Keywords: *Decision Cost Model (DCM), Decision Tree Node, Cost-Overrun Percentage, Probability, Pearson-Tukey Method*

Decision Cost Model for Contractor Selection

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As U.S. Government facilities age and new facilities are constructed, the need to hire contractors for an increasing number of government construction projects is imperative. The current government technical evaluation for contractor selection is less than optimal. This article introduces an alternative technical evaluation methodology to the current government contractor selection process: a Decision Cost Model (DCM) that can be applied to ensure cost-efficient contractors are selected in awarding construction contracts. Applying the DCM ensures contractors with the lowest expected total cost are recommended for project awards. Also presented are ways DCM can be applied to increase efficiency in the selection process for future government construction projects, while simultaneously meeting taxpayers' expectations of receiving maximum value for their tax dollars.

image designed by Diane Fleischer »


800
750
700
650
600
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350
12/10
11/10

Applying decision cost analysis provides the U.S. Government an alternative to the existing process for selecting construction contractors. The Decision Cost Model (DCM) proposed in this article evaluates each prospective contractor against computed cost factors and uses the contractor's cost estimates to compute the total expected cost for construction projects. The DCM can be used with any number of contractors and with any number of construction division categories.

The assessment of cost overruns is based on an evaluation of historic data from recent/similar projects undertaken by government contractors. The model considers five recent/similar projects for each contractor. In general, the more recent/similar projects used in the modeling analysis, the better the modeling of total expected cost. In the event a contractor does not have similar project data, the contractor is omitted from the contractor selection pool. The DCM considers cost factors for specific construction division estimates and cost-overrun percentages. Applying the DCM requires the evaluator or project managers to collect historical cost data to compute the division cost factors. In many cases, historical cost data available for the project cost analysis may be limited. However, with expert judgment and careful evaluation of each division cost factor, the program manager (PM) can ensure each contractor is evaluated equitably. Note that just about every division has the potential of cost overruns. Those without a cost overrun indicate the contractor has cost control over the underlying construction division(s), and this control of costs will not negatively impact the total expected cost of the project.

For purposes of this study, the DCM method is applied using the example of three contractors and three cost factors and their computed division cost overrun percentages. The DCM application compares division costs for electrical, structural, and mechanical contractor expenditures. The cost factors are modeled using historical data and expert judgment combined with a probability model to fit a cost-overrun percentage distribution for each cost factor. The Pearson-Tukey method is used to apply cost-overrun probabilities to chance nodes in a three-outcome decision tree (Clemen, 2001). The central idea is to find three representative points in the distribution and assign respective probability values to each outcome. Accordingly, the Pearson-Tukey method allows the PM to pick the most representative points and probability values for each cost factor.

The intent of this article is to demonstrate the development of the DCM decision method and apply the method with an example utilizing real-world data. The DCM method gives an approximation of how division cost-overrun percentages impact the division estimate and the total expected cost for the project (Clemen, 2001). Hence, the DCM method provides a novel way to improve future government contractor selections for awarding government construction projects. The DCM improves the existing contractor selection process by adding an evaluation of potential cost-overruns in computing the total expected cost for a project.

The next three sections of the article describe the current project award process and how the DCM can easily be inserted into the current process; introduce a cost factor data table; and provide a complete description of the DCM and its methodology. Following the DCM methodology, the article discusses applying the DCM in depth, using a real-world example with historical cost data and expert judgment. Finally, the article concludes by reporting the DCM total expected project costs and the author's recommendation for future use of the DCM.

Current Project Award Process

"Best value technically acceptable" is a term used by the government to select a project contractor meeting the technically acceptable criterion at least cost (General Services Administration, 2005). If a contractor has the lowest cost estimate and has met the technically acceptable criteria, then the contractor is awarded the project contract. The current government "best value technically acceptable" criterion does not take into account the impact of potential project cost overruns on the final cost of a government project. This is a shortcoming in conducting feasibility analysis for construction projects.

Government construction projects are projected years in advance of their purposed construction or operation. To understand the needs, requirements, and budget allocation for constructing facilities, government decision makers require more accurate feasibility studies. In general, a feasibility study contains a needs analysis, mission requirements, and cost estimate for the project. Consequently, the feasibility study is instrumental in awarding project contracts. The government cost estimate contained in the feasibility study provides guidance in the solicitation of contractors for the project. Generally, the contractor solicitation for a given construction project will request two forms of cost information: a project cost estimate for a facility meeting the projected needs and performance standards, and the projected contractor's historical cost and performance data relevant to the project. The aim is to forecast the costs required to complete the construction project in accordance with the contract and plans. Construction project estimation is a difficult and time-consuming process. Engineering and contractor experience are needed to complete a good estimate. The PM must assume the roles of both contractor and engineer to ensure sound contracting and engineering principles are adhered to in the construction project.

The government PM represents the taxpayer and is responsible for developing the construction project's Independent Government Estimate (IGE). Because construction projects are projected years in advance of their need, the government PM will prepare a current year IGE for the project. The current year IGE is utilized to perform the technical evaluation and compare the project cost estimates submitted by contractors. The current IGE represents the total estimated cost of the project and division estimated costs. The IGE is developed using *RSMeans,* an industry standard for construction cost estimation. *RSMeans* is a division in Reed Construction Data that provides costs by discipline format, site prep, mechanical, and electrical. The division specializes in providing material, labor, and building cost information to the North America construction industry. (Note that RSMeans cost data are updated annually and delivered in a book or software application.)

The Construction Specifications Institute (CSI) is an organization that maintains and advances the standardization of construction language, as pertains to building specifications. CSI Master Format is an indexing system for organizing construction data and construction specifications. For purposes of this article, the CSI Master Format considers 16 divisions of construction costs. *RSMeans* cost data are available on a software program called *CostWorks* and in *RSMeans* construction cost data manuals. *RSMeans* is a cost data source, which has 45,000 separate cost line items for all areas of construction. Each cost line item represents data collected to represent the mean average of material, labor, and equipment. This cost is gathered from 30 cities throughout the United States. The *RSMeans* database is updated annually, and the data are adjusted to the area of the country where the construction is occurring. For the purpose of construction cost estimation, the *RSMeans* data come in two formats: *RSMeans* 2004, which has a 50-division format, and *RSMeans* 1998, which has a 16-division format. Both formats have the same basic information, with *RSMeans* 2004 separated into the basic information, which is further separated into more specialty divisions.

RSMeans 1998 defines construction disciplines by 16 separate areas identified as divisions:

1. Division 1 is "General Requirements." General Requirements are items such as supervisor, project manager costs, vehicles, and other general items required for construction.

2. Division 2 is "Site Construction." Site Construction is dirt work, surveys, and the site preparation required for building construction.

3. Division 3 is "Concrete." Due to the expense involved in concrete and the volatile market for concrete, this must be identified separately.

4. Division 4 is "Masonry." This section identifies block work in basements, fencing, and subfloor needs.

5. Division 5 is "Metals." This identifies all metal materials used for construction, including siding, studs, and metal work.

6. Division 6 is "Woods and Plastics." This area identifies all doors, hardware, and special Panduit® products (pertaining to tubing, panels, electronic cables, etc.).

7. Division 7 is "Thermal and Moisture Protection." This identifies items involved in insulation, vapor-barrier protection, and sealants.

8. Division 8 is "Doors and Windows." This includes any that may be required to support the project.

9. Division 9 is "Finishes." Finishes include paint, flooring, and molding.

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10. Division 10 is "Specialties." Specialties include alarm systems and all other special equipment. This could pose huge variability in project costs.

11. Division 11 is "Equipment." This includes items located inside the building, such as safes, electronics, and any other types of equipment (other than Division 15 Mechanical) that could be considered a permanent item inside the building.

12. Division 12 is "Furnishings." This includes items such as furniture for offices or millwork.

13. Division 13 is "Special Construction." This encompasses items that may fall outside normal construction. This would include fire protection and special electronic needs.

