# FACILITY BUDGETING MODEL SELECTION: INCORPORATING THE DECISION-MAKER'S RISK BEHAVIOR

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## ABSTRACT

*This research developed a decision tool to assist in the evaluation of facility recapitalization budget estimation models within the Department of Defense (DoD). Using Value Focused Thinking (VFT), a panel of program managers developed a value hierarchy to evaluate 15 alternatives and found that the proposed DoD model scored well. Another component of the research was to assess the influence of the decision-maker's risk behavior on the VFT results. The decision-makers were subsequently considered risk averse; however, sensitivity analysis showed that the alternative rankings were independent of the decision-makers' risk tolerance level.*

## INTRODUCTION

The design and construction of a typical facility constitutes only 5-10 percent of the total cost of ownership, while operations, maintenance, and upgrades account for 60-85 percent of the overall cost [3]. Therefore, one of the goals of facilities management is to achieve an appropriate balance between facility investments and other financial obligations [13]. From this perspective, facility budgeting can be categorized into three distinct areas: operations, sustainment, and recapitalization. Operating budgets are often easier to develop and require only minimal research, while budget prediction models for sustainment (i.e., maintenance) requirements have been investigated by several researchers [10, 11]. Given the lack of research on recapitalization models though, the purpose of this research was twofold. First, we developed a decision tool to help evaluate facility recapitalization budget models. Second, we incorporated uncertainty by assessing the influence of the decision-maker's risk behavior. The decision model was developed using value-focused thinking (VFT) and is presented with minimal discussion. Instead, the focus of this paper is on the impact of the decision-maker's risk behavior on the VFT results.

## BACKGROUND

As summarized in Table 1, several researchers have categorized the various models available to estimate facility budgets. Early research into facility budgets concluded that budgets should be based on replacement costs [10, 11]. The next stage of research reported that "all construction factors – size, complexity, materials, special facilities, and so on – are all conveniently reflected in construction cost" [12]. A simple plant replacement value (PRV) or current plant value (CPV) calculation that accounted for facility age was thus favored for budgeting purposes. The research then transitioned from PRV/CPV methods to condition assessment and life-cycle approaches. For example, the Building Research Board (BRB) identified several building characteristics that should be considered for accurate budgeting: building size, type of finishes, age, condition, climate, location, level of pervious maintenance, and intensity of use [2]. Subsequent research [3, 5] confirmed that the importance of these factors.

For many organizations, the decision regarding the best model must consider multiple objectives. Additionally, various decision techniques can be used to evaluate alternatives. Examples include the Analytical Hierarchy Process, linear programming, and decision trees; however, these were ruled out in favor of a more straight-forward strategic process that incorporates the values of the decision-makers. With this in mind, Value Focused Thinking (VFT) was considered the most appropriate approach. As a basic definition, VFT can be considered a "structured method for incorporating the information, opinions, and preferences of the various relevant people into the decision making process" [7]. As its names suggest, VFT focuses on using the values of the decision-maker as decision criteria. Values are defined simply as "what we care about" and "as such, should be the driving force for our decision-making" [6]. Focusing on values instead of alternatives, as is usually the case, enables the decision-maker(s) to think more creatively about a problem and facilitate the inclusion of any alternative that could meet the objectives.

**Table 1. Facility Budget Model Categories**

| Researcher | Method Classification | | | | | |
|---|---|---|---|---|---|---|
| | Facility Value | Formula (Depreciation) | Life-Cycle | Condition Assessment | Project Backlog | Facility Size |
| Barco [1] | X | | | | X | X |
| Kaiser [5] | X | X | X | | | |
| Leslie and Minkarah [8] | X | | | X | | X |
| Ottoman [10,11] | X | X | X | X | | |
| Lufkin, Desai, & Janke [9] | X | X | | X | | |

The fundamental objective for the VFT model was to determine the best recapitalization budget estimation method for the Department of Defense (DoD). The decision-makers (DMs) used for the VFT analysis consisted of a panel of subject matter experts from the DoD, Air Force, Army, Navy, and Marines. Various techniques were used to elicit and structure the DMs' values relevant to a successful recapitalization program; the resulting hierarchy is shown in tabular form in Table 2. The process of developing the value hierarchy also included determining evaluation measures, single dimensional value functions, and local/global weights.

