Monte Carlo Simulation Approach to Support Alliance Team Selection

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Abstract: The alliance concept is similar to the design build project delivery system. However, it is denoted by a special form of partnership between the owner and the design-build team, where the owner is very involved in the project. This type of delivery systems is gaining popularity as many infrastructure projects require the owner to order materials ahead of time, before engaging the design-build team in the project. As in design-build, the selection of the engineer-procure-construct team depends not only on the price but also on qualitative factors. This paper lays out the framework that facilitates selecting the best alliance team for a project by quantifying the evaluation factors and combining them into a single score. Using a Monte Carlo simulation and varying all the factors relevant to the decision problem can reveal biases present in the evaluation to assist in making the best possible decision. A case study dealing with a large utility project illustrates this methodology.

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Introduction

The success of a building or a utilities project is very much dictated by the competency of the team designing and building it. Accordingly, selecting the most qualified designer-contractor team for a design-build project can be one of the most important factors in project success. The owner and associated representatives making the selection decision must understand the critical nature of this time in the project and take the necessary steps toward making the correct evaluation of each designer-contractor. The task of developing the selection criteria ultimately falls upon the owner of the project and needs to occur before the competitors submit proposals. There are a multitude of criteria to consider (e.g., cost, schedule, past experience, safety record, quality of work, dealing with the public, etc.), all of which need to be prioritized. Choosing and prioritizing these criteria, many of which are qualitative, can be a daunting task; additionally, analyzing evaluations of each criterion to make the finest final selection decision can be overwhelming. Fortunately, methods exist to make this process easier.

The Monte Carlo simulation is one such method that is very efficient when quantifying qualitative analyses. It provides a way to minimize the subjectivity involved in human selection and optimize the results of a group's individual evaluations. The simulation's application is not limited to the construction industry, as it is used in a variety of fields where uncertainty analysis is needed, such as business, science, engineering, and manufacturing. Knowledge of its importance and education in its use may help to alleviate some of the stress associated with the selection of the best designer-contractor team for a project.

This paper is divided into three sections. First, the alliance concept is introduced and a literature review is presented, followed by the problem statement and purpose of the paper. Second, the authors lay out the alliance selection methodology, starting with the selection of the criteria used in decision problems and proceeding to the alliance solicitation, presentation, and evaluation. An overview of the Monte Carlo simulation is given, and then an outline of the analysis of results is presented. The third section consists of an example in which the developed methodology is applied and the results of an actual Monte Carlo simulation are analyzed.

Alliance Concept

The traditional design-bid-build (DBB) project delivery system faces many limitations, especially with respect to project overrun and litigation caused partly by the late involvement of the contractor in the project. Other project delivery methods such as the design-build method are increasingly used in place of the DBB method. Due to their improved performance, design-build methods are replacing the traditional project delivery systems, particularly on some types of innovative projects (Touran and Lopez 2006).

The DBB system is divided into three separate phases, the construction phase starting only when the design is complete. The design-build method, however, expedites the building schedule by overlapping the design and construction phases. This allows the construction to start after only the first fraction of the final design has been completed. For this type of delivery system to be efficient, the contractor and the designer team up to form what is

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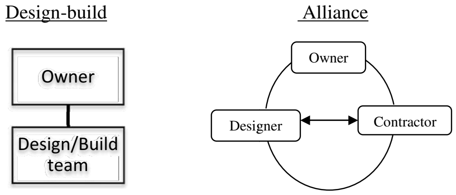

Fig. 1. Difference between design-build and alliance

commonly called a design-build team. The owner has to deal with only one entity, which provides a single point of responsibility. Moreover, the contract type is usually guaranteed maximum price and the owner does not share cost overruns—a major difference between design-build and alliance delivery systems.

The term *alliance* is used in this paper to characterize a complete partnership among the major parties involved in a project: the design professional, the general contractor, and the owner. This concept is used by a multitude of industries, such as the energy, infrastructure, and pharmaceutical industries. The owner is substantially involved in the project; his/her role extends to five different areas which constitute the major differences between design-build and alliance. These areas can be summarized as follows:

1. The owner conducts research to specify certain products even before the alliance selection process has occurred, prequalifies certain suppliers, and orders long-term procurement items.
2. The owner may choose to buy equipment/materials.
3. The owner conducts a cost-estimating procedure to specify target costs for individual components. The schedule of the project is also fixed.
4. The owner has access to the actual cost information, has the right to audit all overhead costs, and sets a fixed percentage of profit based on the total auditable cost of the project.
5. The owner is a partner in risk and reward. Since target pricing has been done in advance, the owner and the design-builder have agreed on prices of components. If the team performs better, the owner and design-builder share equally in the profits; if the cost is higher than the target price, the overrun is also shared.