14. Division 14 is "Conveying Systems." This includes special furnishings.

15. Division 15 is "Mechanical." This includes heating, ventilation, cooling, and special operations of doors or ventilation systems.

16. Division 16 is "Electrical." This addresses electrical supplies used for any electrical needs inside or outside the building. It also includes items that may be used to supply power to the building.

Decision Cost Model

The DCM proposed in this article can be implemented at the technical evaluation stage in selecting a contractor for a given construction project. The proposed model computes the total expected costs of a construction project by modeling cost-overrun percentages for each division cost factor combined with the division cost estimate. The DCM utilizes the same contractor historical data and estimates that are used in the current contractor selection process. The key difference between the current contractor selection process and applying the proposed method is allowing a more detailed evaluation of each division's estimate and the impacts of cost-overrun percentages computed from similar projects. The DCM uses the existing estimates and cost factors to determine which contractor offers the lowest expected construction project costs.

The DCM model takes into account all estimated costs, cost-overrun percentages, and PM expert judgment of cost-overrun risk. The DCM uses the same common *RSMeans* format for comparing contractor's cost estimates, thus reducing subjectivity in the selection process. The DCM uses commercially available software to facilitate contractor selection for project awards. By identifying the lowest total cost contractor for the project, the DCM provides expected value information for improving efficiencies in allocating taxpayer funds for government construction projects.

The DCM example used in this article compares three prospective contractors for a real-world project, identified as Contractors 1–3. The cost estimate data used for calculations are "total estimate" and "percent change" in division costs. Based on the 16 potential cost divisions in *RSMeans*, the study assumes the PM has selected three cost-overrun divisions facing cost-overrun risk. The corresponding cost-overrun factors are: cost factor 1–mechanical, cost factor 2–finish, and cost factor 3–electrical.

To apply the DCM, the PM must specify a probability model for each cost factor under consideration. The beta–general distribution is well suited for cost analysis under uncertainty. The beta distribution is parsimonious and flexible when applying expert judgments. However, in applying the beta distribution in cost analysis, the PM must estimate best-fit parameters. The approach taken in this article is to calculate these parameters by minimization of absolute difference of the probability distribution estimates for various cost-overrun percentages. Accordingly, the following approach is used to pick the best parameter set for cost factors in the [0,1] range $Min\ \sum_{i=1}^{n} d_i$ where $d_i = \left|\int_a^{y_i} f_B\,(y_i) - \int_a^{y_i} \hat{f}_B(y_i)\right|$ are absolute differences of probability distribution estimates for various cost-overrun percentages, with "*B*" subscript denoting the beta distribution. The y_i values are cost-overrun percentage fractiles, expressed as a number in the [0, 1] range for the factor in question. These cost-overrun percentage fractiles and the PM-assessed distribution fractile, i.e., $\hat{f}_B$ combine actual data and expert judgment.

The objective is to find beta distribution parameters for the lower bound "a" and upper bound "b" denoted by α_1, α_2. This ensures the modeled beta distribution $\hat{f}_B$ is the best approximation for various cost-overrun factors. The probability model combines historical data and expert judgment, thus giving the PM the ability to accurately define the boundary location and scale parameters for each cost-overrun percentage cost factor—location giving the minimum bound and scale giving the range between maximum and minimum bounds. This approach allows the PM to apply expert judgment in specifying the impact of cost-risk affecting each cost factor. The PM can easily modify cost-overrun percentages and fractile parameters to re-calculate cost-risk by introducing new cost-overrun percentages and fractiles from the distribution.

To apply the probability model in the decision analysis, this article uses the Pearson-Tukey method. The Pearson-Tukey method gives the PM the ability to easily compute expected costs and their upper/lower bounds using the discrete-form representation of the beta-general distribution. Using this technique, the division cost-overrun percentage and related probabilities are implemented in a three-chance node decision tree. The three-point approximation uses the .05, .5, and .95 fractiles associated with the realization probabilities of 18.5 percent, 63 percent, and 18.5 percent respectively. The resulting solution gives the total expected costs for the project, whereby each division cost factor value (in the tree) is accounted for in the estimating contractor's total cost for the project. Thus, the DCM shows which contractor has the greatest likelihood of minimizing the total expected project cost (Clemen, 2001).

Cost Factor Data Table

Historic project cost data are summarized in the Cost Factor Data (CFD) Table. The table contains a summary of the contractor's division estimate, initial project cost, actual project cost, computed cost-overrun percentage for each project, and the Pearson-Tukey approximated values. Table 1 is an example of Contractor 1 Mechanical Cost Factor. The top header contains the initial cost, actual costs, and cost-overrun percentage. The pink area contains the Mechanical division five previous projects, initial estimate, actual costs, and cost-overrun percentage. The blue shaded area contains the preliminary computed and expert judgment applied minimum, median, and maximum cost-overrun percentages. The green shaded area in Table 1 contains the Pearson-Tukey approximation and the fractile cost-overrun percentage values and probabilities.

TABLE 1. CONTRACTOR 1 MECHANICAL COST FACTOR DATA TABLE

Mechanical				
		Initial	***Actual***	***% Over***
Renovation 1		39000	65000	0.666666667
Renovation 2		78000	96000	0.230769231
Renovation 3		595000	635000	0.067226891
Renovation 4		26000	32000	0.230769231
Renovation 5		464000	52000	0.120689655
		Expert Judgment		
Upper Bound		0.666666667	0.230769231	
Lower Bound		0.067226891	0.067226891	
Median		0.230769231	0.175729443	
Pearson-Tukey Fractile		Value	Probability	
	0.95	0.3839	0.185	
	0.5	0.175	0.63	
	0.05	0.0468	0.185	

DCM Methodology

The DCM methodology may be summarized as follows: development of division cost factors, computation of division cost-overrun percentages, and model of cost factors. There must be a preliminary fit regarding a beta-general distribution as well as an application of expert judgment on a case-by-case basis. Consider model minimization beta distribution from the cost factor, cost-overrun percentages, and fractiles. Additionally, there should be a utilization of the modeled output parameters to generate a beta-general distribution. The PM must also apply the Pearson-Tukey method to approximate the cost-overrun percentage and fractile. The DCM methodology is described in the following five-step process to compute cost-overrun percentage distribution:

1. For each of the three cost factors to generate a preliminary beta-general distribution from the observed five cost-overrun percentages, the PM uses expert judgment, as necessary, to

modify division cost-overrun percentage input parameters. The PM will then go to Step 2 with a reasonable fractile and cost-overrun percentage for the cost factor.

2. The PM models the beta distribution parameters. Many different software packages can be used to solve the formula. This example uses an author-developed minimization solver in Excel. The PM observes the fitted distribution and determines if modification to the distribution is needed. The PM uses the computed cost-overrun percentages and Comulative Distribution Function (CDF) curve to estimate the fractile and bounds to create the best distribution to represent each cost factor. The model then computes the beta distribution parameters.

3. The beta-general distribution will be generated by the minimization process as described in Step 2.

4. Application of the Pearson-Tukey method will be used to turn the continuous distribution into a three-outcome chance node for the decision tree.

5. Completion of the decision tree will be accomplished in determining which contractor has the lowest total expected cost for the project. The PM must examine the input contractor's total estimate, cost factor division cost estimate, and the modeled computed cost-overrun percentage as well as the probability parameters, and subsequently figure them into the DCM Influence Table. (See Table 8).

DCM Example

The beta distribution minimization is the key to identifying the total lowest expected cost contractor for the project. The DCM minimization distribution requires a fractile, which is determined to associate with each cost-overrun percentage. The modeled distribution will be demonstrated with real data provided by the contractor. This creates a project cost-risk baseline. Next, the model distribution will be demonstrated with real data and applied expert judgment. Essentially, the applied expert judgment distribution utilizes the same division cost factor fractile determination and cost-overrun percentage method. The DCM example is demonstrated with real cost-overrun percentage data from the Contractor 1 Mechanical cost factor. The only difference with the applied expert judgment example is due to the fact that the PM develops a more accurate prediction of project cost-overrun risk.