**Table 2. Value Hierarchy and Evaluation Measures**

| Fundamental Objective | Tier One Objectives | Tier Two Objectives | Tier Three Objectives | Tier Four Objectives | Evaluation Measures |
|---|---|---|---|---|---|
| Best Recapitalization Method | Prevent Obsolescence | Predictive Capability | | | Planning Horizon |
| | | Meets Industry Standards | Condition Based Method | | Percent Condition Based |
| | | | Life-Cycle Based Method | | Percent Life-Cycle Based |
| | | | Empirically Based Method | | Supported in Literature |
| | | Sensitivity to Investment Behavior | | | Degree of Sensitivity |
| | Credible Model | Understandable | | | Degree of Comprehension |
| | | Integrity of Inputs | Facility Types | | Number of Facility Types |
| | | | Facility Factors | Type A Factors | Number of Type A Factors |
| | | | | Type B Factors | Number of Type B Factors |
| | | | | Type C Factors | Number of Type C Factors |
| | | Consistency of Budget Requests | | | Degree of Consistency |
| | Implementation | Effort of DoD | | | Hours/year |
| | | Effort of PM | | | Hours/year |
| | | Effort of MAJCOM | | | Hours/year |

Ten potential alternatives were identified from the literature: Current Plant Value (CPV), Plant Replacement Value (PRV), Dergis-Sherman, Facilities Renewal, Depreciation, BUILDER, Renewal Factors, Applied Management Engineering (AME), Q-Rating System, and Bottom-Up. Two existing DoD recapitalization models were also included: Facilities Recapitalization Model (FRM) and Facilities Modernization Model (FRM). Given the insight they gained through the VFT process, the DMs modified the existing DoD models to create two new alternatives: Alternate FRM and Alternate FMM. Lastly, they created a hypothetical model, called the H-Model, in an attempt to maximize the possible value from the hierarchy that is within the realm of feasibility. Fifteen recapitalization models were thus evaluated with the value hierarchy and evaluation measures created during our research. The scoring of these alternatives is presented in the "Results" section along with the probabilistic analysis.

# METHODOLOGY

During the typical deterministic analysis that occurs with the VFT approach, the scoring of alternatives ignores areas of uncertainty and does not incorporate probabilistic analysis. Therefore, to introduce uncertainty to our VFT model, we examined the decision-makers' risk behavior. Of the three first-tier objectives shown in Table 1, perceptions of risk primarily affect *Implementation*; therefore, we focused solely on the impact of risk behavior on the first-tier objective of *Implementation*. Two types of analysis were subsequently conducted. First, the DM's overall risk behavior was assessed using expected utility analysis. Second, sensitivity analysis of the DM's risk tolerance level was performed to determine if the probabilistic ranges and risk behavior have an impact on the alternative rankings.

The two most common approaches to incorporating uncertainty into VFT models are expected utility (E(U)) and certainty equivalent (CE). Since both approaches resulted in the same rank order of alternatives for our research, only the E(U) approach will be discussed. To initiate the E(U) analysis, we converted the continuous range of risk behavior scores into discrete approximations. Once this is done, the most accurate method to determine the expected value of the risk behavior score is to use a probability density function [7]. However, this requires integrating the accompanying probability distribution equation, which is often unknown and difficult for most decision-makers to understand; therefore, an approximation is generally considered adequate [7]. The approximation method we used was the Extended Pearson-Tukey method in which the continuous risk behavior scores are transformed into discrete quantities, with three levels set equal to the 0.05, 0.50, and 0.95 fractiles of the continuous scores. The 0.05 and 0.95 fractiles were assigned probabilities of 0.185, and the 0.5 fractile was assigned a probability of 0.63 [7].

Using this approximation approach, the risk behavior of the decision-maker can be assessed. When considering behaviors, it is important to recognize that there are three general attitudes toward risk: risk averse, risk neutral, and risk seeking [7]. To determine where an individual falls on this continuum, expected utility calculations are used to account for the decision-makers' risk behavior in determining the best alternative. The key parameter in basic utility function calculations is the multi-attribute risk tolerance ($\rho_m$). Positive and negative $\rho_m$ values represent risk-averse and risk-seeking behavior, respectively. Any value of $\rho_m$ generally greater than 10 or less than -10 represents a straight line indicating risk neutrality [7]. As one moves away from neutrality, risk-averse behavior becomes more pronounced as $\rho_m$ values begin to approach zero from the positive side. Similarly, risk-seeking behavior becomes more pronounced as $\rho_m$ values begin to approach zero from the negative side.

