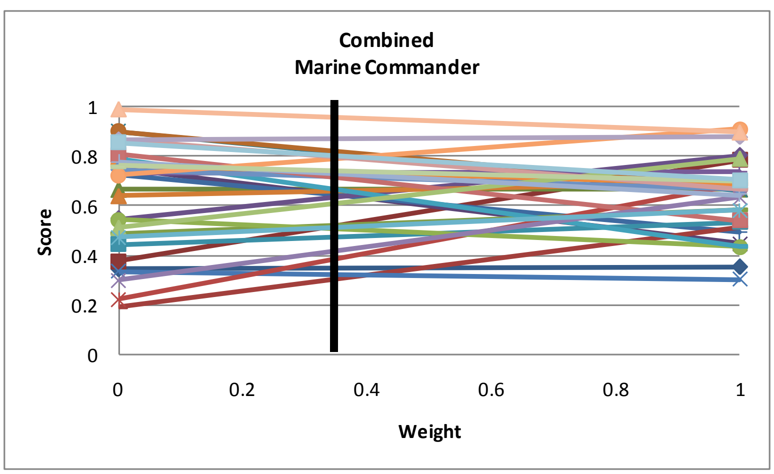




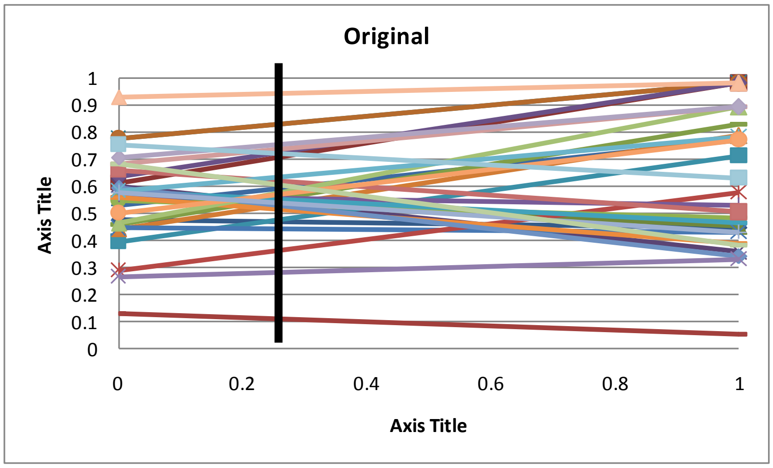
F.2: Sensitivity Analysis (Operational Performance)

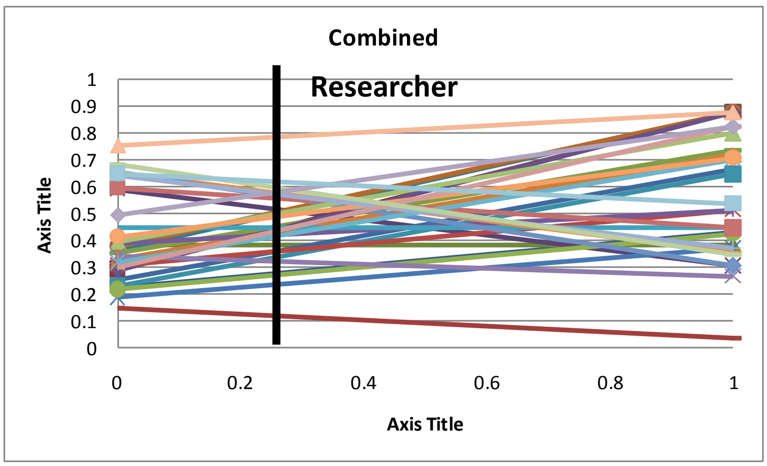


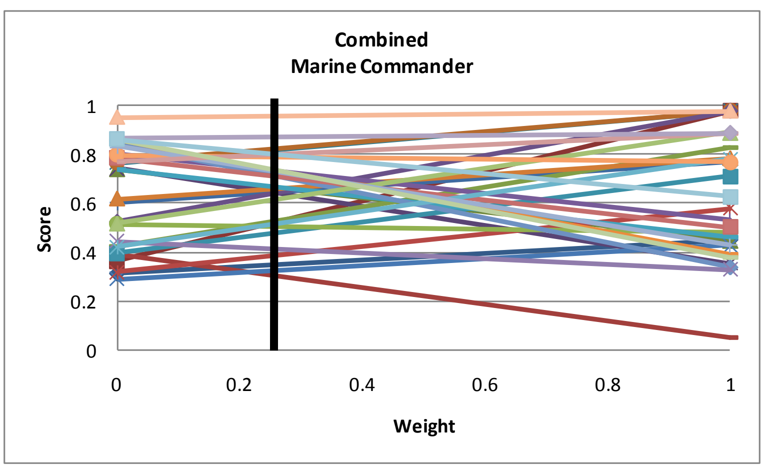




F.3: Sensitivity Analysis (Usability)







Appendix G

"All Models Are Wrong…"

"… but some are useful". George Box the famous industrial statistician uttered those words over 30 years ago and they remain every bit as true to this day. Over the past century modeling technology and computing power have led to an increasing set of tools available to the analyst. Yet they are still all fundamentally abstractions of reality and must still answer the number question of any decision maker confronted with pages of data and analysis: "So, how does this help me?"