In general, fractiles are defined as the points between the range [0, 1] in a distribution. The DCM may use predefined quartiles such as the first quartile = .25, the median = .5, and the third quartile = .75. Although these fractiles may be used for cost-overrun percentage modeling, a more accurate fractile model is needed. Both examples demonstrate a more accurate method for determining fractiles for cost-overrun percentages. The model selects specific cumulative probabilities and associates corresponding fractiles. The cumulative probabilities and the fractile determination method used in the model are estimated from a Cumulative Distribution Curve (CDC) generated from fitted beta general cost-overrun percentage distribution. From the CDC, the PM determines each fractile by estimating CDC distribution of the input p-values to the fitted p-values fractiles (Clemen, 2001). The key idea is to determine the best fractiles using fitted cost-overrun percentages that can be applied to the data set for the computation of the distribution. From the curve of the CDC, the PM estimates the cumulative probability value of the cost-overrun percentage to determine the CDF fractile values for the model.

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For purposes of this computation, the PM will associate each of the five cost-overrun percentage points with five fractile values. Other computation parameters needed are the extreme distribution bounds from the five cost-overrun percentage data. The distribution of the lower boundary will be 0, and the upper boundary will be the cost-overrun percentage plus .1. The CDC estimated the p-value to fitted p-value fractile is inputted into the model. CDF fractiles selected from the CDC are as follows: point .1 is used as the first fractile, the estimated second fractile, the median, a fourth fractile, and the fifth fractile.

A general recommendation for fractile determination is to analyze the computed median and the upper bound $P(X <= x) = .9$. The assumption of the median is the key starting point, and the 90 percent fractile is a reasonable upper boundary because it's a number that construction estimators and/or construction-contract managers can understand. This model makes it possible to determine the fractile values based on the CDC distribution. The model uses a three-step process to compute five fractiles needed to define the alpha 1, alpha 2, and the minimum and maximum boundaries. These parameters are needed to model the beta-general distribution necessary for application of the Pearson-Tukey method.

1. Step 1: Fit the data.

2. Step 2: Estimate the CDC P-values to fitted p-value distribution points and adjust model fractile input to compute fractile. Review match criteria of .1.

3. Step 3: Input computed alpha 1, alpha 2, min and max to fit the Pearson-Tukey distribution.

The first step involves fitting the cost-overrun Contractor 1 with the Mechanical cost-overrun percentage in real data. Contractor 1 Mechanical Division has five historical cost-overrun percentages as follows: .0672, .1206, .2307, .2307 and .6667. The data are limited to five data points with a range of 6.072 percent –-66.67 percent cost-overrun percentage. Note the duplicate 23.07 percent cost-overrun percentage. This may be a concern, but demonstrates how the real data are modeled. The preliminary beta-general cost-overrun data fit the results in Figure 1—28.8 percent median, alpha 1 = .194, alpha 2 .2307, min .067, and max = .6667.

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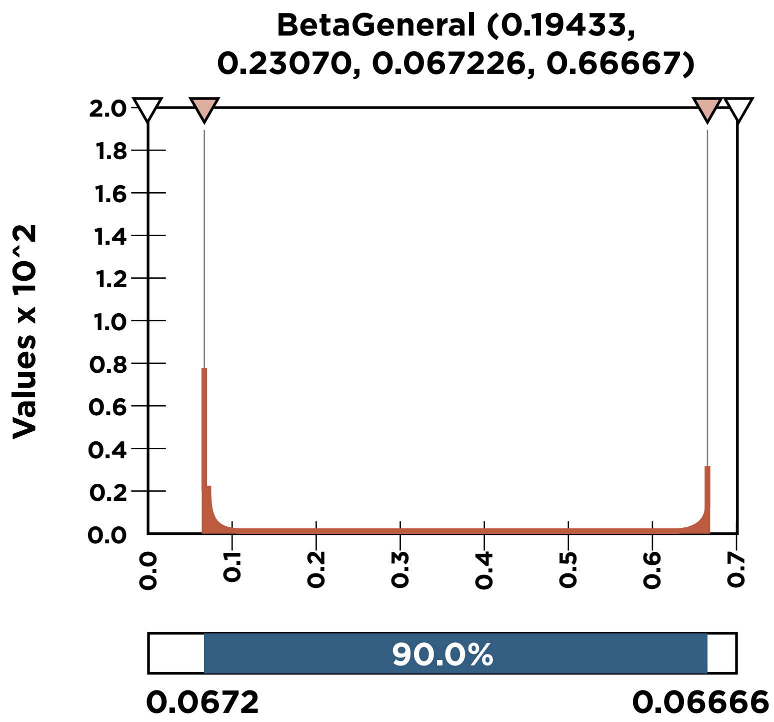
FIGURE 1. CONTRACTOR 1 MECHANICAL COST-OVERRUN PERCENTAGE FITTED REAL DATA.

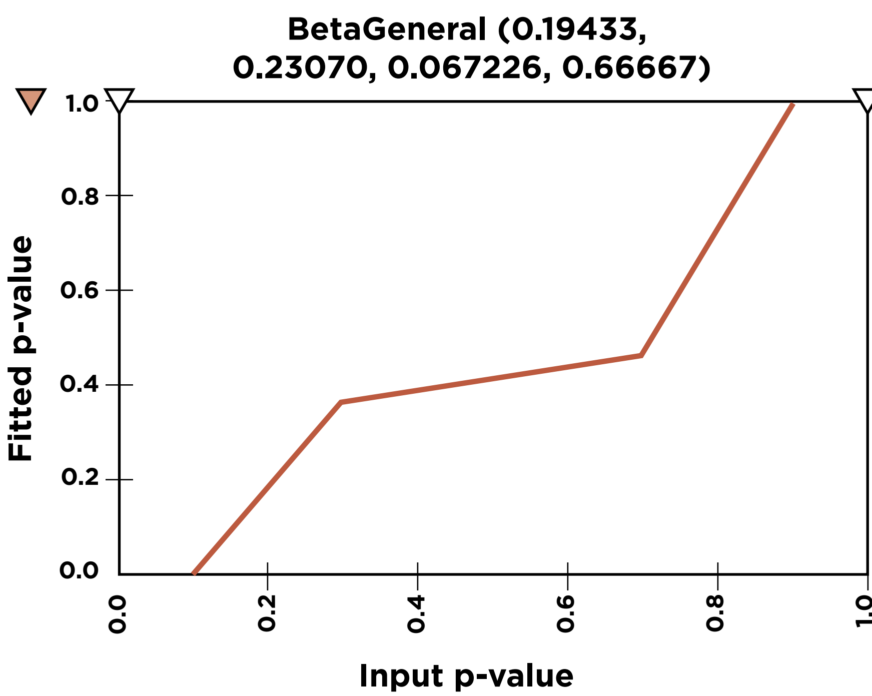


Note. *Adapted from "Making Hard Decisions with Decision Tools," by R. T. Clemen, 2001.*

The second step is to estimate the CDC p-values to fitted p-value distribution points and adjust model fractile input to compute fractile. Review match criteria of .1. Fit the beta-general distribution, and estimate the five fractile points using the CDC. Determine the fractile data points by estimating each distribution point of the p-value to the fitted p-value point by evaluation of the slope of the CDC. Through evaluation of the Contractor 1 mechanical cost-overrun percentage real data CDC curve, one can estimate the p-value/fitted p-value origin fractile as (0, .1), with the first fractile at (.3, .4), the next fractile at (.7, .5), and the fractile termination at (.9, 1). The points in the parentheses (x, y) are points on the CDC curve. From these estimated points, the first fractile is estimated .1. The next fractile, .2, is estimated from the distribution points between point (0, .2) and (.3, .4) on the CDC. The next two fractiles are .49 and .5, and are estimated between (.3, .4) and (.7, .5) on the CDC curve. The

CDC fractile termination will indicate the fifth fractile to be in the 90 percent quartile. Using this estimation method, the PM can estimate the CDF fractile model values as shown in figure 2 (Clemen, 2001, p. 403).