One common method to determine an individual's risk tolerance is to construct a decision tree in which the individual is given a 50/50 chance of selecting the best case or worst case scenario. After determining the expected value of this 50/50 scenario, the individual is asked to define a hypothetical alternative that would make him or her indifferent (i.e., E(U) = 0.5) to choosing between the best and worst case scenarios [4]. The value of the hypothetical alternative is calculated through the additive value function and $\rho_m$ is determined through the following equation [7],

$$0.5 = \frac{1 - e^{\left(-z_{0.5}/\rho_m\right)}}{1 - e^{\left(-1/\rho_m\right)}} \tag{1}$$

where $z_{0.5}$ is the value of the hypothetical alternative. The equation can then be solved for the individual's multi-attribute risk tolerance ($\rho_m$). The values for $\rho_m$ typically range from -0.5 (risk seeking) to 0.5 (risk averse). Most decision-makers (especially those making decisions in the public sector) tend to be more risk averse with a risk tolerance value of 0.2 [7].

After determining an individual's risk tolerance, the expected utility for each alternative being considered can be calculated using equations 2 through 4 [7]. During this process, all possible outcomes must be considered for each alternative. This can be a cumbersome process if there is more than one evaluation measure with uncertainty associated with it. For example, if an alternative has three possible scores for three different evaluation measures, there would be 27 possible outcomes.

$$V_{ji} = \sum \left(W_{jik}\right)\left(V_{jik}\right) \tag{2}$$

$$U_{ji} = \frac{1 - e^{\left(-V_{ji}/\rho_m\right)}}{1 - e^{\left(-1/\rho_m\right)}} \tag{3}$$

$$E\left(U_j\right) = \sum \left(P_{ji}\right)\left(U_{ji}\right) \tag{4}$$

where $V_{ji}$ is the value of alternative *j* for outcome *i*, $W_{jik}$ is the weight of alternative *j* for outcome *i* for evaluation measure *k*, $V_{jik}$ is the value for alternative *j* for outcome *i* for evaluation measure *k*, $U_{ji}$ is the utility of alternative *j* for outcome *i*, $\rho_m$ is the multi-attribute risk tolerance, $E(U_j)$ is the expected utility of alternative *j*, and $P_{ji}$ is the probability of alternative *j* for outcome *i*. Once the expected utilities are calculated for each alternative, the alternatives are rank ordered and sensitivity analysis is performed to determine if the DM's risk behavior has any impact on the results.

## RESULTS

The first step in the probabilistic analysis is to determine the decision-maker's multi-attribute risk tolerance ($\rho_m$). This was accomplished by using the alternative decision tree approach described earlier. Using this method, the value of the hypothetical alternative was calculated to be 0.184. The corresponding $\rho_m$ for this value was found to be 0.269 and indicates risk-averse behavior from the decision-maker [7]. Once the $\rho_m$ is known, the expected utility (E(U)) of the outcomes can be calculated using the power additive utility function equation. Since there were 27 possible outcomes to consider for each alternative; a summary of the expected utilities is shown in Table 3. In addition to the E(U) analysis, the expected values were also calculated by multiplying each value by its probability.

**Table 3. Summary of Expected Utility Values**

| | | Deterministic Analysis | Probabilistic Analysis | |
|---|---|---|---|---|
| **Rank** | **Alternative** | **Value** | **Expected Value** | **Expected Utility** |
| **1** | *H-Model* | 0.7865 | 0.7860 | 0.9697 |
| **2** | *Alt FMM* | 0.7176 | 0.7177 | 0.9538 |
| **3** | *FMM* | 0.6899 | 0.6900 | 0.9461 |
| **4** | *Dep* | 0.6653 | 0.6648 | 0.9383 |
| **5** | *Alt FRM* | 0.6558 | 0.6552 | 0.9352 |
| **6** | *PRV* | 0.6504 | 0.6503 | 0.9336 |
| **7** | *Q Fact* | 0.6400 | 0.6394 | 0.9297 |
| **8** | *FRM* | 0.5964 | 0.5964 | 0.9132 |
| **9** | *AME* | 0.5894 | 0.5889 | 0.9100 |
| **10** | *BUILDER* | 0.5343 | 0.5338 | 0.8840 |
| **11** | *Bottom Up* | 0.4989 | 0.5001 | 0.8691 |
| **12** | *Fac Ren* | 0.4044 | 0.4051 | 0.7975 |
| **13** | *Dergis Sherman* | 0.4013 | 0.4013 | 0.7943 |
| **14** | *CPV* | 0.3942 | 0.3942 | 0.7880 |
| **15** | *Renewal Fact* | 0.3876 | 0.3871 | 0.7817 |

