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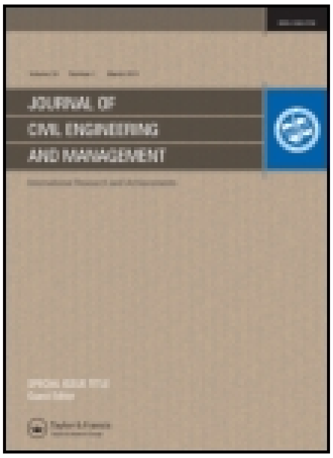

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UTILIZING RANDOM PERFORMANCE RECORDS IN THE BEST VALUE MODEL

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Abstract. Most construction agencies have a quality management system in order to control and manage the quality of their final product. Once the project is over, the testing results are kept in archives in which they are rarely re-visited or utilized. Quality testing results carry much information about the contractor performance that could be useful during the contractor evaluation/selection process. Previous attempts to implement the Best Value (BV) used the average performance records as the expected performance, which was utilized to evaluate contractors. The objective of this research is to develop, based on random data obtained from the contractor's performance records, a methodology that provides decision makers with the level of confidence or risk associated with the contractor selection using the BV model. Simulation technique is used to develop the BV model and analysis. Field performance data have been used to obtain the Percentage Defective, which indicates the contractor's performance in the BV model. The analysis of data indicates that performance follows a normal distribution. Sensitivity analysis of the BV model illustrates the significance of the weights in the BV model, which demands special attention when selecting the parameters' weights. The developed methodology provides the decision makers with the confidence and risk associated with their selection decision.

Keywords: simulation, quality, sensitivity analysis, performance characteristics, procurement, asphalt pavements, contractors selection.

1. Introduction

Owners of construction projects become more interested in adopting a system that ensures qualified contractors for their competitive bids. In low bid contracting, the offer of the most qualified contractor might be rejected if it is higher than the lowest bid by a small percentage. Best Value (BV) is the method that overcomes the problems of low bid selection procedure by including factors other than bid price in the selection process. The BV is defined as "a procurement process where price and other key factors are considered in the evaluation and selection process to enhance the long-term performance and value of construction" (Scott *et al.* 2006). The low bid system encourages contractors to implement cost-cutting measures instead of quality enhancing measures. Therefore, it is less likely that the contracts will be awarded to the best-performing contractors who will deliver the highest quality projects with minimum cost (NAVFAC 1996). Federal highway agencies use the BV in a variety of ways. Sometimes, they develop comprehensive evaluation criteria based on diverse project goals. Too often, evaluation criteria are generic and evaluation processes focus on identifying the technically acceptable proposal with the lowest cost (Sustainable Northwest 2008).

In a broad sense, the risk involved in selecting the contractor based on the past record is not well quantified in the selection process. Using the past performance record to obtain the BV carries the risk of either underestimating or overestimating the contractor and might lead to an inconvenient contractor selection. Underestimating occurs when the contractor has a large amount of records with a high standard deviation. Although the contractor might have a high mean value for a specific parameter, one single record of poor performance could increase the standard deviation dramatically. On the other hand, overestimating occurs when the contractor does not have past performance records. In this case the contractor is assigned the average performance of the population records. Consider the case when the decision maker compares two contractors. The first contractor has no past performance records and is viewed as the risky choice. However, this contractor will be assigned a BV score equal to the average of the population. The other contractor has past performance records that could be used to calculate the BV score. The risk associated with selecting this contractor is quantified. Regardless of the calculated BV score, looking at the risk associated with this score could support the decision of selecting one of them. This situation stres-

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ses the need to consider the risk associated with the contractor BV scores rather than just comparing them. In addition, previous studies used the mean of the performance records as the expected value of the contractor future performance (Abdelrahman *et al.* 2008a). These studies did not address the effect of variability around the mean and uncertainty on the BV model results. Moreover, the confidence limit of the BV model results was not considered as well.

2. Study objectives

The objectives of the presented research in this paper are:

- To analyze the data obtained from contractor's performance quality records;
- To develop a methodology that considers the level of confidence and/or risk associated with the contractor's selection using the BV model.

3. Literature review

Operation research and multi-criteria decision making provides useful tools for many complicated decisions as they are based on criteria values and weights (Zavadskas *et al.* 2008). Singh and Tiong (2005) presented a systematic procedure based on fuzzy set theory to evaluate the capability of a contractor to deliver the project as per owner's requirements in linguistic terms. Singh and Tiong (2006) developed a computer-interactive multi-criteria decision system for contractor selection. The system identified contractor selection criteria, investigate contractor selection criteria preferences of construction practitioners, and establish weights for those contractor selection criteria through a questionnaire survey. Waara and Bröchner (2006) studied how public owners use multiple criteria for the award of construction contracts. The findings showed a typical pattern of 70% price weight combined with three non price criteria. The reference point for price criterion was the lowest bid, bid spread, or average bid. Non price criteria were evaluated on either relative or absolute merits. Elazouni (2006) developed a neural network model to classify contractors into groups based on financial ratios. The model identified contractors with similar performance patterns and considered them as a cluster. Brauers *et al*. (2008) used multi-objective optimization on basis of ratio analysis as a mean to analyze multiple criteria decision based on multi-criteria utility theory. Plebankiewicz (2009) proposed contractor prequalification model using fuzzy sets theory. The model considered different selection criteria considered by decision makers, such as technical ability and financial standing of candidates. Zavadskas *et al.* (2010) studied the applicability of grey theory techniques for defining the utility of an alternative when dealing with multiple criteria decision using uncertain data.

Being a multiple criteria selection method, BV focuses on selecting a contractor with the offer "most advantageous to the government where price and other factors are considered". The considered factors other than bid price can vary, but they typically include technical and managerial merits, financial health, and past performance (Gransberg, Ellicott 1997; Gransberg, Senadheera 1999; Gransberg *et al.* 2006). The BV procurement, that is simple to implement and flexible in parameter selection, is the most effective approach in the context of a traditional bidding system. In a broad sense, the BV strategy aims at using bid price and other key factors in the evaluation and selection process of bidders to enhance the long term performance of projects. The inclusion of key factors that match specific needs of a project guarantees that the selected contractor is the best to construct this project (Abdelrahman *et al.* 2008b). Most BV models include an evaluation process that is conducted based on subjective criteria. It is necessary for an agency implementing the BV to adopt a rational ranking system for contractor qualifications that is based on the agency's expected level of performance (Abdelrahman *et al.* 2008a).

