Contractor Performance Prediction Model for the United Kingdom Construction Contractor: Study of Logistic Regression Approach

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Abstract: An accurate prediction of contractor potential is of vital importance during contractor selection and evaluation process. Such prediction enables identification and classification of contractor performance to ease the selection process. This paper outlines the use of clients' tender evaluation preferences for predicting a contractor performance via a logistic regression (LR) approach. A total of 31 clients' tender evaluation criteria were selected to develop a LR model for predicting contractor performance. The proposed model was developed based on 48 of United Kingdom public and private construction projects and validated in 20 independent cases. It was found that 75% of the cases correctly and the model statistically accurate for contractor performance prediction, where the input variables consist of nominal and interval data. The paper summarized techniques and advantages of LR analysis and discussed literature findings of contractor selection and evaluation methodologies undertaken by construction researchers and commentators from the United Kingdom and Northern America.

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Introduction

The contractor selection issue is normally one of identifying a contractor who can undertake the client's project, and take it to satisfactory conclusion, that is, to meet the client's time, cost, and quality expectations (Holt et al. 1994a; Ng and Skitmore 1995). Earlier investigations into the subject have attempted to redress existing weaknesses in the contractor selection process (i.e., "lowest-prices" selection preference and subjective judgement) and offer rationalized alternative(s) to the present practice (e.g., Hunt et al. 1966; Hardy et al. 1981; Lewis 1981; Martinelli 1986). A variety of qualitative and quantitative selection methods have evolved as a result of such attention (e.g., Russell and Skibniewski 1990a; b; Moore 1985a. b; Herbsman and Ellis 1992; Russell and Jaselskis 1992a; CIRIA 1998; Holt 1998). Generally, construction clients and practitioners who have embraced the aforementioned contractor selection procedures have tended to favor a quantitative and multicriteria selection approach. Nevertheless, the issues of contractor selection continue to generate tremendous interest among the construction management research community (e.g., Ng and Skitmore 1995; Kumaraswamy 1996; Hatush and Skitmore 1997a; Wong et al. 1999). New findings pertaining to contractor prequalification, tender evaluation, and modeling techniques for predicting contractors' performance are confirming that the subject area still justifies investigation (e.g., Abidali and Harris 1995; Tam and Harris1996; Chinyio et al. 1998; Ng et al. 1999; Lam et al. 2000; Wong and Holt 2001). This situation also reflects the importance of this client decision task, and the need for judicious contractor selection (Holt 1995; Jennings and Holt 1998; Wong et al. 2000a, 2001).

Both the industrial and academic worlds have expanded the study of contractor selection (e.g., CIC 1993; CIDA 1995; Holt 1995; Hatush 1996; CIB 1997). The rationale underpinning this effort is to recognise unscrupulous contractors at an early stage. Such as to ensure that only the "right" contractors are invited to tender; to deter poor project performance, and in the extreme, avoid project (contractor) failures. In other words, an accurate objective selection approach, able to provide an early "warning" sign to clients (before the final selection decision) would be optimal. Another ongoing feature of the construction industry is an increased use of objective (via-a-vis subjective) approaches in the selection process (Holt 1998). As these more recent approaches have emerged, there has been a trend away from a "lowest-price wins" principle, to a multicriteria selection approach (RICS 1997; Wong et al. 2000a).

This paper presents an alternative contractor performance prediction model, which investigates the relationship between clients' tender evaluation preferences and contractor performance. That is, to investigate levels of importance assigned (LIA) to the tender evaluation criteria during evaluation process that give impact on the selection of a "good" contractor. The model presented herein is derived from the logistic regression (LR) analysis of 68 case studies of United Kingdom building and civil engineering projects.

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Literature Review

Significant investigations into contractor selection and evaluation methods have more recently expanded and given rise to a vast variety of contractor selection practices. For example, in Northern America, there has been extensive work to improve the contractor selection process (e.g., Hunt et al. 1966; Hardy et al. 1981; Diekman 1983; Nguyen 1985; Juang et al. 1987; Harp 1990; Moselhi and Martinelli 1990; Russell and Skibniewski 1990a, b; Herbsman and Ellis 1992; Russell et al. 1992), while in the United Kingdom, the construction industry has witnessed development of several alternative selection processes and objective evaluation methods (e.g., Moore 1985a; b; CIC 1993; Holt et al. 1994b; Holt 1998; Hatush and Skitmore 1997b). Research into this subject domain also includes:

1. Helmer and Taylor (1977): a conceptual model for evaluation of contractor management and project execution capabilities when selecting a contractor;
2. Russell (1990): a decision model for contractor prequalification;
3. Liston (1994): the contractor prequalification criteria for civil engineering work;
4. Potter and Sanvido (1994): the investigation of design and build prequalification systems;
5. Tam and Harris (1996): discriminant analysis model for predicting contractor performance;
6. CIRIA (1998): the selection of "value" versus the "lowest-tender price" practices; and
7. Palaneeswaran and Kumaraswamy (2000): the benchmarking contractor selection practices conceptual model.