As resources and capital become increasingly scarce in the current economic environment decision makers are being forced to take a closer look at what projects and investments they pursue before committing their resources. Not only are these choices complex but in an age of increased accountability they require a high level of transparency and objectivity. "We felt it was best at the time" is no longer a good enough answer.

Decision Analysis (DA) fills this gap with models designed to accurately and consistently reflect the values of decision makers. By breaking down large decisions into manageable and measurable pieces DA helps companies and individuals quickly and accurately calculate tradeoffs and rank alternative sets.

With much research in the field of DA, the challenge is to balance mathematical rigor while keeping the decision maker at the center of the model. A decision maker will not use a model they do neither understand nor believe and they should not use a model which does not accurately reflect their values.

Consider JIEDDO, the Joint Improvised Explosive Device Defeat Organization. They are the primary government body charged with evaluating potential counter-IED solutions and determining which proposals should be funded to maximize the impact against the war on terror. DA provides a perfect fit to help JIEDDO filter through the thousands of proposals and weigh them against the myriad of strengths they bring to the fight. Like many organizations before it JIEDDO settled on a Value Focused Thinking model due to its relative simplicity and clear requirements.

JIEDDO's model can be thought of as thirteen people each grading a single quality of a specific counter-IED technology. Once each of them has assigned their variable a score, the scores for each alternative are placed in separate boxes. Finally each alternative is ranked based on whose box has the most score.

But in JIEDDO's case this isn't the full story. The problem comes later when the different evaluators get to talking. Consider a rock, submitted as a medium-range, hand-held technology for soldiers to fight the threat of human-borne IEDs. Both raters for "Fielding Timeline" and "Technical Risk" gave the rock full marks because it's ready now and because "rock" technology is definitely mature. It's not until they find out that the "Technical Performance" rater gave the rock a score of zero for providing virtually none of the capability required by the mission that both the previous raters want their score sheets back. If they'd known it performed so poorly they would have never given it such a high score.

JIEDDO's model lost usefulness because it assumes independence between factors which doesn't exist. It fails to capture interactions between variables and misses the mark in reflecting some of the decision maker's holistic evaluations of measures. While techniques exist to handle such interactions, many of them are based on complex equations and require more intensive and lengthy interview sessions to create such models. Again, usefulness has been lost by implanting a process which may be more complex than the original decision.

Researchers at the Air Force Institute of Technology have risen to this challenge and proposed a new methodology for handling such inconsistencies in decision models. With a small set of solicited information the model is able to mathematically generate all possible interactions between two variables with a very low margin of error. Furthermore, this new technique is applicable either during model creation or after. This means that organizations like JIEDDO will be able to increase the applicability of their existent model without having to return to square one. All models may be wrong, but by putting more of the decision maker back into the model government organizations like JIEDDO may never again have to explain a two thousand dollar toilet seat to congress, and that would definitely be useful.

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Vita

Captain Christopher D Richards graduated from Anacortes High School in Anacortes, Washington. He entered undergraduate studies at the Pepperdine University in Malibu, California where he graduated with Bachelor of Science degrees in both Computer Science and Mathematics in April 2002. He taught high school math and physics until receiving his commission through the Officer Training School at Maxwell AFB, Alabama and nominated for a Regular Commission.

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14. ABSTRACT

Decisions are made every day and by everyone. As these decisions become more important, involve higher costs and affect a broader group of stakeholders it becomes essential to establish a more rigorous strategy than simply intuition or "going with your gut". In the past several decades, the concept of Value Focused Thinking (VFT) has gained much acclaim in assisting Decision Makers (DMs) in this very effort. By identifying and organizing what a DM values VFT is able to decompose the original problem and create a mathematical model to score and rank alternatives to be chosen. But what if the decision should not be completely decomposed? What if there are factors that are inextricably linked rather than independent? In the past several years, Improvised Explosive Devices (IEDs) have quickly become the number one killer of American troops overseas. To this end the Joint IED Defeat Organization worked to create a VFT model to solicit and grade countermeasure proposals as candidates for funding. While much time and care was put into soliciting a valid VFT hierarchy from the appropriate DM, it does not represent the only option. With JIEDDO as an example this paper examines a strategy to better reflect a DM's combined values in a way which is understandable to the DM and maintains a level of mathematical rigor.

15. SUBJECT TERMS

Joint Improvised Explosive Device Defeat Organization (JIEDDO), Value Focused Thinking (VFT), Preferential Independence, Single Dimensional Value Function (SDVF), Cross Terms, Multi Dimensional Value Function, Decision Analysis (DA), Interaction, Linear Interpolation

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