Agencies should base BV selection criteria only on project elements that add measurable value to the project. Agencies must think carefully of what is "valuable" in the product and not just "important" or "required" in the selection process. One of the algorithms used to combine parameters' scores for the contractor is represented by Eq. (1) as follows (Abdelrahman *et al.* 2008a, b):

$$BV_j = \sum_{i=1}^{n} NS_i \times W_i , \quad (1)$$

where: BV_j – Best Value for contractor j; n – number of parameters included in the BV model; NS_i – normalized score of parameter i; W_i – weight of parameter i.

The parameters of each project are identified and their scores are calculated and normalized on a scale of 50 to 100 depending on which parameters are most important for the new project. Eq. (2) is used to normalize the contractor parameter relative to the parameter score of the other contractors (Abdelrahman *et al.* 2008a, b):

$$NS_i = \left(NS_{URL} - NS_{LRL}\right)\frac{S_i - LRL}{URL - LRL} + NS_{LRL} , \quad (2)$$

where: NS_i – the normalized score of parameter i; S_i – the score of parameter i; URL (Upper Reference Limit) – the best parameter score; LRL (Lower Reference Limit) – the worst parameter score; NS_{URL} – the normalized score of the URL; NS_{LRL} – the normalized score of the LRL.

The contractor who has the best and the worst parameter scores get NS_i equal to 100 and 50, respectively. The normalized scores of the parameters scores that fall in between the best and the worst scores would range between 50 and 100. Contractor selection is typically based on multiple factors, such as cost, schedule, quality management, safety, and technical ability, which are considered as the model parameters (Dorsey 1995). The relative weight (W_i) of the parameters included in the BV model are determined based on the opinions of the agency's experts using a questionnaire. A high bid price weight is recommended to maintain the clarity of the selection and to match the preferences of most owners (Scott *et al.* 2006). A rational and flexible BV model, based on expected performance, was proposed by literature (Abdelrahman *et al.* 2008a). The model rationality

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was achieved through relating all awarded scores to the agency's expected performance. This research incorporates prequalification as the first level screening technique in selecting top contractor bids in the BV procurement, then, applies a rational scoring system in the final selection. Contractor's BV was the base in selecting the most appropriate contractor that has the best qualifications in a given project (Abdelrahman *et al.* 2008a). This model used the past contractor records to assign a score for the contractor. However, the model does not address the variability and uncertainty involved in the calculated BV score. There is also a need to consider the confidence interval of the random data in the calculation of the BV score and to quantify the risk of selecting a contractor using the BV model.

4. Study methodology

The presented methodology considers the Percent Defective (PD) of quality testing as a probability distribution instead of only using deterministic values. Using Monte Carlo simulation, the Total Percent Defective (PD_T) is estimated based on the PD distributions of different quality characteristics. PD_T, which will be represented by a probability distribution, is used to calculate the BV score. The contractor BV score will become a range of values, which creates the different selection scenarios, instead of a single score. The simulation is used in the methodology to run all possible combinations of the expected contractors' performance and provide the results at a different level of confidence. Only bid price and quality of past performance are included in the current BV model in order to show the effect of quality on the contractor selection decision. The methodology involves the following main steps, which are discussed in detail in the following sections:

1 – Collect and Analyze the Percent Defective (*PD*) of various pavement quality characteristics.
2 – Estimate the Total Percent Defective (PD_T) for pavement quality performance score.
3 – Develop the Contractor Selection Algorithm (*CSA*).
4 – Rank contractors based upon the *CSA*.

4.1. Percent Defective (*PD*) of various pavement quality characteristics

Quality Characteristics

The quality of Superpave mixes is dependent on several materials and construction factors. Several quality tests are performed on site and/or in the laboratory as part of the quality control/assurance processes. Three main pavement quality characteristics are considered in the development of PD_T: the testing results of Asphalt Content (*AC*), Air Voids (*AV*), and Gradation (*GR*).

Quality Measure

The results of quality testing are transformed to Percent Defective (*PD*) as a quality measure that indicates how far the contractor from the specification limits. Percent Defective has been preferred in recent years because it simultaneously measures both the average and the variability level in a statistically efficient way. PD can be calculated using another quality measure, i.e., the Percent within Limits (*PWL*). It is related to PWL by the simple relationship, $PD = 100 - PWL$. The use of PD as a quality measure has some advantages, particularly with two–sided specifications, because PD below the lower specification limit can simply be added to the PD above the upper specification limit to obtain the total PD value (Breakah *et al.* 2007). PWL and PD are capable of combining more than one stochastic measure into one single number. Conceptually, the PWL procedure is based on the normal distribution features. The area under the normal curve can be calculated to determine the percentage of population that is within certain limits. Similarly, the percentage of the lot that is within the specification limits can be estimated. The interested readers may refer to Burati *et al.* (2003) for the detailed procedures used to calculate PWL and PD.

4.2. Estimating *PD*

PD data are collected from a number of projects (*N*) to form the population of the quality characteristics and tested to assure whether it follows normal distribution. Data are tested using both the Anderson-Darling (A-D) and Kolmogorov-Smirnov (K-S) tests for normality. It is assumed that failing to reject H_0 (null hypothesis: it is normal distribution) for one of the normality tests is enough to consider the data follow normal distribution. Based upon this statistical probability fitting, the PD distributions for various characteristics are developed.

4.3. Total Percent Defective (PD_T)

The objective of this step is to obtain PD_T using *PD* of multiple quality characteristics. The ultimate way to estimate PD_T refers to the basics of the acceptance and rejection of quality tests procedures. This study uses the basic statistical concepts to combine different quality characteristics distributions. The first assumption is that PD_T is equivalent to the probability of accepting the contractor work with partial pay. The quality characteristics are the inputs of the model and represented by the percentage defected of the contractor work as measured during the quality control process.

The actual practice in the pavement industry does not reject the sample if the test result falls outside the specification limit. Shifting the focus from accepting/rejecting the sample to *PD* allows the agencies to accept the contractor defected work. Two scenarios for accepting the contractor work based on the estimated *PD* could occur: first to accept the work with full or bonus pay, second to accept the work with reduced pay. Agencies have developed their own equations to reword or penalize the contractor using the pay factor, which assumes that giving the contractor a fraction of the full pay would motivate improved performance.