The need for further revision of present selection practices to improve its adaptability and widespread use in construction industry remains. Empirical findings from the 1990s research in the United Kingdom construction industry found that a majority of current practices are subjective; they rely on prequalification and tender sum during final selection; and there is no universally accepted approach towards the contractor selection process (Merna and Smith 1990; Holt et al. 1995; Wong et al. 2000b). Furthermore, the United Kingdom construction industry, especially with respect to procurement is dynamic, and no one particular selection method has yet evolved able to cope with all different selection scenarios, which themselves, change constantly over time. The present diversity of selection methods has also cultivated a wide variety of "in-house" practices and individuals' selection preferences (Wong et al. 1999). Such divergence has inexorably contributed towards the inefficiency of the construction process, this being particularly so in the United Kingdom public sector, as criticized by Latham (1994). It is costly and time consuming to use "unstandardized" and diversified practices (i.e., numerous forms of prequalification questionnaires and contractor standing/tender lists). The need for standardization and streamlining of practice in striving for greater efficiency and reduced costs has also more recently been reiterated by Egan (1998).

Lam et al. (2000) introduced a decision support system in contractor prequalification using an artificial neural network model. Lam et al. (2000) described the relation between the client's decision and contractor's attributes (input variables) is nonlinear and always complicated, when incorporating subjective evaluation and decision-maker's evaluation experience. Sonmaz et al. (2001) proposed an evidential reasoning (ER) approach for use in tender evaluation process. This method embraces both qualitative and quantitative measures of client's preferences for a multiple criteria decision process and is particularly useful to overcome the imprecise and ambiguous contractor information during tender evaluation. This approach uses the concept of multiple attributes utility theory, aggregating and transforming assessments of a main criterion, and its associated subcriteria (or subsubcriteria). The assessment deals with multidisciplinary (qualitative and quantitative) data in each level and transforms into a higher level to determine an aggregated value for each alternative. The whole assessment involved systematic synthesis and modification of the uncertain attributes (e.g., uncertain decision knowledge and imprecise contractor information) and transformation of assessments. However, this method involved cumbersome calculation and transferring aggregated values from a single level to its higher level. The detailed mechanism of ER technique in multiple attribute design evaluation can be found in Yang and Singh (1994) and Yang and Sen (1997).

The aforementioned methodologies strengthened the use of the multicriteria approach to contractor selection and placed greater emphasis on the use of alternative selection methods: for instance, the desire to evaluate the strengths and weaknesses of contractor performance as a means of predicting their likely performance. The need for such research has emanated due to increasing construction project complexity and uncertainty, increasing clients' expectations, and demands, increased competition, and higher performance requirement.

This paper focuses on the application of the LR technique along with its potential for use in a contractor performance prediction during the evaluation process. Therefore, the locus of discussion shifts from the comparison with foregoing selection methods, to the theoretical debates of the potential use of the LR technique and its advantages for predicting contractor performance using a case study approach.

Questionnaire Design and Sample Selection

In order to establish an in-depth study of relationship between clients' evaluation preferences and contractor performance based on real-live data, a total of 68 previously completed projects were collected from United Kingdom public and private construction sectors, for both building and civil engineering construction works. These were selected from various United Kingdom public client lists (e.g., Housing Associations and Directory Year Book and Municipal Year Book—Public Services Directory) and construction professional organizations (e.g., Association of Project Management and the Property Profession Chartered Surveyor Regional Directory) within England, Wales, Northern Ireland, and Scotland (Table 1). The questionnaire consisted of two main components. Component (1) consists of sample characteristics, i.e., respondents types and geographical spread, and annual turnover. Component (2) was concerned with tender evaluation criteria, where these criteria thought to affect clients' evaluation aspirations and were to develop the LR model.