As shown in Table 3, the ranking of alternatives from both types of probabilistic analyses are not only the same but also match the ranking from the deterministic analysis. Note that the scores from the E(U) analysis are higher than the other two sets of scores; furthermore, all of the possible alternatives score well compared to the hypothetical alternative shown. This is due the fact that the DMs are considered risk averse with a $\rho_m$ value of 0.269. Typically, alternatives with more uncertainty will score lower than those with less uncertainty. However, uncertainty did not have an impact on the alternative rankings because of the low weight assigned to each of the evaluation measures associated with the *Implementation* value (weights ranged from 0.0185 to 0.0555).

To illustrate the potential impact of more uncertainty, the deterministic and probabilistic analyses were calculated for a hypothetical case where the weight of *Implementation* increased to 0.333 (from 0.111) to reflect a change in the decision-makers' preferences for the first-tier values. The weight of 0.333 was selected because the sensitivity analysis conducted during the deterministic analysis revealed that the alternative rankings began to change as the weight of *Implementation* exceeded about 0.2. To keep the ratio of weights consistent, the weights of the other first-tier values, *Prevent Obsolescence* and *Credible Model*, were adjusted to 0.25 and 0.417, respectively. Table 4 shows a summary of the new deterministic and probabilistic rankings.

**Table 4. Summary table for revised weight of *Implementation***

| | | Deterministic Analysis | Probabilistic Analysis | |
|---|---|---|---|---|
| **Rank** | **Alternative** | **Value** | **Expected Value** | **Expected Utility** |
| **1** | *Alt FMM* | 0.7241 | 0.7242 | 0.9667 |
| **2** | *FMM* | 0.7031 | 0.7032 | 0.9620 |
| **3** | *Alt FRM* | 0.6789 | 0.6778 | 0.9553 |
| **4** | *PRV* | 0.6549 | 0.6548 | 0.9474 |
| **5** | *Depreciation* | 0.6506 | 0.6505 | 0.9416* |
| **6** | *H-Model* | 0.6446 | 0.6431 | 0.9396* |
| **7** | *FRM* | 0.6381 | 0.6381 | 0.9447* |
| **8** | *Q Factors* | 0.5703 | 0.5685 | 0.9223 |
| **9** | *Bottom Up* | 0.5391 | 0.5427 | 0.9141 |
| **10** | *AME* | 0.5298 | 0.5287 | 0.8990 |
| **11** | *BUILDER* | 0.4573 | 0.4557 | 0.8525 |
| **12** | *Dergis Sherman* | 0.4374 | 0.4374 | 0.8444 |
| **13** | *CPV* | 0.4321 | 0.4321 | 0.8407 |
| **14** | *Fac Ren* | 0.4294 | 0.4314 | 0.8403 |
| **15** | *Renewal Fact* | 0.4094 | 0.4084 | 0.8283 |

* NOTE: Scores are no longer in numerical order; this shows that FRM moves up to 5$^{th}$ place in the rankings.

As Table 4 shows, increasing the weight of *Implementation* and altering the weights of the other first-tier values accordingly caused the deterministic rankings to change. Additionally, while the rankings from the deterministic analysis and expected value analysis agree, the rankings between the deterministic and probabilistic analyses in Table 4 differ. One major difference which illustrates the effect of uncertainty is that the FRM moved up in ranking. The FRM has the least uncertainty because it is currently in use; therefore, the decision-makers were knowledgeable about it and able to better predict the implementation hours. This shows how alternatives with less uncertainty score better for a risk-averse decision-maker. Although the level of uncertainty had no impact on the alternative rankings at the original weights, uncertainty impacts the results as the weight of *Implementation* increases.