The proposed model assumes each pavement sample is tested for three quality characteristics; *AC*, *AV*, and *GR*. Using the methodology discussed earlier, each sample

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will have three estimated *PD* values for *AC*, *AV*, and *GR*. For each quality characteristic, *PD* is considered the probability of test result falling outside the specified limits. Based on the results of the three tests, samples could be classified into three groups; acceptance with full pay, acceptance with reduced pay, or rejection. The area outside the three circles, in Fig. 1, indicates the acceptance with full pay. The area of the three circles, including the intersection area, represents the acceptance with reduced pay. Both regions together form 100% of the space. The area of the intersection between the three circles represents the percentage of tests rejected in the three quality characteristics. Ideally, eliminating the contractor who fails in all the quality characteristics tests guarantees a better quality. However, the current practice penalizes the contractor for the poor performance without elimination. Eq. (3) estimates the Total Percent Defective (PD_T):

$$PD_T = 100 - \frac{[(100 - PD_{AC}) \times (100 - PD_{AV}) \times (100 - PD_{GR})]}{10000}, \quad (3)$$

where: PD_{AC}, PD_{AV}, and PD_{GR} are Percent Defectives for *AC*, *AV*, and *GR*, respectively. This equation assumes there is an interaction between the quality characteristics as represented by the area shared between the three circles in Fig. 1.

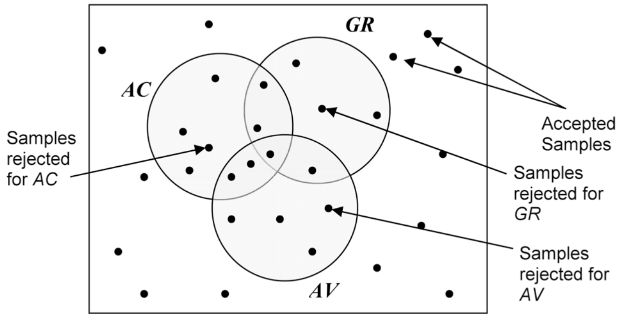

Fig. 1. Samples acceptance and rejection

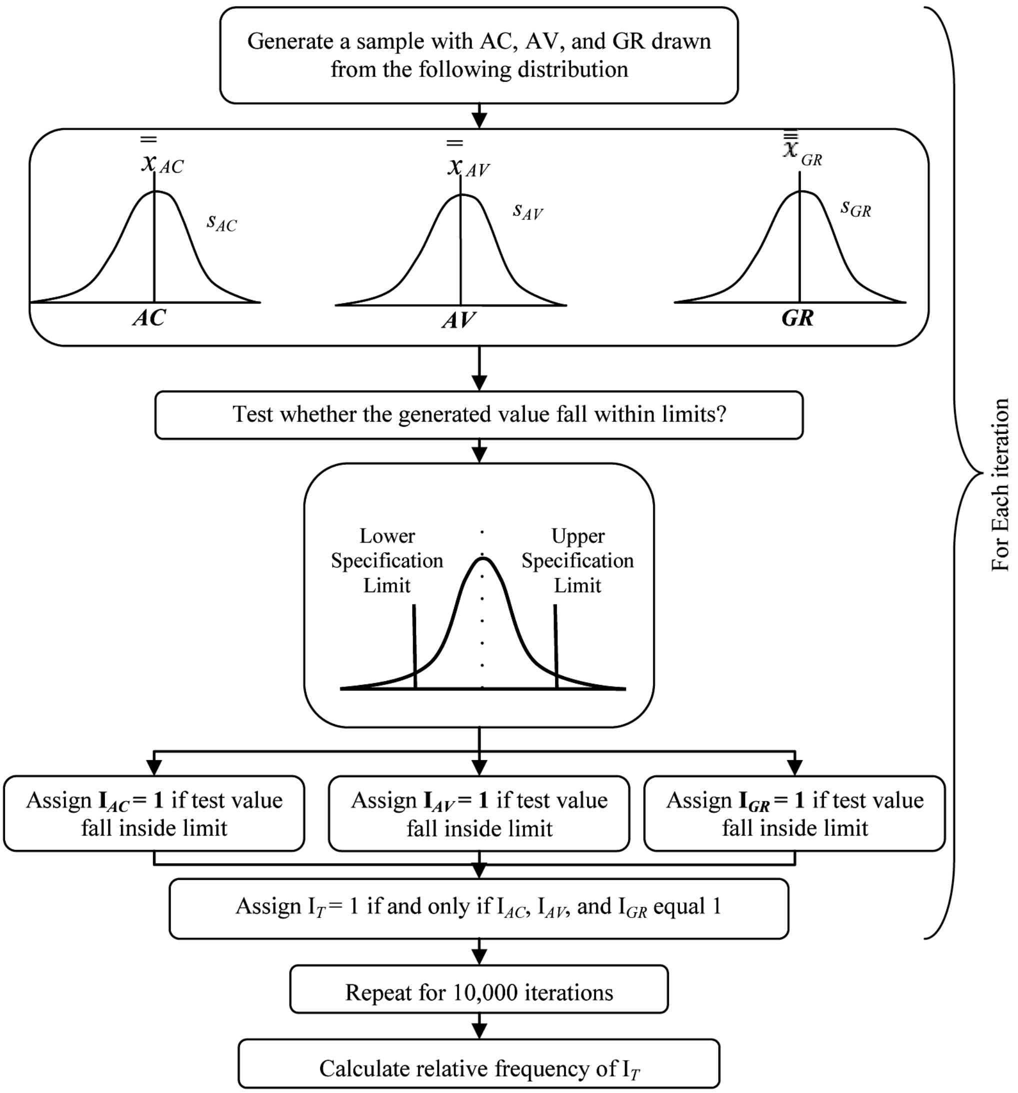

Fig. 2. PD_T simulation procedure

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PD_T using Simulation

Monte Carlo simulation technique is designated for the use of random sampling procedures to analyze deterministic mathematical situations (USDOE 2008). The simulation is used here as a tool to verify using Eq. (3) in calculating PD_T and the belief that the distribution of the contractor PD values may not necessarily follow the normal distribution. If the distribution of the contractor PD values is normal there would not be a need to use the simulation. The distribution of contractor PD values should be checked to determine the type of distribution it follows. The simulation procedure estimates the percentage of rejected samples as an equivalent to the probability of acceptance with reduced pay. Fig. 2 summarizes the steps used to calculate the percentage rejection for each project. The simulation combines PD of different quality characteristics with different means ($\bar{x}$) and standard deviations(s) into a single distribution (PD_T) with mean ($\bar{x}_T$) and standard deviation (S_T). Crystal Ball software has been useful in running the simulation and providing the outputs (Oracle 2008).