FIGURE 2. CONTRACTOR 1 MECHANICAL REAL DATA FITTED P-VALUE/INPUT P-VALUE CURVE



Note. Adapted from "Making Hard Decisions with Decision Tools," by R. T. Clemen, 2001.

The PM will model the minimization beta distribution. The PM will input each cost-overrun percentage in progression with the associated fractile into the model; 6.72 percent = .1, 12.06 percent = .2, 23.07 percent = .49, 23.07 percent =.5, and 66.67 percent = .9. The model utilizes a beta distribution, which returns the cumulative beta probability density of the inputted cost-overrun percentage and the inputted CDF fractile. The result is a computed fractile, which the PM compares to the inputted CDF fractile. If the computed fractile is within .01 of the inputted CDF fractile, the PM considers this a computed fractile match. The PM then utilizes the modeled output parameters—alpha 1, alpha 2, and the min and max—to fit the beta-general distribution.

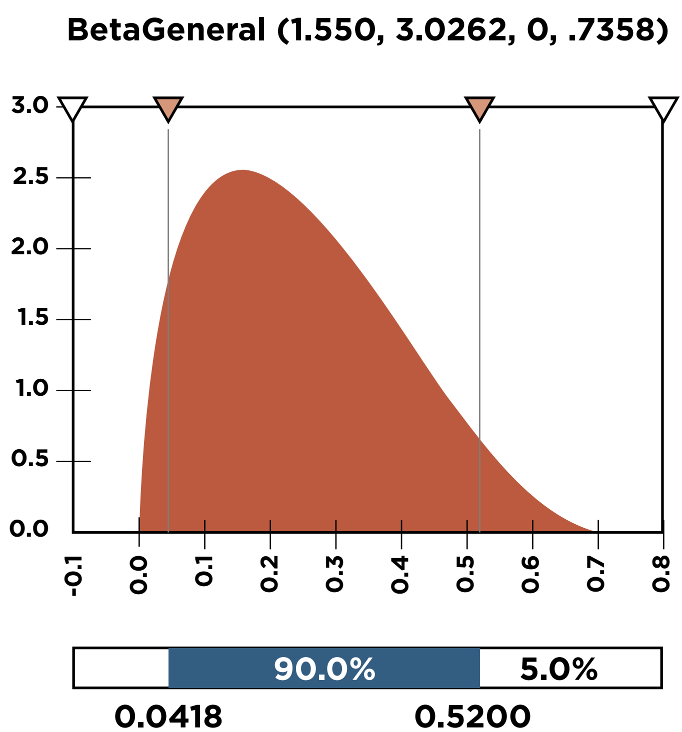
The Contractor 1 Mechanical cost-overrun real example results are alpha 1 = 1.55, alpha 2 = 3.026, min = 0, and max = .73. The parameters are used to fit a beta-general distribution for estimation of the Pearson-Tukey overrun percentage and probability values used in the decision tree. Table 2 displays the model with the beta-distribution computation of the fractile from the cost-overrun percentage and CDF fractile inputs. Note the CDF fractile is computed within the .15 range—a PM-considered match. This will indicate that the alpha 1, alpha 2, and the min and max are ready for the next step—fit the beta-general Pearson-Tukey distribution.

TABLE 2. CONTRACTOR 1 MECHANICAL FRACTILE REAL DATA SOLVER

Step 2:					
	Objective Function		0.133445735		
		alpha 1	**1.550436497**		
		alpha 2	**3.026241986**		
		max	**0.735866163**		
		min	**0**		
0.248449		Overrun %	CDF Fractile	Computed	
		0.0672269	**0.1**	0.1	Fitted
		0.1206897	**0.2**	0.225208	0.249222
		0.230769	**0.49**	0.499879	
		0.230769	**0.5**	0.499879	
		0.66667	**0.9**	0.998237	

The third step involves determining the Pearson Tukey overrun percentage and probability values. The computed model results are as follows: alpha 1 = 1.55, alpha 2 = 3.02, min = 0, and max = .73. Parameters are used to model the beta-general distribution. The Pearson-Tukey method is applied to identify the cost-overrun percentages and 5 percent, median, and 95 percent probabilities for the decision tree. Through application of the Pearson-Tukey method, the PM estimates the 95 percent fractile is equal to the probability of 18.5 percent, with a cost-overrun of 52 percent. The median fractile probability is equal to 63 percent, with a 23.07 percent cost-overrun. The 5 percent fractile is equal to the probability of 18.5 percent, with a cost-overrun of 4.18 percent. These values are entered into the decision tree to compare each contractor's project cost-overrun risk to their project completion. Figure 3 depicts the Contractor 1 Mechanical real data fitted beta-general distribution results from the modeled parameters.

FIGURE 3. CONTRACTOR 1 MECHANICAL REAL DATA DISTRIBUTION



Note. Adapted from "Making Hard Decisions with Decision Tools," by R. T. Clemen, 2001.

Fractile Determination with Applied Expert Judgment

Figure 4 reflects the Contractor 1 Mechanical cost-overrun percentage with applied expert judgment. The modeling and fractile determination process are the same as modeling with real data. The main difference is the PM applies expert judgment to the real data to adjust cost-overrun outliers. Because of limited data provided by the contractor, the PM must rely on experience and sound judgment to make any adjustments to the data set. Using expert judgment, the PM modifies distribution parameters to best represent the contractor. The PM accomplishes the modification by careful evaluation of the project scope of work to be performed, division cost-overrun percentage range, and identification of cost-overrun outliers.

The PM must also understand the many factors that impact a cost-overrun risk on a construction project. The PM uses past experience to reasonably evaluate the cost-overrun risk to the project. Some common cost-overrun examples are: unclear documented scope of work, unforeseen problems, project location, and abatement of facility. These examples are common and add enormous cost to a construction project. A prime contractor's project experience on special projects and a prime contractor's experience with the subcontractor also impact the cost-overrun risk. Lower cost-overrun risk occurs when a prime contractor has an established, longstanding relationship with a subcontractor. The project tends to run more effectively with better cost control.

The construction industry identifies the contractor responsible for the overall project as the "prime contractor." The subcontractor works for the "prime contractor." An example of a prime contractor with a limited working relationship with a subcontractor is what the construction industry calls a construction broker. These construction brokers estimate a construction project and hire local subcontractors to complete the project. Because of lower overhead and remote capability, a construction broker's estimate may be lower than other prime contractors. Because of limited working relationships with local subcontractors, the prime contractor broker incurs large project cost-overruns. Other cost-overrun examples include: subcontractor experience, project location (whether the project is in a city or in the middle of a desert), and weather (such as snow, wind, and rain). All these variables influence the PM's expert judgment application to division cost factors.

Every division cost factor is modeled independently of one another. For example, the mechanical cost-overrun percentage does not depend on the cost-overrun (or any other) estimate such as electrical or finish. Division cost factors such as mechanical and electrical are primarily managed by independent subcontractors. The finish division cost factor is also independent from the other cost factors and is primarily managed by the "prime" contractor. The prime contractor is the contractor who is responsible overall for the project and the subcontractors' division impacts.

The DCM process is accomplished in the following Steps 1 through 3.