This exceptional involvement of the owner in the process, as well as his/her commitment to share overruns, differentiates this new alliance team concept from the common design-build team as shown in Fig. 1.

Literature Review

An extensive body of literature has been developed in the areas of delivery methods, decision making, and team selection, more extensive than the scope of this paper could adequately cover. Rather than attempting to summarize the impressive span of this literature in its entirety, this review covers a representative sample of the key conclusions relevant to this paper. For a more comprehensive and nuanced list, refer to the reference list for additional sources consulted (e.g., Molenaar and Yakowenko 2007).

More previous research shows that design-build project delivery systems can perform better than traditional systems on certain types of projects—especially innovative ones—with respect to cost, schedule, and quality performance; this has been studied for the construction industry as a whole, in both privately and publicly financed projects (Konchar and Sanvido 1998). Molenaar and Johnson (2003) and Palaneeswaran et al. (2003) showed that optimum contractor selection can be done through comparison of the "best value," which is a measure of cost, time, and quality performance, where quality can account for many factors such as environmental, aesthetic, and safety factors. Alsugair (1999) developed a framework for evaluating contractors. Additionally, several authors have documented the various team selection methods for design-build projects. Palaneeswaran et al. (2000), for example, studied the best practices and formulated a structured approach to design-build contractor selection. Abi-Karam (2005) also illustrated different design-build selection methods. El Wardani et al. (2005) studied the correlation between the performance of a design-build project and the method used to procure the design-build team.

Although many authors have investigated the various methods for selecting a design-builder, no methods are available that account for any biases that may enter into these design-build evaluations. A Monte Carlo simulation can be used to identify bias in the alliance selection process.

Monte Carlo simulations have been previously used in the construction engineering industries mainly to determine the risk associated with change orders. Baxendale (1984) developed construction resource models via Monte Carlo simulation for use in project planning. Back and Bell (1995) demonstrated that Monte Carlo simulation is an excellent tool for analyzing the potential impact of modifications proposed for a complex process. McCabe (2003) developed a probabilistic model to translate project characteristics into schedule risk boundaries by means of a Monte Carlo simulation. Touran and Lopez (2006) used Monte Carlo simulation to model cost escalation in large infrastructure projects.

Problem Statement

Previous studies on design-build and alliance team selection lack a methodology to account for evaluation bias. The selection process is similar for both design-build and alliance team selection. It usually consists of inviting a small number of prequalified teams, and evaluating them on a number of selection criteria (mostly qualitative) that are—together with their weights—known upfront.

The weighting of the selection factors—denoted by the weighting model—can heavily impact selection. As an example, considering the weight of the factor "experience with owner" to be exactly 10% of the total score, versus 15%, can affect the selection results. Another form of bias could result from the inclinations of an evaluator, whether they are deliberate or whether they enter in just because assessing qualitative criteria is a tough task. This leads to our presentation in this study of a comprehensive selection framework that helps to quantify qualitative evaluations and, through the use of Monte Carlo simulation, complements and adds to previous methods by reducing biases in the assessment. The two possible sources of bias are investigated: those due to the weights assignment for the different factors included in the assessment, and biases due to the evaluators' subjectivity.

Purpose

The purpose of this study is to demonstrate the effectiveness of Monte Carlo simulation as a scientific/statistical tool to diminish the biases that enter into the evaluation of alliances. Use of this tool would complement the high performance of design-build project delivery systems and increase it further by ensuring that

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the selected alliance is the best one for the job, thus lowering project risks. The Monte Carlo method has already been used to assist in making decisions and it has proven to be efficient when considering the effect of numerous factors on a specific output. We next explain the methodology and then describe a supporting case study.

Alliance Selection Methodology

The process of selecting a designer-contractor alliance consists of four major successive steps that can be summarized as follows.

Alliance Selection Criteria and Their Respective Weights

After the needs of the project are identified, a set of selection criteria is developed from which to evaluate the alliance teams desiring the contract. A level of importance (a weight) must also be assigned to each criterion with respect to the other criteria. Consequently, a rating system is created for owner representatives to use in evaluating the alliance teams' presentations.