4.4. Selection algorithm and ranking of contractors

The BV model shown in Eq. (1) is flexible enough to consider any parameter during the contractor selection process. Only two parameters, bid price and quality of past performance, are included in the current study in order to clearly prove the research concept. The bid price is a discrete variable equal to the bid price value offered by the contractor at the time of bidding. On the other hand, quality of the past contractor performance, represented by PD_T, is a random variable which follows a normal distribution of μ_T and σ_T. The bid price amount and PD_T are considered the initial scores of the contractor for bid price and quality, respectively. Both are normalized using Eq. (2), assuming that low PD_T and bid price amount correspond to higher values of the normalized score (NS_i).

Fig. 3 shows the methodology employed to obtain the BV score and rank contractors using two methods or approaches: Three Points (TP) and Combination (C). Both approaches consider the risk associated with the selection decision; however, they are different in how to determine this risk. The TP approach assumes three possible scenarios of achieving the expected performance. Either the optimistic, average, or pessimistic scenario occurs, to all contractors, at the same time with no crossing among them. On the other hand, the C approach assumes that each contractor has an independent chance to achieve one of the three performance levels defined in terms of μ_T and C_T (confidence limit). One of the contractors may achieve the best expected performance in a project. Another may achieve the worst or average expected performance. The chances of achieving the expected performance are not equal for all contractors. The C approach

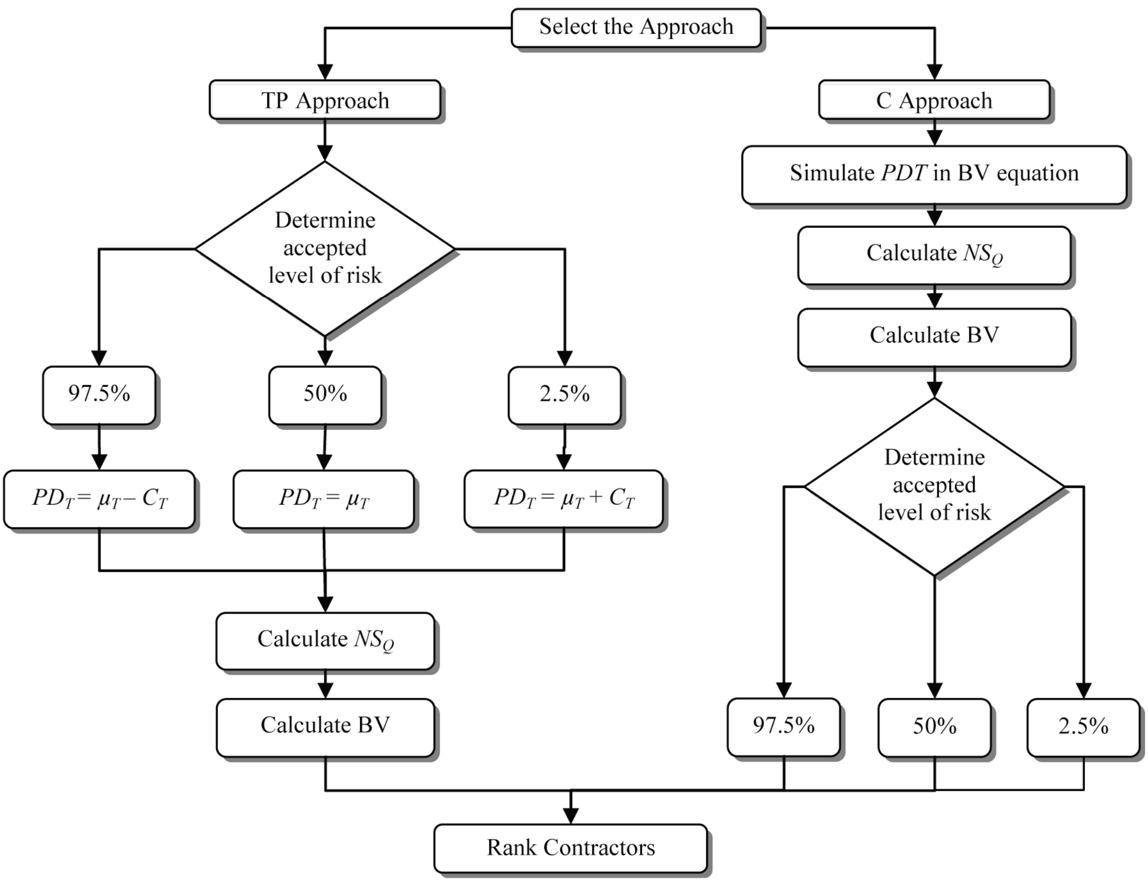


Fig. 3. Contractor Selection Algorithm (CSA)

uses simulation to determine all possible combinations of performance levels and classify the results into three scenarios depending on the level of risk associated with each one.