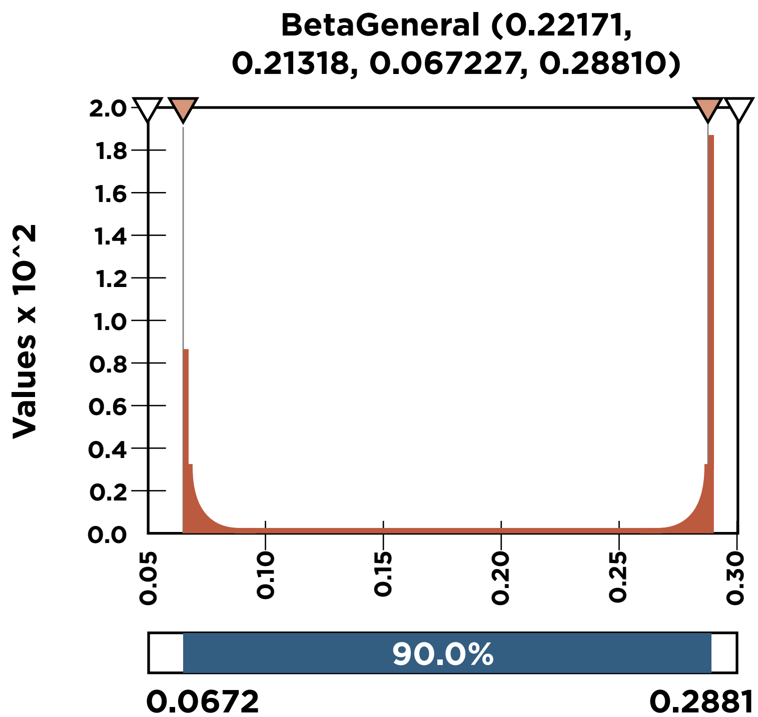
Step 1

The first step is to review the divisional "real" data and apply expert judgment to determine the most likely cost-overrun percentage and, if needed, determine the least likely cost-overrun percentage. The observation of Contractor 1 Mechanical cost-overrun percentage is that 4 of the 5 cost-overrun percentages are in the range between .067–.2307. The PM has determined that the .6667 cost overrun appears to be an outlier. This cost-overrun is from a lower cost mechanical project where minor changes in cost amplify a larger change in cost-overrun percentage. This mechanical project initial estimate was $39,000, and the final actual cost was $65,000. After review of the contractor's initial proposal, the PM had determined the contractor initially estimated this mechanical division estimate as a repair of the existing mechanical system. The contractor's good-faith estimate was proposed to save materials, labor, and the ability to use the existing system. After further analysis, the mechanical project became a total mechanical replacement, thus reflected in the actual cost, not in the good-faith estimate.

With limited data to evaluate the contractor, and judging from the cost-overrun percentages, 4 of the 5 are less or equal to 23.07 percent cost-overrun percentage. More than likely, a 23.07 percent or smaller cost-overrun may occur, while a cost-overrun of 66.67 percent is least likely. Contractor 1 proposed this mechanical project for $480,000. From the contractor project real data, the contractor's two similar mechanical projects were for $595,000 and $464,000; the contractor had a 6.7 percent and 12 percent cost-overrun respectively. Because of risk to costs, the PM cannot completely discount the 66.67 percent cost-overrun, so the PM will use the complete contractor mechanical real cost-overrun dataset (.067-.66667) to compute the median .2881. The high median is driven by the one high .6667 cost-overrun percentage. The PM will replace the .6667 cost-overrun percentage with the median .2881 and input into the cost-overrun percentage in the 5th fractile of the model. Keep in mind that this will be the only applied expert judgment made to the Contractor 1 Mechanical overrun percentage dataset.

The Contractor 1 Mechanical real cost-overrun percentage (Figure 1) fits beta-general distribution with a computed median .2881. The PM determines this is a better representation of the Contractor 1 Mechanical cost-overrun. Next, determine the fractiles using the developed model and proceed to Step 2.

FIGURE 4. CONTRACTOR 1 MECHANICAL APPLIED EXPERT JUDGMENT REAL DISTRIBUTION

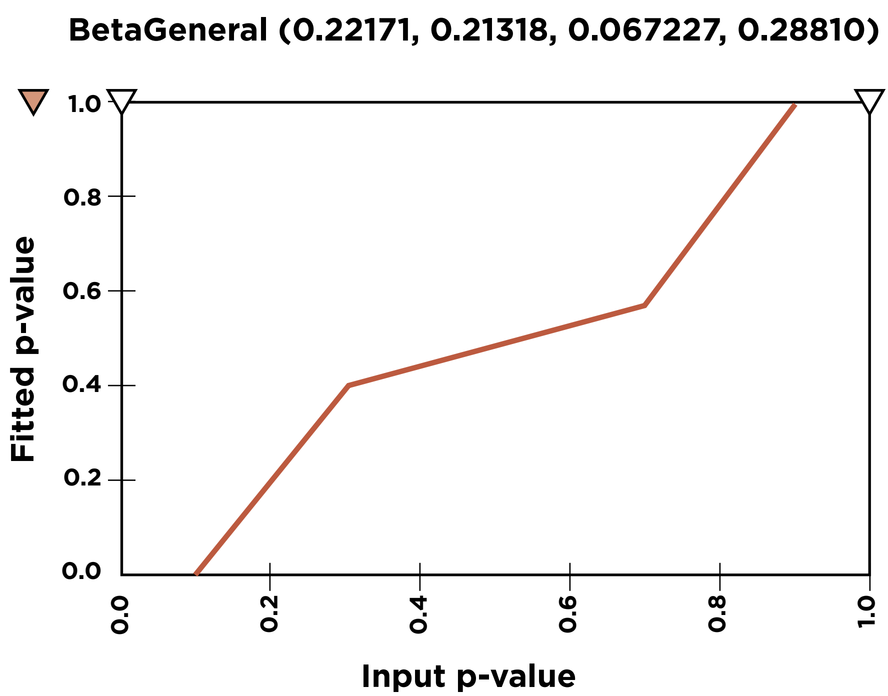


Note. Adapted from "Making Hard Decisions with Decision Tools," by R. T. Clemen, 2001.

Step 2

Estimate the CDC P-values to fitted p-value distribution points and adjust the CDF fractile input to compute the model fractile. In this example, the fractile determination, the PM demonstrates Contractor 1 Mechanical real data with applied expert judgment. From the curve estimate, the p-value/fitted p-value origin fractile is (0, .1), the second fractile point is (.3, .4), the third fractile at (.5, .5), the fourth fractile is (.7, .6), and the fractile termination is (.9, 1). From the CDC estimated points, the model fractiles are estimated to be .1, .3, .55, and .75. The CDC .9 fractile termination is the model fifth fractile. The fractile estimated values are inputted into the CDF fractile model.

FIGURE 5. CONTRACTOR 1 MECHANICAL EXPERT APPLIED DATA P-VALUE CDF



Note. Adapted from "Making Hard Decisions with Decision Tools," by R. T. Clemen, 2001.

Observations on Table 3:

1. Alpha 1 = 2.596, alpha 2 = 6.303, min = 0, max = .585.

2. Application of PM expert judgment, the .6667 cost-overrun is replaced with .2881 median.

3. The 1st fractile .1, .3, .75, and .9 is within the .15 match criterion. The 3rd fractile, .2307, is a duplicate of the 4th fractile, which accounts for the .764 computed median fractile. The .184 fitted

median and .2881 upper bound model the applied expert judgment shape or bounds for the distribution. The PM uses the modeled parameters to fit the beta-general distribution.