Selecting the Criteria

The first step in the process of selecting an alliance team to design, manage, and build a project is to establish a set of criteria or categories that are most important for the owner to use for the evaluation. The cost and schedule are quantitative entries and are taken into account early in the selection process, since the owner has specified a target cost and has fixed the time frame in advance. In order for the alliance teams to bid for the project, they should already have accepted these two conditions. In contrast to these two quantitative factors, the remaining criteria are mostly qualitative. For this step we are looking at those qualitative criteria that are deemed important for project success. Brainstorming a list of criteria from which to prioritize is necessary to ensure that no aspect of the project goes unnoticed. Chosen from this list are those criteria that are the most relevant to the company, the type of contract, and the type of work. The Monte Carlo simulation has no requirement for the number of criteria chosen to use in the evaluations; discretion is left to the owner to decide on the length of the evaluation. Although there are a large number of factors that contribute to an owner's ultimate decision, selection of the criteria most pertinent to the project should facilitate the selection process. Narrowing the selection criteria has two effects. First, the panel of owner's representatives evaluating each alliance team is less overwhelmed by the magnitude of the set of criteria. If an owner representative has a long list of criteria to evaluate after listening to a particular alliance's proposal, chances are strong that the representative will not retain enough information to assess the criteria accurately. The problem would then lie in trusting these evaluations, as they might tend to omit relevant data. The second effect of narrowing the selection criteria is that the results will be easier to analyze and will illustrate a clearer choice of the most qualified alliance. Further discussion of this effect is presented in the section describing the Monte Carlo simulation.

The following is a sample list of criteria commonly used in selecting an alliance: previous experience with the alliance partner; owner experience with either partner in the alliance; existence of employee training programs; workforce stability and turnover rate; safety record or "experience modification rate"; references from other owners; performance guarantees; team/departmental integration approach; experience with this type and size of project; approaches to unique aspects of the project; experience and authority of key individuals; extent of quality control/quality assurance; measures to evaluate performance in construction; enhancement to the request for proposal (RFP); approach to involve stakeholders; geometric enhancements; structural enhancements; innovation of design and construction quality management plan; aesthetics; ease of future maintenance; public involvement; and traffic mitigation. This is only a sample list of criteria. These can vary depending on the owner's needs and the specific project.

Table 1. Sample Score Input Page

Alliance 1		
Evaluator A		
Criteria	Weights (%)	Score (out of 4)
Experience with owner	10	
Experience with alliance projects	15	
Alliance team capabilities	20	
Alliance methodology approach	25	
Alliance team business history	10	
Cultural fit	10	
Efficiency and effectiveness	10	
Total	100	

The listed criteria are qualitative, and it is a challenge to make a decision based on subjective criteria. The process, however, requires a quantitative evaluation for input into the simulation, qualitative comments serving no purpose in simplifying the selection process. A rating system ranging anywhere from one to five points is typically used to assess the owner's satisfaction with an alliance team's adherence to the criteria. The rating system chosen for the example presented here used a four-point scale. For each criterion, a one meant that the alliance team did not meet expectations at all. A two meant that the alliance team was below expectations. A three meant that the alliance team met expectations. Finally, a four meant that the alliance team exceeded expectations represented by the specific criterion.

Assigning Levels of Importance

In addition to deciding on the criteria for selection, it is necessary to assign an importance level to each criterion; these are shown in the "weight" column of Table 1, where the letter A is used to represent the first evaluator and the number 1 represents the first alliance team. The weights percentages assigned for the selection criteria are decided on by the owner prior to the completion of the evaluations and are based on which factors the owner deems the most important. This allows the simulation to weigh each of the ratings given by the evaluators based on the criteria that are more or less critical to the success of the project. After a level of importance has been assigned to each criterion, the sum of the percentages should equal 100%. This paper presents a more robust decision making process by varying these criteria weights—decided on by the owner—to study to what extent they are impacting the selection decision.

Alliance Solicitation, Presentations, and Evaluation

Once the criteria and their respective weights are decided on, the owner can proceed to the next step, which consists of inviting alliance teams to a presentation of the project and evaluation of

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the markup. Competition is always healthy in the sense that it ensures that the owner gets the best available product in terms of cost, time, quality, and other factors. But competition between a large number of alliance teams is not realistic. Time is a significant issue, and the evaluation process can be costly and requires substantial effort for both the owner as well as the alliance teams. It must be remembered that contrary to what occurs in DBB, the alliance bidders are not competing for one number—the lowest bid—but evaluations on different grounds are taking place. A limited number of competing bidders shortens the process time while still allowing for competition; this also allows the owner to perform a thorough evaluation, hence minimizing risks involved in selecting an alliance. The owner's belief in the alliance teams' qualifications to apply for the job, as well as knowledge of their performance capabilities, is a main player in this preselection. These preselected potential alliances capable of performing on the project are solicited for work, and the selection criteria are sent to them to be used as guidelines for developing their designs.

Selected alliance teams may give presentations, hold phone conferences, host meetings, or use other mediums to present their project approach to the owner. It is at these presentations that owner representatives evaluate prospective alliances based on the criteria identified. Owner representatives should be given evaluation sheets with the list of criteria and directions on how to rate each alliance. Score assignment is both an independent and group process. Teams are evaluated in a collective group setting, where evaluators may pose clarification questions to presenters openly but each evaluator independently assigns a score without consulting other evaluators. Once the evaluations are completed, they can serve as inputs for the Monte Carlo simulation explained next. Based on the simulation of the teams' evaluations, the project is awarded to the alliance team that optimizes the client's requirements. Table 1 presents a sample evaluation sheet.