A total of 33 contractor evaluation criteria were carefully selected from the initial survey and modified for use in LR analysis. The work for collecting these input variables was achieved via an initial survey (Wong et al. 2001). These criteria were applied during tender evaluation for prequalified contractors who have submitted their tender for a specific (proposed) project (Table 2). Comments and written feedback were received from a number of respondents including the recommendation of individual tender evaluation preferences. However, taking into account the need for a consistency in input variables for all the case studies, these recommended tender evaluation criteria were excluded in the LR analysis. Moreover, the excessive number of evaluation criteria

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Table 1. Characteristics of Respondents

Characteristic	Public (number of respondent)	Client's R. (number of respondent)	Totals:
Regional classification:			
England	31	16	47(69.1%)
Northern Ireland	1	3	4 (5.9%)
Wales	2	2	4 (5.9%)
Scotland	3	10	13 (19.1%)
	37	31	68 (100%)
Project types:			
Building	30	27	57(83.8%)
Civil engineering	7	4	11.(16.2%)
	37	31	68(100%)
Annual turnover/Budget (£ million):			
<£5 million	12	18	30 (44.1%)
£5 m–£50 million	19	11	30 (44.1%)
>£50 million	6	2	8 (11.8%)
	37	31	68 (100%)

Table 2. Project-Specific Criteria

Catagory	Criteria
Staff Quality and Experience	1: Staff training program
	2: Performance of the project managers
Plant and equipment resources	3: Condition and procedures of equipment
	4: Suitability of the equipment
Contractor site management/execution capability	5: Type of control and monitoring procedures
	6: Cost control and construction progress reporting systems
	7: Ability to deal with unanticipated problems (e.g., risk management)
	8: Provision of trained/skilled staff for the particular project
	9: IT knowledge, e.g., electronic document management systems
Health and safety	10: Proposed health and safety program
	11: Health and safety records on previous projects
Past performance records in similar projects	12: Time
	13: Cost
	14: Quality
Contractor reputation/image	15: Contractor reputation and image
	16: Origin of the company
	17: Number of years in the business
	18: Listed on the stock market
Contractor proposals	19: Construction schedules and procedures
	20: Construction methods/statements
	21: Site organisation, works rules/procedures and policies
	22: Proposed site management and productivity improvement procedures
	23: Proposed tender price
Other evaluation criteria	24: Contractor familiarity with weather conditions
	25: Contractor familiarity with local labor
	26: Contractor familiarity with local suppliers
	27: Contractor familiarity with geography area
	28: Contractor relationship with local authority
	29: Home office location to job site location
	30: Communication and transport method from office to job site
	31: Experience with specific type of facility

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Table 3. Good and Poor Contractor Groupings

Group	Good contractors	Poor contractors	Totals:
A[a]	36(75%)	12(25%)	48(100%)
	Public: 33(69%)	Private: 15(31%)	48(100%)
B[b]	11(55%)	9(45%)	20(100%)

[a] [a] Modelling data.

[b] [b] Test group data.

might lead to difficulty in a LR modeling process and the aspect of "parsimony" in research design. The contractor performance prediction model is derived from 48 United Kingdom construction projects (i.e., Group A data, Table 3) and tested by 20 independent cases (i.e., Group B data), using the LR stepwise technique.

In the case studies questionnaire, respondents were asked to designate LIA for each criterion during tender evaluation for the particular project under scrutinizing and the contractor project performance (when completed). These LIA consist of ordinal data, ratio variables, and categorical data. For instance, staff training program is measured on a Likert scale (1=poor and 5 =good); past performance in time measured in the ratio of actual completion time to estimated duration; and origin of the company: national or international? The LR analysis was performed using *SPSS 10.0*, which also facilitated provision of a stepwise procedure for the selection of input (independent) variables and goodness-of-fit statistics for the developed model. A detailed description of the basic concept and technique of the program can be found in *SPSS- Advanced statistics 6.1* (Norusis 1994).

Why Logistic Regression?

This paper is devoted to applying the LR technique to determine how the probability of a contractor performance can be predicted (good or poor) using the client's tender evaluation preferences from their previous completed projects. When describing a contractor performance to the clients' evaluation preferences, a typical question arises: "what is the relationship of client's multivariable (qualitative and quantitative) evaluation criteria to a contractor performance?" In arithmetic terms, this relationship takes the form of