The TP Approach

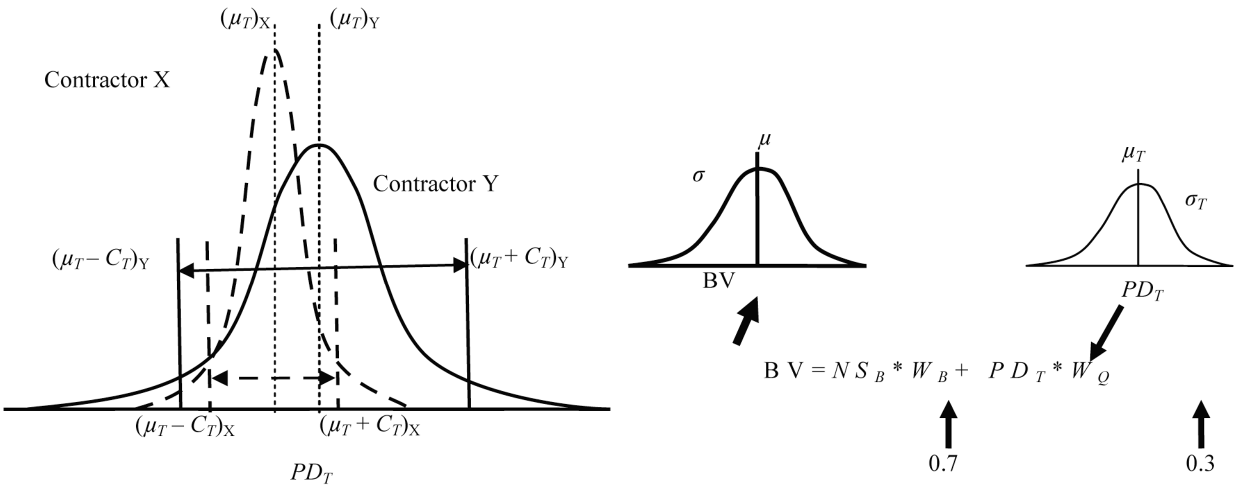
The TP approach has two assumptions to fairly asses the contractors' performance: (1) the contractor achieves one of three performance levels and (2) all the contractors will achieve the same performance level in the project. The optimistic, average, and pessimistic scenarios occur when the contractor achieves PD_T equal to $\mu_T - C_T$, μ_T, and $\mu_T + C_T$, respectively. The risk associated with selecting the contractor based on the optimistic, average, and pessimistic scenarios is 97.5%, 50%, and 2.5%, respectively. The 97.5% and 2.5% risk refer to the two limits of the 95% confidence interval, while the 50% risk refers to the average value of the calculated BV. In the TP approach, the model is implemented three times with the same Normalized Bid Price Score (NS_B) and different Normalized Quality Score (NS_Q). The BV score of the contractor will be different based on the attitude of the agencies toward risk. The contractor selection will follow the optimistic, average, or pessimistic scenarios for agencies with a risk-seeking, risk-neutral, or risk-averse attitude, respectively. For example, if the pessimistic scenario is the agency choice, all contractors are assumed to achieve PD_T equal to $\mu_T + C_T$. These values are scaled to NS_Q using Eq. (2) and added to NS_B to obtain the BV score using Eq. (1). Fig. 4a introduces a graphical representation of the TP approach. For example, contractor X has μ_T lower than contractor Y while contractor Y has σ_T larger than contractor X. If the TP method is used to rank the contractors based on only NS_Q, contractor X would come first with low PD_T and high NS_Q. On the other hand, the TP approach provides the decision maker with three scenarios to choose from depending on how C_T (confidence limit) is considered with PD_T when calculating the NS_Q.

The C Approach

The TP approach assumes that the contractor performance has only three levels. However, there are, in reality, endless levels of performance to be achieved in the project. This advocates the need to run all the combinations of possible levels of contractors' performances considering PD_T as a distribution rather than just three levels. The Monte Carlo simulation is used to run different scenarios of combinations and optimize the solution. The simulation is used with the BV model in Eq. (1), to simulate the PD_T with μ_T and σ_T for each contractor and calculate the corresponding BV. The inputs of the simulation are PD_T distributions, while the output is the corresponding BV distribution. Fig. 4b graphically illustrates the C approach implementation.

5. Data collection and case study

To study the implementation of the proposed BV methodology, data are collected from Nebraska Department of Roads (NDOR). A group of Superpave projects is used to demonstrate the implementation of the proposed methodology. In project number NH-83-3(107), the decision makers received five bid offers from contractors CONA, CONB, CONC, COND, and CONE. This project includes the construction of a road section that is part of US-83, District 6, state of Nebraska. The specification recommends using the Superpave mix type SP4 for medium volume roads. Only two parameters are included in the selection criteria; bid price and quality of past contractor's performance. The past performance data used in the case study collected from NDOR for 500 projects constructed between 2003 and 2005. The past performance data are collected in the form of quality testing results for Asphalt Content (AC), Air Voids (AV), and Gradation (GR). The testing results are used to estimate PD_T and NS_Q.



(a) TP Approach (b) C Approach

Fig. 4. Best value score approaches

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Bid prices offered by the contractors are collected from NDOR. Previous studies shows that a ratio of 70% is used by most federal and state agencies, who prefer to assign the bid price a weight equal to or greater than all other parameters (Scott *et al.* 2006; Abdelrahman *et al.* 2008a). A study indicates that the weight of bid price should be less than 82% (Abdelrahman *et al.* 2008b; Gransberg *et al.* 2006). The decision to assign 70% for the weight of bid price and 30% for that of quality of past performance would maximize the effect of the performance parameter on the results of the BV model and provide the required balance between both parameters.

6. Implementation of the developed methodology to case study

The developed methodology is implemented to case study data to prove the methodology concepts. The above-mentioned four main steps are applied to the case study as discussed in the following sections.

6.1. Percent Defective (*PD*) of various pavement quality characteristics

Three main pavement quality characteristics are considered in the development of PD_T: the testing results of Asphalt Content (*AC*), Air Voids (*AV*), and Gradation (*GR*). The results of quality testing are transformed to *PD* in order to consider variability and uncertainty. The quality data used in this study was obtained from the NDOR for 500 projects of six Superpave mix types constructed between 2003 and 2005. Higher-level mixes correspond to higher Average Daily Truck Traffic (ADTT) (NDOR 2005) as follows: (i) SPS, SP1, SP2 for ADTT < 160 Trucks/day; (ii) SP3, SP4 for ADTT > 160 and ADTT < 500 Trucks/day; and (iii) SP5, SP6 for ADTT > 500 Trucks/day.