Monte Carlo Simulation

Subjective evaluations are rarely quantified precisely, as deliberate or unintended bias can always be present in such evaluations. A way to deal with bias is to build a model describing the ongoing process, followed by running a Monte Carlo simulation that will reproduce it. One can vary this procedure by eliminating evaluators or changing the weights of criteria to account for any biases. An overview of the Monte Carlo simulation is presented next; steps to follow when one is performing a simulation are then highlighted.

Statistical sampling began in the early 1900's and existed prior to the invention of the Monte Carlo method. However, this method was the first to use a computer to automate such sampling. Stanislaw Ulam, a Polish-born mathematician, invented the method in 1946. The process has since been refined, but the set of underlying principles remains the same.

The Monte Carlo method is a technique employed to approximate solutions to quantitative problems. This is the reason for quantifying an inherently qualitative analysis of an alliance by using the four-point scale. Replicating or modeling real systems to predict a certain behavior and investigating thousands of different scenarios for the same case reveal a system's sensitivity to random variation of inputs, lack of knowledge, or input error. Understanding this sensitivity facilitates decision making.

The method transforms a deterministic model, in which the equation gives one output based on the original input parameters, into a stochastic one. The latter model randomly generates input variables from probability distributions that sample a certain population and in which the output is different for every run of the model. Fig. 2 shows the triangular distribution used for the weight of factor 1 in the stochastic model. For example, let the score for factor 1 = S1, the weight for factor 1 = W1, and so on for the remaining criteria. The total score will be a weighted average of all these qualitative criteria. In the deterministic case, the weights are fixed: W1 = 10%, W2 = 15%, and so on. To reduce the bias from the model that specifies the respective weights, we use a stochastic model. In the stochastic case, W1 equals a random percentage taken from the triangular distribution shown in Table 2, with a mode of 10%, a lower limit of 5%, and an upper limit of 15%. All the other weight factors, W2 to W7, have their own distributions too. In other words, the off-the-shelf software simulates the model many times, taking for each iteration a different point from the specified probability distribution for every input. The calculated output will also be different for every run, and its distribution will be calculated. This assures the owner that the importance factors were not the only aspect of the analysis driving the results.

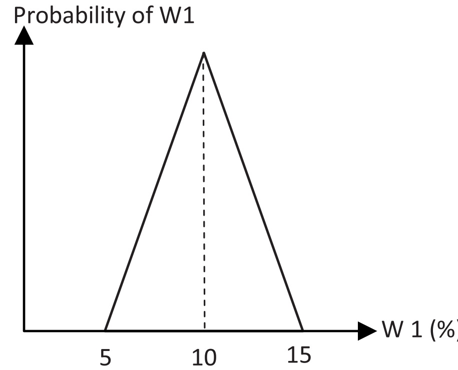

Fig. 2. Triangular distribution for W1

Performing a Monte Carlo simulation is a major stage in the alliance selection process and involves three steps:

- Step 1, the parametric model is developed, which in our case is the equation averaging the weighted scores of an alliance.
- Step 2, the evaluation data are inputted, and the probability distribution that fits the data set is identified to generate random inputs. The Monte Carlo simulation requires four types of data inputs:
  a. Input of the evaluator's name, initials, or designated reference (e.g., Evaluator A);

Table 2. Importance Factors with Minimum and Maximum Values of Iteration

Criteria	Original weight (%)	Triangular distribution Lower limit (%)	Mode (%)	Upper limit (%)
Experience with owner	10	5	10	15
Experience with alliance projects	15	5	15	25
Alliance team capabilities	20	10	20	30
Alliance methodology approach	25	15	25	35
Alliance team business history	10	5	10	15
Cultural fit	10	5	10	15
Efficiency and effectiveness	10	5	10	15
Total	100			

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Table 3. Alliance Team 1 Presentation Summary Scorecard (Raw Data)

		Alliance Team 1							
		Evaluator							
Criteria	Weight (%)	A	B	C	D	E	F	G	H
Experience with owner	10	2	2	2	4	3	3	3	3
Experience with alliance projects	15	3	4	3	3	4	4	3	3
Alliance team capabilities	20	3	4	2	3	4	3	3	2
Alliance methodology approach	25	2	4	4	3	4	3	3	3
Alliance team business history	10	3	4	3	2	3	3	2	3
Cultural fit	10	2	4	3	2	3	3	2	4
Efficiency and effectiveness	10	1	4	3	3	4	3	2	3
Total score	100	16	26	20	20	25	22	18	21
Average		2.29	3.71	2.86	2.86	3.57	3.14	2.57	3.00
Weighted score		2.35	3.80	2.95	2.90	3.70	3.15	2.70	2.90
Average of evaluators' scores		3.00							
Weighted average		3.06							

b. Input of the importance levels outlined in Step 2 of the alliance selection process;
c. Input of all evaluators' ratings on the criteria for each designer-contractor pair; and
d. Input of the weights' distribution types and their variables.