In the deterministic analysis, sensitivity was assessed by varying the weights of the values to determine if the ranking of alternatives changed. In the probabilistic analysis, sensitivity is assessed by varying the decision-makers' risk tolerance ($\rho_m$) to determine if the risk behavior of the DMs has any bearing on the alternative ranking. Using the E(U) calculations, the utility values were found for each alternative as the $\rho_m$ values were varied to represent risk-seeking behavior ($\rho_m$ = -0.1 and -0.5), risk-neutral behavior ($\rho_m$ = 10), and risk-averse behavior ($\rho_m$ = -0.1 and -0.5). For all $\rho_m$ values, the ranked order of alternatives did not change and the H-Model remained the best alternative. Therefore, the results were considered to be independent of the decision-makers' risk behavior.
To further examine the potential impact of a change in risk tolerance level, another realistic scenario was created in which the scores for each of the *Implementation* evaluation measures for the FMM alternative was assumed to span the gamut from 0-2000 hours. Since the FMM is an existing model for which the decision-makers could provide a tight prediction, expanding the ranges of scores essentially introduced uncertainty. The results, shown in Table 5, indicate that the ranking of the FMM increases for a risk-seeking decision-maker. In fact, the FMM moves up three positions for an extremely risk-seeking decision-maker and only one position for a more conservative risk-seeking decision-maker. Similarly, the FMM moves down two positions for an extremely risk-averse decision-maker.

## CONCLUSIONS

For the deterministic analysis, the H-Model was found to be the most preferred alternative; however, the ranked order of the other alternatives was sensitive to changes in the weights. To take the analysis one step further, the multi-attribute risk tolerance ($\rho_m$) of the decision-makers was assessed, and the decision-makers were subsequently considered risk averse ($\rho_m$ = 0.269). Initially, there were no changes in the ranking of the alternatives between the deterministic and probabilistic analyses, thereby indicating that incorporating uncertainty had no impact on the model results. However, as the weight of the *Implementation* value increased, there were several changes in both the deterministic and probabilistic analyses. Sensitivity analysis during the E(U) analysis showed that the alternative rankings were independent of the decision-makers' risk tolerance level. The alternative rankings were also insensitive to the probabilities included in alternative scores in the *Implementation* values and that the preferred alternative was consistent throughout. However, an increase in the weight of *Implementation* during the probabilistic analysis had a significant impact on the preferred alternative and the alternative rankings. Furthermore, an increase in the amount of uncertainty in the model could result in changes to the results as the DMs' risk-behavior changes. Knowing that the model outcomes are independent of the uncertainties that were introduced and the risk-behavior of the decision-makers should increase the decision-makers' confidence in the model and their decision.

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**Table 5. Revised sensitivity of $\rho_m$**

| $\rho_m$ = | 0.269 | Risk Seeking | | Risk Neutral | Risk Averse | |
|---|---|---|---|---|---|---|
| **Alternative** | **E(U)** | $\rho_m$ = -0.1 | $\rho_m$ = -0.5 | $\rho_m$ =10 | $\rho_m$ = 0.5 | $\rho_m$ = 0.1 |
| Alt FMM | 0.9667 | 0.1020 | 0.5762 | 0.7800 | 0.9095 | 0.9996 |
| Alt FRM | 0.9553 | 0.0630 | 0.5087 | 0.7334 | 0.8844 | 0.9993 |
| PRV | 0.9474 | 0.0472 | 0.4715 | 0.7052 | 0.8683 | 0.9991 |
| FRM | 0.9456 | 0.0443 | 0.4636 | 0.6990 | 0.8646 | 0.9990 |
| FMM | 0.9435 | 0.0576* | 0.4765* | 0.7035* | 0.8639 | 0.9986* |
| Depreciation | 0.9416 | 0.0393 | 0.4480 | 0.6863 | 0.8569 | 0.9989 |
| H-Model | 0.9396 | 0.0377 | 0.4415 | 0.6807 | 0.8532 | 0.9988 |
| Q Factors | 0.9223 | 0.0224 | 0.3840 | 0.6312 | 0.8214 | 0.9980 |
| Bottom Up | 0.9120 | 0.0175 | 0.3572 | 0.6059 | 0.8037 | 0.9974 |
| AME | 0.8990 | 0.0134 | 0.3292 | 0.5777 | 0.7827 | 0.9964 |
| BUILDER | 0.8525 | 0.0056 | 0.2531 | 0.4930 | 0.7137 | 0.9916 |
| Dergis Sherman | 0.8444 | 0.0049 | 0.2423 | 0.4800 | 0.7023 | 0.9906 |
| CPV | 0.8407 | 0.0046 | 0.2381 | 0.4746 | 0.6974 | 0.9901 |
| Fac Ren | 0.8403 | 0.0046 | 0.2376 | 0.4740 | 0.6968 | 0.9900 |
| Renewal Fact | 0.8283 | 0.0040 | 0.2254 | 0.4577 | 0.6813 | 0.9880 |

* NOTE: Scores are no longer in numerical order; this shows that FRM moves up to 5$^{th}$ place in the rankings.

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