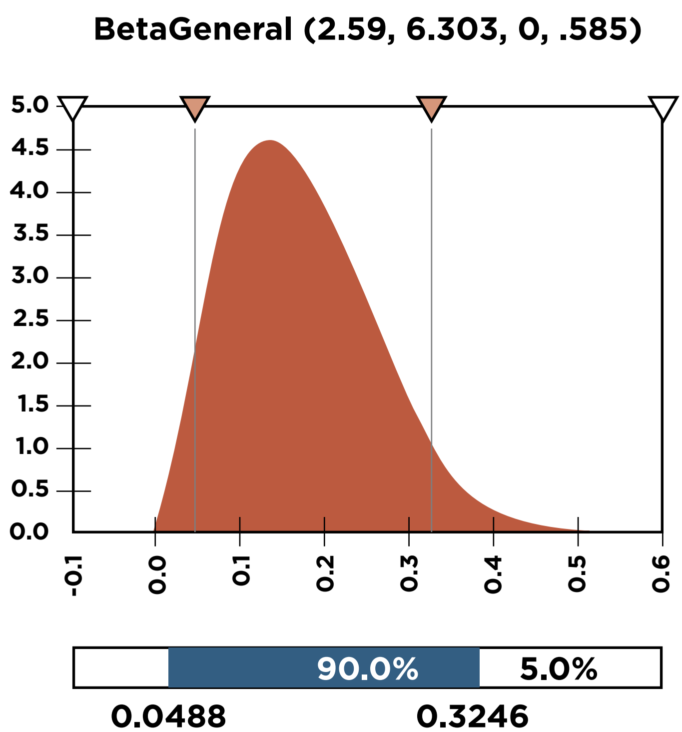
TABLE 3. CONTRACTOR 1 MECHANICAL EXPERT JUDGMENT APPLIED DATA SOLVER

Step 2:	Expert judgment decision to discard upper bound and insert real data fitted median .2881				
	Objective Function		0.243971668		
		alpha 1	**2.596224508**		
		alpha 2	**6.303480736**		
		max	**0.58571502**		
		min	**0**		
		Overrun %	CDF Fractile	Computed	Fitted Dist
		0.0672269	**0.1**	0.1	0.179829619
		0.1206897	**0.3**	0.314529	
		0.2307692	**0.55**	0.764705	
		0.2307692	**0.75**	0.764705	
.6667 replaced with fitted median		0.2881	**0.9**	0.899968	

Step 3

Determine the Pearson Tukey values. The model parameter results are alpha 1 = 2.5906, alpha 2 = 6.303, minimum = 0, and maximum = .585 are used to fit the beta-general distribution. The Pearson-Tukey method is applied to approximate the median, upper, and lower cost-over-percentage and probabilities for the decision tree. The Pearson-Tukey method estimates the 95 percent fractile is equal to the probability of 18.5 percent, with a cost-overrun percentage of 32.46 percent. The median is equal to 63 percent, with a 16 percent cost-overrun. The lower 5 percent fractile is equal to the probability of 18.5 percent, with a cost-overrun percentage of 4.88 percent. These values are entered into the decision tree to compare each contractor project cost-overrun risk to their project estimate. In Figure 6, the Pearson-Tukey cost-overrun percentage and probability values are entered into the decision tree to compare each contractor project cost-overrun risk to their project completion.

FIGURE 6. CONTRACTOR 1 MECHANICAL PEARSON-TUKEY WITH EXPERT JUDGMENT APPLIED DATA



Note. Adapted from "Making Hard Decisions with Decision Tools," by R. T. Clemen, 2001.

In summation, the PM first demonstrated the model with limited real data provided by the contractor. The model was then demonstrated with the application of expert judgment to the same Contractor 1 Mechanical real data. The DCM results show that with the provided real data, and without the application of expert judgment, Contractor 1 would be the suggested contractor for project award with a total project cost of $5,571,137. The DCM results, with applied expert judgment to the real data, demonstrate that Contractor 2 is the suggested contractor for project award, with a total project cost of **$5,438,781**.

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DCM Data Summary

The DCM model input and output parameters are in Tables 4-7. Table 4 contains the model parameters for each contractor's real data cost factor distribution shape parameters. Table 5 contains the contractor's real data cost factor Pearson-Tukey cost-overrun percentage and probability values. Table 6 contains the model cost factor distribution parameters for each contractor's real data with applied expert judgment. Table 7 contains the summarized Pearson-Tukey cost-overrun percentage and probability values for contractor's real data cost factor with the applied expert judgment.

Table 4 is the summary of the output model parameters for each contractor. The model parameters computed with real data provided by the contractors. The computed parameters did not have any expert judgment applied. The output parameters are used to define each contractor's division cost factor distribution shape.

TABLE 4. CONTRACTOR'S DIVISION COST OVERRUN MODEL OUTPUT PARAMETER RESULTS (NO EXPERT JUDGMENT APPLIED)

Contractor 1	α_1	α_2	Min	Max
Mechanical	1.550	3.026	0	.735
Finish	.562	4.371	0	.313
Electrical	2.252	14.056	0	.487
Contractor 2	α_1	α_2	**Min**	**Max**
Mechanical	1.354	2.665	0	.850
Finish	2.269	3.88	0	.254
Electrical	.968	.959	0	.628
Contractor 3	α_1	α_2	**Min**	**Max**
Mechanical	1.052	.976	0	.72
Finish	2.382	5.383	0	.914
Electrical	.641	.698	0	.709

Table 5 is a summary of the Pearson-Tukey cost-overrun percentage and probability for each contractor's real data division cost factor. The Pearson-Tukey cost-overrun percentage and probability approximation will be inputted to create the decision tree.

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TABLE 5. CONTRACTOR'S DIVISION PEARSON-TUKEY REAL DATA COST-OVERRUN RESULTS (NO EXPERT JUDGMENT APPLIED)

Contractor 1	18.5% probability	63% probability	18.5% probability
Mechanical	4.18%	23.07%	52%
Finish	.08%	5.21%	313%
Electrical	1.481%	5.931%	14.2%
Contractor 2	**18.5% probability**	**63% probability**	**18.5% probability**
Mechanical	3.9%	26.3%	61%
Finish	3.03%	10.5%	19.4%
Electrical	2.88%	31.2%	59.2%
Contractor 3	**18.5% probability**	**63% probability**	**18.5% probability**
Mechanical	4.2%	37.8%	72.0%
Finish	7.5%	26.4%	54%
Electrical	1%	32.88%	68.48%

Table 6 is the summary of the output model parameters for each contractor. The model parameters were computed with the application of expert judgment to the real data. These parameters are used to define the cost factor distribution shape.

TABLE 6. CONTRACTOR'S DIVISION COST-OVERRUN MODEL OUTPUT PARAMETERS RESULTS (WITH EXPERT JUDGMENT APPLIED)

Contractor 1	α_1	α_2	Min	Max
Mechanical	1.948	2.024	0	.359
Finish	2.246	3.144	0	.571
Electrical	3.006	10.283	0	.2307
Contractor 2	α_1	α_2	**Min**	**Max**
Mechanical	2.262	8.266	0	.72
Finish	2.004	4.063	0	.439
Electrical	5.086	7.567	0	.261
Contractor 3	α_1	α_2	**Min**	**Max**
Mechanical	2.216	2.146	0	.388
Finish	1.937	2.173	0	.600
Electrical	.641	.698	0	.709

Table 7 contains the summary of the Pearson-Tukey cost-overrun percentage and probability for each contractor's division cost factor real data with applied expert judgment. The Pearson-Tukey cost-overrun percentage and probability approximation are used to create the decision tree.

TABLE 7. CONTRACTOR'S DIVISION PEARSON-TUKEY COST-OVERRUN PERCENTAGE RESULTS REAL DATA WITH APPLIED EXPERT JUDGMENT.

Contractor 1	18.5% probability	63% probability	18.5% probability
Mechanical	4.48%	17.1%	30.06%
Finish	6.05%	23.1%	43.1%
Electrical	1.61%	4.87%	9.87%
Contractor 2	**18.5% probability**	**63% probability**	**18.5% probability**
Mechanical	4.86%	16.2%	33.91%
Finish	3.26%	13.35%	20.86%
Electrical	5.1%	10.3%	16.37%
Contractor 3	**18.5% probability**	**63% probability**	**18.5% probability**
Mechanical	5.94%	19.8%	33.39%
Finish	7.18%	27.9%	50.41%
Electrical	1.01%	33.08%	69.37%

Table 8 contains the Decision Cost Model influence summary with the application of expert judgment to the real data provided by the contractor. The DCM Influence Summary input parameters are initial estimate, division cost factor estimate, and computed Pearson-Tukey cost-overrun percentage and probability. The DCM computed the model and identified that Contractor 2 had the lowest variability of division cost overruns, resulting in the selection of Contractor 2 as the "best value" contractor, with a project estimated expected total cost of $5,438,781.