- Step 3, several iterations are performed to evaluate the model. The number of iterations should allow the output's convergence to be satisfactory for the analysis.

One of the major benefits of the Monte Carlo method is that, in contrast to deterministic models, it can generate random variables in order to look at a decision problem from many angles. In the case of an alliance team selection, it can change the weights of one or more criteria and observe how this affects the results. Additionally, the Monte Carlo simulation can recalculate the scores after one or more evaluators have been eliminated from the analysis to minimize any sort of team bias, which refers here to any unfairness on the part of an evaluator in rating a particular alliance. The program is also coded to report the winning alliance in all situations, making the decision value based and observable.

Analysis of Results

The results of the simulation are analyzed to quantitatively arrive at a decision on the most qualified alliance team for the project. The results of the simulation are given in two forms. The first uses only the raw data and yields an average of all evaluators' scores, both weighted and not weighted. A sample page of one alliance team's ratings for this form of results is shown in Table 3, where the weights of the percentages represent the individual weight of every criterion, and the letters from A to H represent the eight evaluators. It should also be noted that the alliance teams are numbered from one to four. The closer the nonweighted average score of the evaluators is to the weighted average, the greater the reliability of the model, because this would signify that the criteria are scored in a way where the weights used did not influence the selection results significantly. This can be the case when a team's scores are very similar for the different criteria; the weights will not matter much. Again, this is based on a four-point scale with 4 representing the most desirable rating.

The second method uses sensitivity analysis to examine the data. A sensitivity analysis involves varying or removing some of the inputs in the simulation and observing the effect. A sample portion of a sensitivity analysis can be seen in Table 4. This sample makes changes to the simulation by seeking out those evaluators who may have had the largest impact on the results. The changes are listed in Table 4. It is important to note that this sample is only one aspect of the sensitivity analysis. Another aspect is dealing with the bias attributable to the model itself by varying the weights of the input factors. Further discussion of the results is presented in the case study.

Table 4. Evaluator Change with Winner in Boldface Type

Evaluator change	Team 1	Team 2	Team 3	Team 4
Original weighted score	3.06	2.52	2.50	**3.09**
After deleting the highest score in each team	2.95	2.41	2.43	**3.03**
After deleting the lowest score in each team	3.16	2.61	2.59	**3.17**
After deleting both the highest and lowest	3.05	2.51	2.52	**3.10**
Without the evaluator whose score had big range (B)	2.95	2.53	2.59	**3.17**
Without the evaluator whose score had second big range (H)	**3.08**	2.61	2.54	3.06
Without both B and H	2.96	2.64	2.64	**3.14**
Without the evaluator who scored team 2 highest (C)	3.07	2.44	2.49	**3.15**
Without the evaluator who scored team 3 highest and scored team 1 lowest (A)	**3.16**	2.48	2.43	3.11
Without both C and A	**3.19**	2.38	2.41	3.18

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Alliance Selection Illustrative Case Study

In order to fully reveal the use and efficiency of the Monte Carlo simulation in selecting an alliance, this paper includes an example case study of the previously discussed methodology. This case study involves a large company and project, demonstrating the critical nature of the methodology and increasing the impact of the decision.

Project Scope and Delivery System

The nature of the utility project in the case study was such that it required an extremely large budget that would be spent over a period of 5 years. Additionally, it involved construction in 30 different locations spread over approximately $50{,}000$ mi^2 of land. The project was funded by a big company whose need for on-time completion was rapidly increasing. These facts combined to encourage the owner to use an accelerated-type schedule or a fast track type of project delivery system, namely design-build, whereby the contract would be awarded to the best value competitor. Moreover, because of the special involvement of the owner, explained in the first part of the paper, we can differentiate this special type of design-build as the alliance delivery system. The demands on the alliance partnership chosen for the project were substantial. Consequently, it became imperative that an accurate analysis of each team be performed in order to minimize the risk of financial loss and maximize the benefits.

The delivery system included the engineering, procuring, and constructing of all 30 facilities. The project would be completed by an alliance among a design firm, a general contractor, and the owner. A number of challenges existed with this contract. The selected alliance team needed to provide sufficient construction labor, systems to support construction needs, sufficient design support to meet deadlines, proper leveling of resources by the contractor, careful budgeting and forecasting, and sufficient lines of communication, among others. These factors should be assessed either in the selection criteria or through additional questions during the teams' presentation. One example of how these issues can be addressed during the presentations is the need for linemen. In fact, this need was going to peak at some point in the project, and linemen were in very short supply at that time. The successful presenter would show his understanding of resource leveling, in that it would reduce the need for linemen at its expected peaks.