The testing data were available for five contractors: CONA, CONB, CONC, COND, and CONE. *PD* data for all contractors are collected to form the population of the quality characteristic and tested for normality to assure it follows the normal distribution. Data were tested using both the Anderson-Darling (A-D) and Kolmogorov-Smirnov (K-S) tests for normality. Table 1 shows the results of the normality test for contractor CONA using *AV* data. For example, using the data for SP4, there are 99 data points in which the fitted normal distribution has a mean (μ) of 48.89 and standard deviations (σ) of 20.02. The test statistics for K-S and A-D in addition to the critical values at significance level (α) = 0.15 are shown in Table 1 as well. Based on K-S and A-D test statistics, it is concluded that normal probability distribution cannot be rejected as the best fit for PD values using 15% significant level (α). Similarly, the normal distribution cannot be rejected at 1%, 5%, 10% and 15% significant levels. For example, the critical value for *PD* at 15% significant level (α) is 0.08 using K-S and 0.56 for A-D; however, the test statistics is 0.05 and 0.39 for K-S and A-D, respectively. Because the critical values are higher than test statistics for both methods; then, null hypothesis (H_0) cannot be rejected in which the best probability fit is normal distribution. Similarly, the rest of SP types are analyzed where they show for most of them that normal distribution is the best fit. Current research considers the expected values and 95% confidence interval for most of the stochastic variables in order to analyze results of the developed methodology. Table 1 also shows the 95% confidence interval for each SP type. For example, the value of *PD* factor for SP4 has a 95% confidence interval limits as 44.90 (lower limit) and 52.88 (upper limit). However, its average value is 48.89 and normal distribution fit test was successful using both K-S and A-D. Similarly, the other SP types are analyzed where all of them follow the normal distribution using K-S test. There are two types fail to follow normal distribution using the A-D test: SPS and SP1; however, the test is successful using K-S algorithm. Similarly, the normality test is performed for all contractors' characteristics using the six Superpave (SP) types, which shows successful results. It is concluded that *PD* data for the Asphalt Content (*AC*), Air Voids (*AV*), and Gradation (*GR*) could be represented by a normal distribution when it is used as an input in the simulation process.

6.2. Estimating PD

Stochastic analysis is used to analyze the past performance records and provide the confidence interval of the calculated PD_T. The 95% confidence interval of PD_T (C_T)

Table 1. Normality Test of *AV* for contractor CONA

	Mix Type					
	SPS	SP1	SP2	SP3	SP4	SP5
N	5	16	21	6	99	8
μ	65.20	70.24	57.33	54.63	48.89	70.29
σ	8.52	27.04	17.61	8.21	20.02	20.48
95% confidence interval (C)	7.42	14.41	8.01	8.61	3.99	17.12
$\mu + C$	72.62	84.65	65.34	63.25	52.88	87.41
$\mu - C$	57.78	55.83	49.31	46.02	44.90	53.17
A-D Statistic	0.66	0.56	0.45	0.24	0.39	0.35
Critical Value @ α = 0.15	0.54	0.53	0.54	0.47	0.56	0.50
Reject H_0?	Yes	Yes	No	No	No	No
K-S Statistic	0.26	0.16	0.15	0.21	0.05	0.18
Critical Value @ α = 0.15	0.28	0.18	0.16	0.28	0.08	0.25
Reject H_0?	No	No	No	No	No	No

means that we are 95% confident that the contractor will achieve PD_T within the range of $\mu_T \pm C_T$. The simulation uses μ and σ of PD for AC, AV, and GR to estimate μ_T, σ_T, and C_T for PD_T. For example, Table 2 shows that CONB and COND has the lowest μ_T and σ_T among the contractors for SP3, respectively. Considering the confidence limits, an agency may consider CONB is the best with 95% confidence that he/she will achieve PD_T between 42.12 and 40.2, while another agency may consider COND the best with 95% confidence that he/she achieves PD_T between 42.34 and 41.34.

6.3. Total Percent Defective (PD_T)

The simulation is performed assuming that the variables are independent and the results are compared to the results from Eq. (3). Crystal Ball software (Oracle 2008) has been useful in running the simulation and providing the outputs shown in Table 2. The paired t-test is used to check the null hypothesis that the mean PD_T values for the two methods are equal. The p-value of the t-test is 0.637 which is greater than 0.05. In this case we will not reject the H_0 and conclude that the mean PD_T calculated using statistics is equal to that calculated using simulation. The output of simulation is the distribution of PD_T with mean (μ_T), standard deviation (σ_T), and 95% confidence interval (C_T).

Table 2. Simulation output data

Mix	Contractor	μ_T	σ_T	C_T
SP1	CONA	67.9	19.43	0.38
	CONB	52.49	35.13	0.69
	CONC	89.42	17.06	0.34
	COND	21.75	41.27	0.81
	CONE	71.5	34.19	0.67
SP2	CONA	61.18	9.98	0.19
	CONB	60.84	23.92	0.47
	CONC	67.35	12.24	0.24
	COND	90.23	12.51	0.25
	CONE	29.11	45.43	0.89
SP3	CONA	58.22	26.51	0.52
	CONB	41.16	49.21	0.96
	CONC	72.97	44.41	0.87
	COND	41.84	25.63	0.5
	CONE	62.74	35.6	0.7
SP4	CONA	80.52	3.62	0.07
	CONB	53.97	6.9	0.13
	CONC	77.81	10.45	0.2
	COND	79.98	6.18	0.12
	CONE	32.59	18.58	0.37
SP5	CONA	85.76	14.83	0.29
	CONB	61.01	10.47	0.2
	CONC	89.79	18.85	0.37
	CONE	39.24	30.79	0.6
SPS	CONA	59.23	6.19	0.12
	CONB	70.87	6.94	0.14
	CONC	74.33	6.75	0.13
	COND	51.37	11.53	0.23
	CONE	79.72	16.09	0.31

6.4. Contractor selection algorithm

The Quality Score in the BV model is represented by PD_T, which has a probability distribution. The contractor selection decision will be hard to take as the BV will no longer become a single score but rather a range of BV scores. Using one of the selection approaches as shown in Figs 4a and b, i.e. TP and C, solves this problem considering more than one scenario of achieving the expected contractor performance. Stochastic measures, such as the confidence interval, are integrated with the BV model to develop multiple selection scenarios. The decision makers are allowed to select the scenario that matches their attitude towards risk. As mentioned earlier, one out of three levels of risk defines the behavior of the decision makers; risk-averse, risk-neutral, and risk-seeking. Each of them matches one of the above-mentioned selection scenarios.