TABLE 8. DECISION COST MODEL SUMMARY (WITH APPLIED EXPERT JUDGMENT)

Diagram #1	
EV	**-$5,438,781.01**
STDEV	**$88,110.91**
MIN	**-$5,687,267.00**
MAX	**-$5,212,076.00**

INPUTS						
Initial Cost	**Contractor 1** $5,300,000.00	Probability	**Contractor 2** $5,100,000.00	Probability	**Contractor 3** $4,990,990.00	Probability
Cost 1 Mech	$480,000.00		$760,000.00		$750,000.00	
High Overrun	0.3246	0.185	0.3391	0.185	0.3339	0.185
Median Overrun	0.16	0.63	0.162	0.63	0.198	0.63
Low Overrun	0.0488	0.185	0.0486	0.185	0.0594	0.185
Cost 2 Finish	$1,100,000.00		$850,000.00		$1,200,000.00	
High Overrun	0.431	0.185	0.2086	0.185	0.5041	0.185
Median Overrun	0.231	0.63	0.1335	0.63	0.279	0.63
Low Overrun	0.0659	0.185	0.0326	0.185	0.0718	0.185
Cost 3 Electrical	$750,000.00		$930,000.00		$780,000.00	
High Overrun	0.0987	0.185	0.1637	0.185	0.6937	0.185
Median Overrun	0.0487	0.63	0.103	0.63	0.3308	0.63
Low Overrun	0.0161	0.185	0.051	0.185	0.0101	0.185

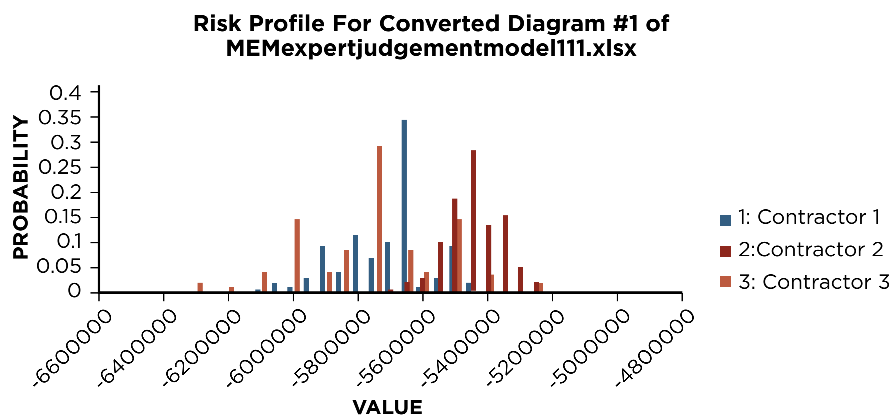
Table 9 contains the Statistics and Risk Profile charts generated from the model. The charts provide an analytical data summary to the end user for this decision. The statistics chart shows the range for each contractor's estimate with the cost factor inputs. The model identifies Contractor 3, who initially had the lowest project estimate, as the contractor with the highest total expected cost of the three contractors. Contractor 3 has a cost range from $5,111,140 to $6,387,421, with a mean cost of $5,742,003. Contractor 1, who had the highest initial estimate, is the second lowest total expected cost contractor. Contractor 1 has costs that range from $5,461,365 to $6,082,365, with a mean cost of $5,720,684. Contractor 2, the model-recommended contractor, had costs that ranged from $5,129,768 to $5,687,267, with the mean cost of $5,438,781.

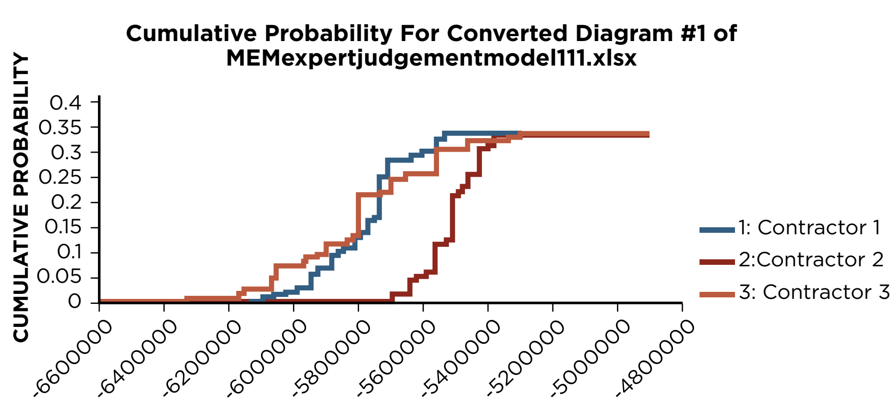
Table 9 also displays total cost variability by contractor. Contractor 1 has the cost standard deviation of $138,554, and Contractor 3 has the highest variability of cost standard deviation of $234,952. Contractor 2 has the lowest cost standard deviation of $88,110. The risk profile chart in Table 9 displays how each contractor's cost probability and overruns are distributed. This gives the decision maker confidence for the decision and provides further support for the selection of Contractor 2.

The total expected cost risk profile for the project demonstrates that Contractor 1 has a 35 percent confidence the contractor will meet the computed "mean" total expected cost of the project, and that Contractors 2 and 3 both have a 30 percent confidence they will meet the computed "mean" total expected cost of the project. The cumulative probability plot shows that Contractor 1 and Contractor 3 are grouped together with total expected cost risk. Contractor 2 has separated from the other two contractors' project selections and offers the lowest total expected cost with the highest confidence.

TABLE 9. CONTRACTOR'S STATISTICS, RISK AND CUMULATIVE PROBABILITY PROFILE

Contractor Selection	***1: Contractor 1***	***2: Contractor 2***	***3: Contractor 3***
STATISTICS			
Mean	-5720684	-5438781	-5742003
Minimum	-6082365	-5687267	-6387421
Maximum	-5461365	-5212076	-5129578
Mode	-5667425	-5432385	-5732314
Std Dev	138554.1	88110.91	234952
Skewness	-0.29076	-0.25133	-0.10148
Kurtosis	2.806697	2.920348	2.873793





Note. Adapted from "Making Hard Decisions with Decision Tools," by R. T. Clemen, 2001.

Figure 7 demonstrates the DCM minimum expected cost solution decision tree. The decision tree will demonstrate how each division estimate is impacted by the computed division cost-overrun percentage and probability. The DCM utilized the top three divisions determined by the PM as cost factors for the decision tree. The DCM demonstrates how the mechanical, electrical, and finish division cost factors have an overall impact on the total cost for the project. The DCM will also demonstrate how the initial estimate from the contractor is not the expected cost provided to the government. To better represent the decision tree in this report, the single decision tree is shown in Figure 7 as Decision Tree Contractor Selections, Parts 1 and 2. The decision tree chance node demonstrates how each Pearson-Tukey chance and percentage impact each division cost for the project, and collectively impact total cost of the project.