Alliance Selection Criteria

The first step in the process was to choose the appropriate selection criteria. The owner decided on the criteria shown in Table 1, as described below.

- Experience with the owner: Has either of the partners participated in previous projects with this owner, and were the projects successful?
- Experience with alliance projects: Are there other alliance projects that each partner has separately participated in?
- Alliance team capabilities: Does the alliance have the ability to complete a project of this magnitude both physically and financially?
- Alliance methodology approach: Has the alliance presented a competent plan for the project with a probability of success?
- Alliance team business history: Has this alliance worked together before, and if so, what was the result?
- Cultural fit: Does the alliance promote a working environment consistent with that of the owner and the surrounding community?
- Efficiency and effectiveness: Generally speaking, does the alliance seem to have an efficient and effective plan for and attitude toward the completion of the project?

The alliance methodology approach, alliance team capabilities, and experience with alliance projects were deemed the most important criteria, with all others being equal. The respective percentages are shown in Table 1.

Solicitation, Presentation, and Evaluation

Four alliance teams were solicited for this project. All were asked to submit a proposal package and give presentations describing their qualifications, methodology, and project plan. It should also be mentioned that the owner has prior experience working with all four teams. Eight evaluators represented the owner during these presentations and judged the alliance teams based on the criteria outlined in Table 1. It should be noted that after the owner's preparation up front to select the evaluators, the selection criteria, and the four alliances, the selection process lasted for about three months. Evaluations were made and the results compiled.

Simulation

A simple triangular distribution was used to generate stochastic inputs. This requires only three values: a lower limit or "minimum," a mode or "most probable," and an upper limit or "maximum" value for the criteria. For the purpose of the Monte Carlo simulation, these values are usually obtained from historical data or estimated by a professional in the area based on his/her knowledge and experience. Because of the originality of this simulation, historical data are lacking for this process, and the distribution inputs were estimated by Dr. Awad Hanna. The simulation model was simple, consisting of the average scores for each alliance, with the project to be awarded to the alliance with the highest score. The Monte Carlo simulation was coded to reflect the assigned levels of importance and yield the winning alliance in gray for each of the results in the sensitivity analysis. One thousand iterations were performed; this number of iterations was sufficient for the output's convergence. It should be noted that other types of distributions such as uniform, β, and normal distributions were also used to evaluate the same model and that the results were similar.

Analysis and Results

Untreated Results

As mentioned previously, the results for this simulation exist in two forms: raw data and sensitivity analysis data. The results from the untreated average scores of all evaluators in this case are shown in Table 3 for Alliance Team 1 and in Table 5 for Alliance Team 4, to serve as an example.

Using these results, Alliance Team 4 appeared to be the alliance that the contract would be awarded to. It is important to note, however, that Alliance Team 1 was not drastically different from a statistical standpoint from Alliance Team 4. Also of importance is the fact that all weighted average scores were reasonably close to their nonweighted counterparts, which indicates that the importance levels did not seem to have an effect on the out-

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Table 5. Alliance Team 4 Presentation Summary Scorecard (Raw Data)

Criteria	Weight (%)	Alliance Team 4 Evaluator A	B	C	D	E	F	G	H
Experience with owner	10	3	4	3	3	3	3		4
Experience with alliance projects	15	3	3	3	4	3	3		2
Alliance team capabilities	20	3	2	3	4	4	3		3
Alliance methodology approach	25	3	2	2	4	4	3		4
Alliance team business history	10	3	3	3	2	3	3		3
Cultural fit	10	3	3	3	3	3	3		4
Efficiency and effectiveness	10	3	3	3	3	3	3		3
Total score	100	21	20	20	23	23	21		23
Average		3.00	2.86	2.86	3.29	3.29	3.00		3.29
Weighted score		3.00	2.65	2.75	3.50	3.45	3.00		3.30
Average of evaluators' scores					3.08				
Weighted average					3.09				

come of the analysis in this particular case. It was at this point that the sensitivity analysis became helpful in determining a clear statistical winner of the project.

Sensitivity Analysis

The raw data analysis may include biases due to the model, or out-of-the-ordinary ratings on the part of one or more of the evaluators. Altering some of the constants in the analysis and performing one thousand new iterations of the simulation several times should minimize this bias. The sensitivity analysis is carried out with two different analytical techniques, a regression analysis that measures sensitivity by input variable, and a rank correlation calculation that measures the correlation between the output values and each set of sampled input values.