(i) Risk-Averse Agency

The pessimistic scenario is the best for the agencies with risk-averse attitude and occurs when the contractor achieves the worst expected level of performance. Table 3 shows the bid price, NS_B, PD_T, and NS_Q for project NH-83-3-(107) with SP4 mix. Eq. (3) is used to determine the BV and rank the contractors. It is clear that CONB has the highest BV score in the pessimistic scenario using both the TP and C approaches. While CONA offers the lowest bid, CONB offers the third lowest bid with an increase of 3.8% over CONA. In the pessimistic scenario, the selection of the lowest bidder is supported by the proposed methodology with high confidence that CONB will achieve the acceptable level of performance for SP4 mix.

(ii) Risk-Neutral Agency

The average scenario is the best for agencies with a risk- neutral attitude. Table 3 shows the agreement of both approaches that CONB has the highest ranking among contractors and should be awarded the project. The lowest bidder, CONA, comes in the second place after CONB using both approaches.

(iii) Risk-Seeking Agency

The optimistic scenario is applicable for agencies with risk-seeking attitude. This scenario assumes the contractor will achieve the lowest PD_T corresponds to 5% confidence level which means a higher risk of not occurring. Table 3 shows that CONB and CONA have the highest ranking among contractors using the TP and C approaches, respectively. As mentioned earlier, the C approach uses simulation to calculate all the possible scenarios and obtain the pessimistic, average, and optimistic scenarios using the confidence interval of the simulation results. This provides more confidence regarding the C approach results and suggests selecting CONA for the job.

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Table 3. Contractor BV and Ranking for Project NH-83-3(107) with SP4

Scenario	Contractor	PD_T	NS_Q	Bid Price ($)	NS_B	TP Approach		C Approach	
						BV	Rank	BV	Rank
Pessimistic	CONA	80.59	50.00	4627371.00	100.00	85.00	2	89.51	2
	CONB	54.11	77.80	4804336.00	90.42	86.63	1	93.29	1
	CONC	78.02	52.70	5550902.00	50.00	50.81	5	57.98	5
	COND	80.10	50.52	4701134.00	96.01	82.36	3	87.60	3
	CONE	32.95	100.00	5259604.00	65.77	76.04	4	76.04	4
Average	CONA	80.52	50.00	4627371.00	100.00	85.00	2	86.35	2
	CONB	53.97	77.69	4804336.00	90.42	86.60	1	87.73	1
	CONC	77.81	52.82	5550902.00	50.00	50.85	5	52.36	5
	COND	79.98	50.56	4701134.00	96.01	82.37	3	83.79	3
	CONE	32.59	100.00	5259604.00	65.77	76.04	4	75.42	4
Optimistic	CONA	80.45	50.00	4627371.00	100.00	85.00	2	85.00	1
	CONB	53.84	77.59	4804336.00	90.42	86.57	1	82.80	2
	CONC	77.61	52.94	5550902.00	50.00	50.88	5	50.00	5
	COND	79.86	50.61	4701134.00	96.01	82.39	3	82.20	3
	CONE	32.22	100.00	5259604.00	65.77	76.04	4	71.22	4

Table 4. Summary of contractor's BV and ranking for different SP mixes

Mix	Project	Contractor	Pessimistic Scenario				Average Scenario				Optimistic Scenario			
			TP Approach		C Approach		TP Approach		C Approach		TP Approach		C Approach	
			BV	Rank	BV	Rank	BV	Rank	BV	Rank	BV	Rank	BV	Rank
SPS	STPD-70-3(107)	CONA	92.53	2	96.63	2	92.47	2	91.33	2	92.40	2	81.63	2
		COND	100	1	100	1	100	1	98.09	1	100	1	85.00	1
		CONE	50.00	3	64.44	3	50.00	3	51.29	3	50.00	3	50.00	3
SP1	IM-80-1(170)	CONA	51.17	4	65.00	4	54.77	4	54.53	4	54.75	4	50.00	4
		CONB	90.74	1	100	1	93.19	1	92.42	1	93.21	1	85.00	1
		COND	80.53	3	80.53	3	80.53	3	77.63	3	80.53	3	65.53	3
		CONE	81.36	2	96.36	2	85.33	2	85.66	2	85.38	2	81.36	2
SP2	IM-80-1(170)	CONA	58.59	3	66.37	3	58.50	3	59.00	3	58.41	3	52.86	3
		CONB	57.23	4	65.00	4	57.21	4	57.49	4	57.19	4	50.00	4
		COND	85.00	2	91.73	2	85.00	2	85.95	2	85.00	2	85.00	1
		CONE	96.29	1	96.29	1	96.29	1	93.46	1	96.29	1	81.29	2
SP3	IM-80-1(170)	CONA	57.14	4	65.00	4	56.96	4	56.15	4	56.77	4	50.00	4
		CONB	87.50	3	87.50	3	87.50	3	81.41	3	87.50	3	72.50	3
		COND	92.36	1	92.46	2	92.14	1	86.78	2	91.93	1	77.46	2
		CONE	89.92	2	100	1	89.83	2	90.50	1	89.73	2	85.00	1
SP5	IM-80-1(170)	CONA	85.00	1	92.58	1	85.00	1	85.92	1	85.00	1	85.00	1
		CONB	58.06	3	65.00	3	57.98	3	58.39	3	57.90	3	50.00	3
		CONE	78.68	2	78.68	2	78.68	2	76.41	2	78.68	2	63.68	2

The conclusion is to award the project to CONB, if the agency has the risk-averse or risk-neutral attitude. Alternatively, the agency should award the project to CONA if it has the risk-seeking attitude. Table 4 shows the results of model implementation on five other projects with different SP mixes. The results include the BV score and contractor ranking using both approaches. It is concluded that both approaches have similar results in most mixes using the average and pessimistic scenarios. They are in difference when using the optimistic scenario.