FIGURE 7.DECISION TREE CONTRACTOR SELECTIONS PART 1

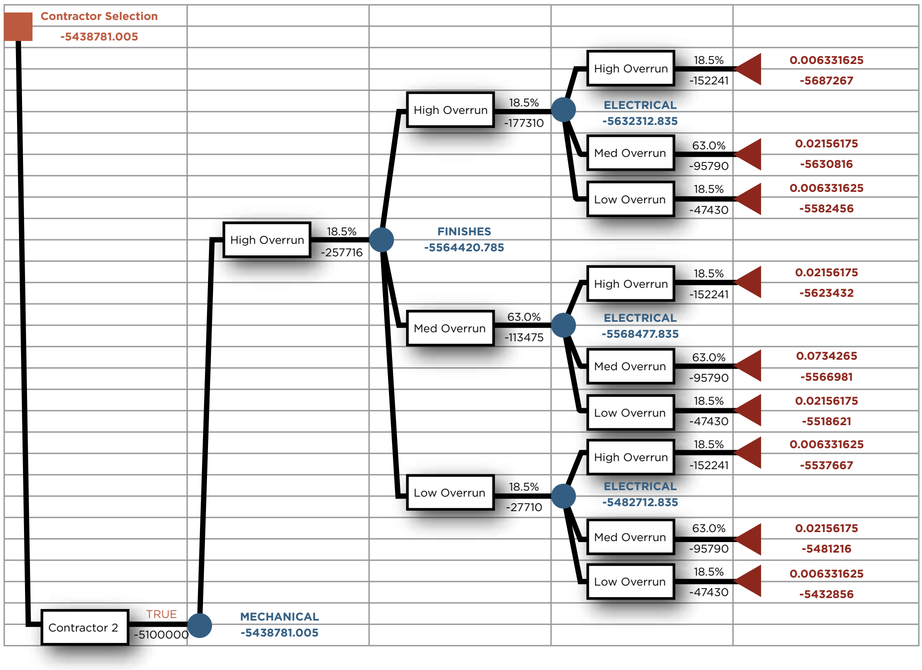
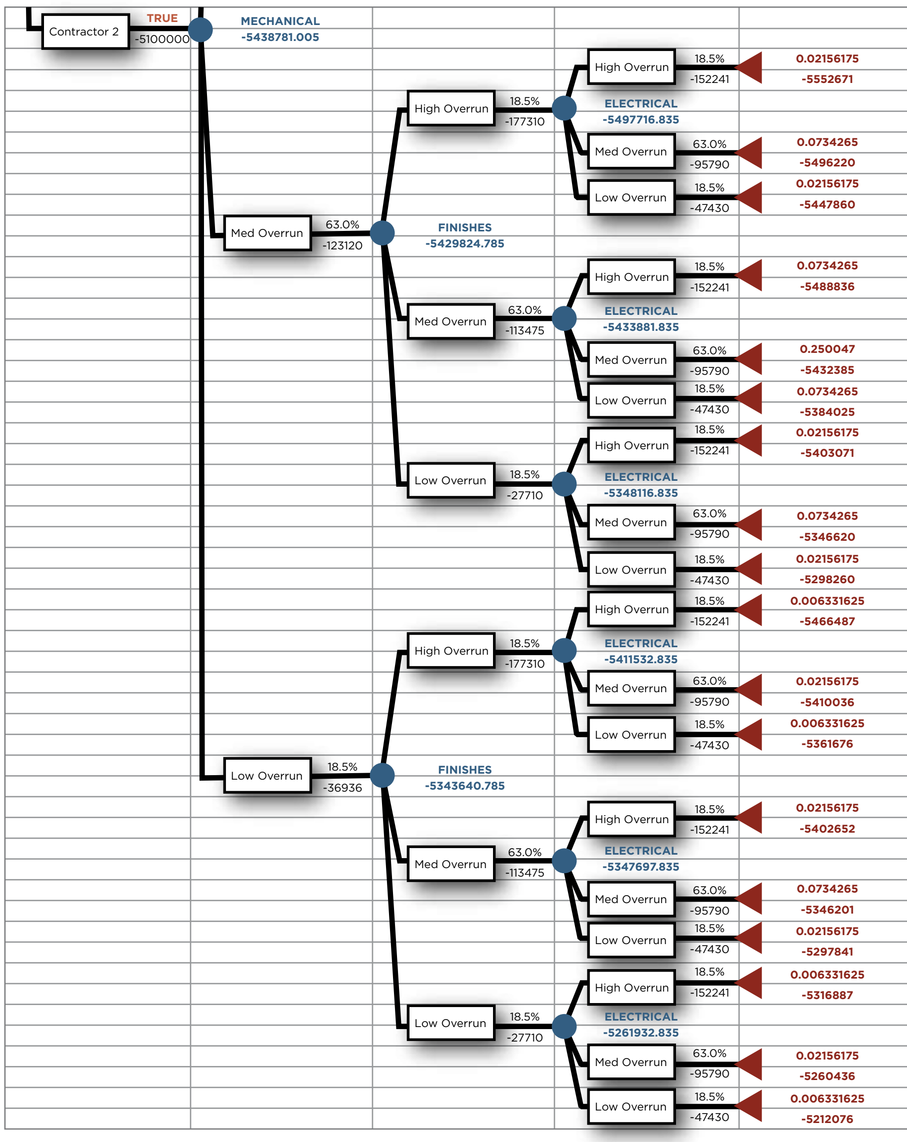


FIGURE 7. DECISION TREE CONTRACTOR SELECTIONS PART 2



Note. *Adapted from "Making Hard Decisions with Decision Tools," by R. T. Clemen, 2001.*

CONCLUSIONS

In summation, from a pool of certified contractors, the government contracting office solicited estimates for the project. Utilizing RSMeans as a standard format for construction costs, the PM completed a current year IGE, collected five similar project estimates, and final project costs from the three potential contractors. After review of each contractor's project history and computing the division cost-overrun percentage, the PM identified three common cost factors for the DCM.

The PM fit a primary distribution for each of the three division cost-overrun percentages. With the historical project dataset and expert judgment, the PM modeled a minimization beta distribution to best represent each contractor's cost factor. The model computed output parameters used to generate a beta-general distribution. The PM applied the Pearson-Tukey method to approximate the cost-overrun percentage and probability for each cost factor. The modeled cost-overrun percentage and probabilities are imputed into the DCM Influence Table. With the modeled cost overrun percentages and fractiles, the total estimate, and cost factor division estimates, the DCM computed the lowest total expected cost contractor for the construction project.

Initially, each contractor presented a total cost estimate for the construction project. Contractor 1's estimate was $5.3 million, Contractor 2's estimate was $5.1 million, and Contractor 3's estimate was $4.9 million. Contractor 3 appears to be the lowest total cost contractor for the project. With the current contractor selection process, Contractor 3 would have been awarded the construction project. With the same data from the contractor's initial cost estimate, cost factor division cost estimates, modeled cost-overrun percentages, and chance parameters, the DCM model demonstrated that a lower total expected cost decision for the construction project may be made. The DCM provides a valid, data-driven decision process to select the contractor best suited to meet the tax-payers' objective—a value-driven government construction project.

Future application of the DCM is a software program that can be developed and added to *RSMeans* CostWorks to streamline the contractor evaluation process. The DCM is not limited to construction projects. The DCM can be adapted to any problem with defined variables and historical costs. The decision model can be used for private, municipal, state, and federal construction projects.

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Annually, many U.S. Government construction projects and funds need to be obligated for projects. The government PM, at times will look at a contractor's project estimates at face value. A common scenario in the government construction process is that a government-certified construction contractor will state, "It will cost $5 million dollars to construct a facility." If the government has the facilities project programmed, and the IGE is within 25 percent of the contractor's estimate, the government will obligate the funds to the construction project. The project will be funded without the knowledge of the contractor's project cost-overrun percentage history and the potential unknowns surrounding project cost overrun.

Under the current government contractor selection process, the government would have awarded the project to Contractor 3, who had the lowest initial estimate of $4.9 million. The DCM demonstrated that Contractor 3 is not the lowest cost, but indeed has the largest cost risk for project award.

The author's experience in construction management and evaluation of project historical cost data indicates the majority of construction projects will have at least a division cost-overrun. Cost-overruns are often termed by the contractor as "modification, change order, or upgrade." On several occasions, a contractor proposes to win a government project by bidding the lowest estimate. The contractor later makes up the difference in modifications or change orders throughout the project, as was demonstrated by DCM in Contractor 3's situation.

The recommendation of this study is for U.S., state, and municipal governments to take careful consideration of construction division cost-overruns before project contractor project award selection. This article demonstrated that by utilizing a good DCM and a common format, a valid, data-driven decision can be made for project award. Using this process will bring more cost-effective contractor selection solutions for the government and construction engineers. Using this DCM, the federal government's stimulus and project funding could be used more efficiently, thus meeting the taxpayers' expectations of responsible government construction spending for their tax dollars.

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