As a first step, only the number of evaluators contributing to the final score was changed while all importance levels were kept constant. The results shown in Table 4 had Alliance Team 1 winning the contract in three out of nine conditions. This was a change from the original weighted score, which showed Alliance Team 4 as the absolute winner. After that, the importance levels of the several factors were varied without removal of any of the evaluators. Out of 1,000 iterations of changes in the importance levels, the results of this test, shown in Table 6, had Alliance Team 4 winning 96% of the time.

Additionally, the importance levels and the evaluators were varied and shifted simultaneously in order to discover and assess potential biases that may have existed in the first part of the sensitivity analysis. The importance levels were varied as was done previously, but, in addition, the highest and lowest scores from each criterion were removed. The results from this test were similar to those seen before in that Alliance Team 4 remained the winner of the contract about 97% of the time. Another test removed Evaluator B from the analysis because of the wide range of scores that this evaluator reported across different alliances. The results of this test also showed that Alliance Team 4 won on every condition. One more test changed the importance levels and removed Evaluator C from the study because of the high rating given to Team 2. The idea here was to reduce a potential team bias toward Alliance Team 2. Alliance Team 4 was once again the winner of the contract in this scenario. At this point in the evaluations, the data seemed conclusive enough to award Team 4 the contract. One last test, however, focused on Evaluator A, who gave Alliance Team 3 a score much higher than its average score. The results of removing Evaluator A from the analysis revealed Alliance Team 1 as the winner. This suggests that some of Evaluator B's ratings were erroneous or subject to bias against Team 1 and would be examined further.

This last part of the sensitivity analysis section explores the results, showing some of the statistical facts behind the study such as the teams' score distributions and the factors that contributed most significantly toward these scores. Table 6 presents the mean and standard deviation of every alliance's score. To serve as an example, the data for Team 1 are visualized in Fig. 3 and illustrate the distribution of the simulated scores.

The sensitivity analysis performed on each team's score and each team's possibility of winning used a multivariate stepwise regression analysis. The stepwise regression results for the scores and the possibility of winning are shown in Tables 7 and 8, respectively, which present values for both the regression and correlation. A possible interpretation of the regression values for Team 1's score is that a one standard deviation increase in the

Table 6. Weighted Scores

Outputs	Team 1	Team 2	Team 3	Team 4
Minimum	2.274	1.871	1.871	2.312
Maximum	3.813	3.141	3.112	3.856
Mean	3.059	2.521	2.502	3.095
Standard deviation	0.265	0.215	0.211	0.262
Variance	0.070	0.046	0.044	0.069

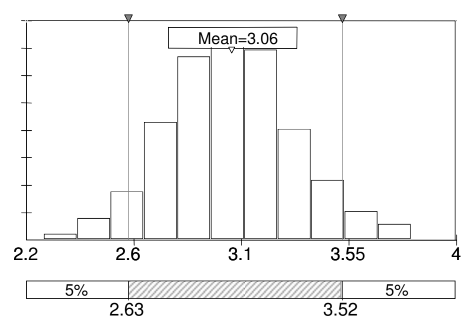

Fig. 3. Weighted score for Team 1

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Table 7. Sensitivity—Alliance Team Score

Rank	Name	Regression	Correlation
Team 1			
1	Experience with alliance projects	0.523	0.541
2	Alliance methodology approach	0.472	0.531
3	Alliance team capabilities	0.469	0.488
4	Efficiency and effectiveness	0.226	0.263
5	Alliance team business history	0.224	0.270
6	Cultural fit	0.218	0.243
7	Experience with owner	0.204	0.171
Team 2			
1	Alliance team capabilities	0.507	0.519
2	Experience with alliance projects	0.502	0.519
3	Alliance methodology approach	0.403	0.464
4	Experience with owner	0.286	0.248
5	Alliance team business history	0.264	0.311
6	Cultural fit	0.234	0.260
7	Efficiency and effectiveness	0.194	0.228
Team 3			
1	Alliance methodology approach	0.572	0.630
2	Experience with alliance projects	0.464	0.480
3	Alliance team capabilities	0.345	0.359
4	Cultural fit	0.275	0.300
5	Experience with owner	0.257	0.240
6	Efficiency and effectiveness	0.235	0.279
7	Alliance team business history	0.209	0.255
Team 4			
1	Alliance team capabilities	0.497	0.512
2	Experience with alliance projects	0.470	0.487
3	Alliance methodology approach	0.461	0.523
4	Experience with owner	0.246	0.212
5	Cultural fit	0.241	0.268
6	Efficiency and effectiveness	0.238	0.277
7	Alliance team business history	0.225	0.271