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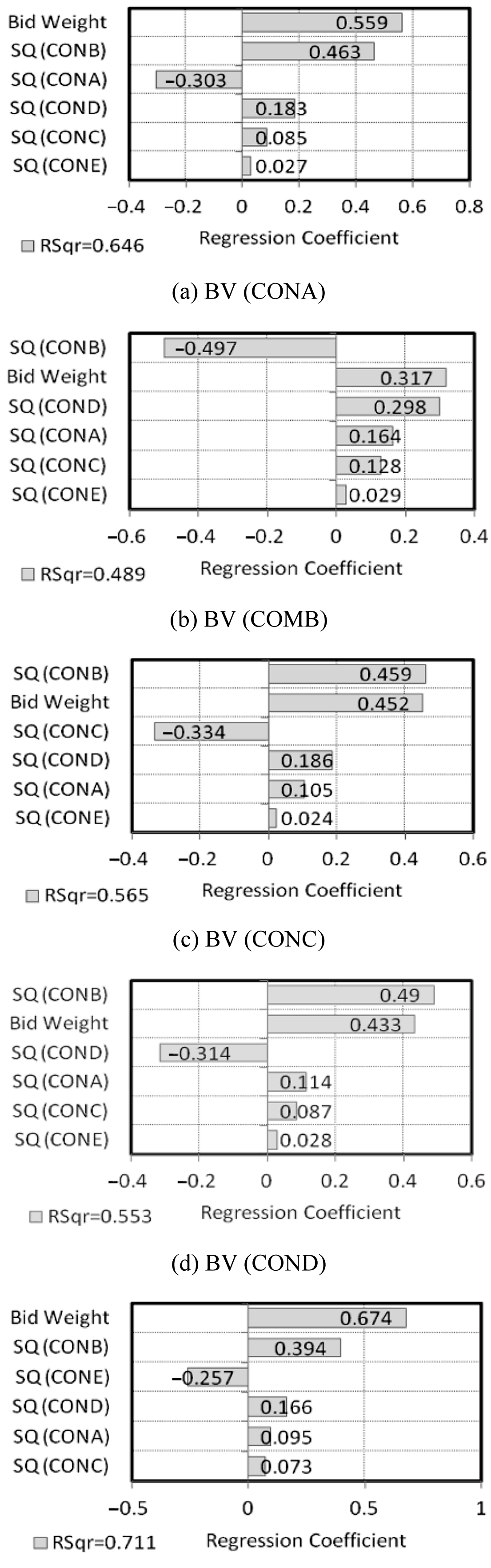
6.5. Sensitivity analysis of BV

The sensitivity analysis is conducted as part of the simulation process. The simulation inputs are PD_T for CONA, CONB, CONC, COND, and CONE and the bid weight. The sensitivity analysis does not consider the bid price as a variable in the sensitivity analysis since the bid prices are actual numbers offered by the contractors. Each input variable is increased by one unit and the output, BV score, is measured accordingly. The bid weight is changed within a range of 0 to 100. Fig. 5 shows the results of the sensitivity analysis. The R-square of the regression models, developed by the sensitivity analysis, ranges between 0.49 and 0.71 which is fairly low. The regression coefficient of PD_T for the same contractor has a negative sign which agree with the first assumption that a high PD_T is assigned a low BV score. All other variables in the BV model, including the weight of the bid price, have a positive effect on the calculated BV. Figs 5a and 5e indicate that bid weight has the largest effect on the BV score of CONA and CONE, respectively. Figs 5b, 5c and 5d indicate that PD_T of CONB has the large effect on the BV scores for CONB, CONC, and COND, respectively. Figs 5a, 5b, 5c and 5d show that changing the PD_T for CONE has a minimum effect on the BV score for all the contractors including CONE.

7. Conclusions

The BV procurement aims at using bid price and other key factors in the evaluation and selection process to enhance the long term performance of contractors in highway projects. The previous attempts to select the performing contractor, based on the BV score, are not efficient when past performance records are used. Two improvements are added in the current model compared to the previous models. The first is using Monte Carlo simulation technique to calculate the stochastic value of PD_T from PD of multiple quality characteristics. The previous approach defines PD_T as the average, or weighted average, of PD values for available quality characteristics. The second improvement is considering the variability and uncertainty of calculated BV score. This variability resulted from using historical records as probability distribution(s). The variability of the calculated BV score creates a risky situation for decision makers once the model selects a higher priced bid. One of the main contributions of the new approach is providing decision makers with confidence interval and risk associated with their decision in ranking contractors.



(a) BV (CONA)

(b) BV (COMB)

(c) BV (CONC)

(d) BV (COND)

(e) BV (CONE)

Fig. 5. Sensitivity analysis of BV scores for various contractors

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ATSITIKTINE TVARKA PARINKTŲ VEIKLOS EFEKTYVUMO DUOMENŲ NAUDOJIMAS GERIAUSIOS VERTĖS MODELYJE

A. H. Elyamany, M. Abdelrahman, T. Zayed

Santrauka

Dauguma statybos įmonių galutinio produkto kokybę kontroliuoja ir valdo naudodamos kokybės vadybos sistemą. Projektui pasibaigus, patikrinimo rezultatai laikomi archyvuose ir retai peržiūrimi arba naudojami. Kokybės patikrinimo rezultatuose daug informacijos apie rangovo veiklos efektyvumą, kuri praverstų vertinant (renkantis) rangovą. Anksčiau mėginant diegti geriausios vertės (GV) modelį, veiklos efektyvumas buvo numatomas pagal vidutinius veiklos efektyvumo duomenis ir pagal tai būdavo vertinami rangovai. Šio tyrimo tikslas – pasitelkus atsitiktine tvarka atrinktus duomenis iš įrašų apie rangovo veiklos efektyvumą, sukurti metodiką, kuri sprendimus priimantiems asmenims suteikia pasitikėjimo arba mažina riziką, susijusią su rangovų atranka pagal GV modelį. Kuriant GV modelį ir atliekant analizę taikomas imitacijos metodas. Naudojant faktinius veiklos duomenis apie efektyvumą buvo nustatyta procentinė defektų dalis (angl. *Percentage Defective*), kuri GV modelyje rodo rangovo veiklos efektyvumą. Duomenų analizė rodo, kad veiklos efektyvumas nenukrypsta nuo normaliojo skirstinio. GV modelio jautrumo analizė rodo, kad jame svarbūs reikšmingumai, taigi parametrų reikšmingumus reikia rinktis itin atidžiai. Sukurta metodika sprendimus priimantiems asmenims suteikia pasitikėjimo ir mažina riziką, susijusią su pasirinkimo sprendimais.

Reikšminiai žodžiai: imitacija, kokybė, jautrumo analizė, veiklos efektyvumo savybės, pirkimas, asfaltuota danga, rangovų atranka.

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