Table 8. Sensitivity—Possibility of Winning

Rank	Name	Regression	Correlation
Team 1			
1	Experience with alliance projects	0.303	0.273
2	Experience with owner	−0.214	−0.207
3	Cultural fit	−0.177	−0.161
4	Alliance team capabilities	−0.112	−0.089
5	Alliance methodology approach	0.074	0.068
6	Efficiency and effectiveness	−0.055	−0.064
7	Alliance team business history	0.000	−0.013
Team 2			
1	Experience with owner	0	0
2	Experience with alliance projects	0	0
3	Alliance team capabilities	0	0
4	Alliance methodology approach	0	0
5	Alliance team business history	0	0
6	Cultural fit	0	0
7	Efficiency and effectiveness	0	0
Team 3			
1	Experience with owner	0	0
2	Experience with alliance projects	0	0
3	Alliance team capabilities	0	0
4	Alliance methodology approach	0	0
5	Alliance team business history	0	0
6	Cultural fit	0	0
7	Efficiency and effectiveness	0	0
Team 4			
1	Experience with alliance projects	−0.303	−0.273
2	Experience with owner	0.214	0.207
3	Cultural fit	0.177	0.161
4	Alliance team capabilities	0.112	0.089
5	Alliance methodology approach	–0.074	–0.068
6	Efficiency and effectiveness	0.055	0.064
7	Alliance team business history	0.000	0.013

factor "experience with alliance projects" increases Team 1's score by 0.523 standard deviations, and a one standard deviation increase in the factor "alliance methodology approach" increases Team 1's score by 0.472 standard deviations. Other factors, such as "efficiency and effectiveness," "alliance team business history," "cultural fit," and "experience with owner" are not the main criteria that affect Team 1's score. The same type of interpretation can be given for each team's score and its possibility of winning. Now, moving to the interpretation of correlation values, the correlation coefficient ranges in value from −1.0 to +1.0. The closer r is to +1 or −1, the more closely the two variables are related. If r is close to 0, this means there is no relationship between the variables. If r is positive, this means that the two variables are positively related. A negative *r* means that they are inversely related. In Tables 7 and 8, the values show that the factor experience with alliance projects is most highly correlated (0.541) with Team 1's score; the alliance methodology approach factor is the second highest correlated factor (0.531), and so on.

The results of the sensitivity analysis from Tables 7 and 8 can also be displayed graphically, as a tornado-type chart, with longer bars representing the most significant input variables. A sample tornado graph is shown in Fig. 4, describing the regression sensitivity for Team 1's score.

Interpretation of the Results

The sensitivity analysis is open to more interpretation than just averages of the ratings and presents a good educational scenario to analyze. Varying the importance levels and evaluators both individually and together had a minimal effect on the results: Team 4 was always the winner and Team 1 followed very closely, except with one test. Removing Evaluator A from the analysis left Alliance Team 1 as the winner of the contract. Evaluator A scored

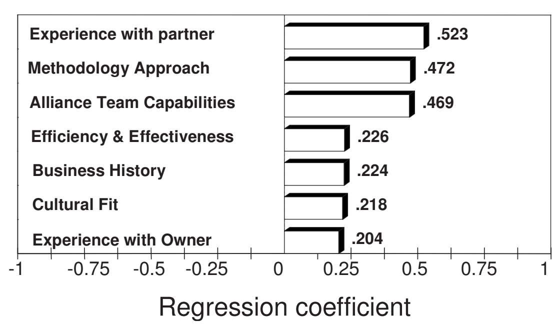

Fig. 4. Regression sensitivity for the weighted score of Team 1

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Team 3 much higher than its average score. However, a closer look at Tables 3 and 5 reveals that Evaluator A was also the one who gave Team 1 the lowest score, a score much lower than its average. This suggests a strong potential for team bias. Possible reasons are that Evaluator A had bad relations with the partners in Team 1 on a previous project or heard negative comments from other contractors who worked with Team 1. If Evaluator A were removed from the simulation, Alliance Team 1 would have been selected. From the owner's point of view, repeating the entire simulation without Evaluator A was necessary in order to ensure that this particular assessor skewed all of the results of the simulation. This was actually the case, and the contract was awarded to Team 1.

Conclusions

Employing Monte Carlo simulations to assist in the alliance team selection was extremely useful in this project. The results showed that the developed weights model was fair for all competitors. However, the study uncovered a bias from one of the evaluators that skewed the alliance selection results.

The Monte Carlo simulation has evolved into an excellent tool for decision problem analysis in the construction industry. What seemed to be a qualitative analysis was turned into reassuring quantitative analyses and results. Making decisions under uncertainty and handling decisions that involve a number of variables are two of the key benefits that the Monte Carlo method has to offer. The limits of this analysis have not yet been reached; researchers and other industry practitioners may find this method useful in more ways than those described in this paper. The professional implications for the alliance selection methodology, with respect to increasing confidence in selecting the best project team, are key aspects for a financially successful project.

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