$$Y = C_0 + C_1X_1 + C_2X_2 + \ \ldots C_nX_n \tag{1}$$

where Y=contractor performance (dependent variable); C_0=exposure variable or constant; C_1, C_2, and C_n=are coefficients; and X_1, X_2, and X_n represent contractor attributes (independent/input variables). When relating a set of X_n (qualitative and quantitative independent variables) to a dependent variable, such as contractor performance, this is considering a multivariable equation. Some kind of mathematical model is typically used for solving multivariable equation (e.g., discriminant analysis, cluster analysis, or multiple regressions). However, if the input variables relationship is used to describe in a dichotomous dependent variable and when the client evaluation preferences are a mixture of qualitative and quantitative variables, LR is highly recommended (Tung 1985; Kleinbaum 1994). In this instance, the dichotomous dependent variables were described as good and poor, where good is defined as "fair" and "satisfactory" and poor is described below as "fair" and "satisfactory" performance, as denoted by the clients (respondents) from the contractor overall project performance. Another advantage is that other multivariate statistics require normality assumption (which is difficult to satisfy in practice), whereas LR analysis has been found to be very robust without strongly adhering to this assumption (Sharma 1996). In this analysis, the selection of dichotomous variables (good and poor) simplified the prediction process and facilitated a robust LR computation. Although LR analysis can be extended beyond dichotomous variables to the analysis of polychotomous or multinomial LR models, in the present investigation the dichotomous LR model is adopted to limit the prediction of contractor performance into good and poor groups.

Logistic Regression Technique

Logistic regression analysis has long been used in epidemiological research for calculating the probability disease outcome (Kleinbaum 1994). This technique is recommended for modeling and analyzing epidemiological data when the illness measure is dichotomous (Kleinbaum 1994; Sharma 1996). In ecology research, LR was used to predict the occurrence (probability) of freshwater aquatic macrophytes using a set of biophysical variables (Narumalani et al. 1994). Tung (1985) proposed a LR technique to evaluate and assess the potential for channel scouring in water resources engineering research. In construction research, a logistic model was used to predict the likelihood of contract disputes in construction projects (Diekmann et al. 1994), albeit, LR application in construction procurement is less popular compared to other statistical analysis techniques.

Logistic regression is a mathematical modeling approach which describes the occurrence or nonoccurrence of an event (Kleinbaum 1994; Tung 1985). This dichotomous probability is measured by 0 or 1. In this study, 0 is for indicating the occurrence of "good" contractor and 1, otherwise. A LR model "predicts" the odds of an event occurring (i.e., ratio of the probability that good contractor performance will occur to the probability that it will not). Suppose a linear sum expression for deriving a functional relationship between Y and X_n i.e., Eq. (1). In order to construct a logistic model that can be used to describe the dichotomous (binary) dependent variable as a function of a number of independent variables, the probability function can be written as (Norusis 1994; Sharma 1996)

$$\ln\left(\frac{p}{1-p}\right) = C_0 + C_1X_1 \tag{2}$$

or

$$P = \frac{1}{1 + e^{-(c_0+c_1x_1)}} \tag{3}$$

Assume there is only one independent variable, where P=to probability occurrence; C_0=constant; C_1=coefficient estimated from the data; and X_1=independent variable. When the independent variable is more than one, the LR model can be written as

$$P = \frac{1}{1 + e^{-(Y)}} \tag{4}$$

where probability (of a good contractor) is given by 1 over 1 plus e to the minus the quantity of Eq. (1). This generates a cumulate distribution function of S shape, where the probability must lie between 0 and 1; and to be either $-\infty$ or $+\infty$. Fig. 1 shows the S-shape plot and the range of a probability occurrence between 0 and 1.

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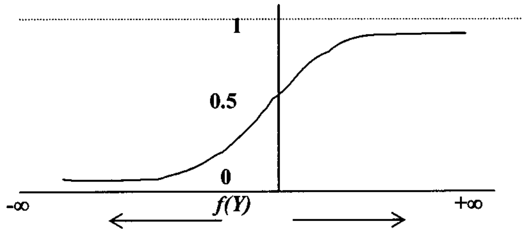

Note: 0 < Probability < 1; the cut off value is 0.5.

Fig. 1. Logistic regression plot

Table 5. Logistic Regression Classification Table

		Predicted		
		Good	Poor	
Observed		*G*	*P*	Percent correct
Good	G	33	1	97.06%
Poor	P	2	12	85.71%
Overall 93.75%				

Note: Classification Table for OVERALL. The cut value is 0.50.

It is noted that the relationship between probability and the independent variables is nonlinear [Eq. (3)], whereas the relationship between the log of the odds and the independent variables is linear [Eq. (2)]. Compared to multiple linear regression, the logistic coefficient gives a rather different interpretation of relationships between independent variables and dependent variable. The coefficients of the independent variables should be with respect to their effects on the log of odds and not the probability. Therefore, from Eq. (3) logistic coefficients can be interpreted as change in the log odds associated with a one-unit change in independent variables. To shorten the notation, when considering the probabilities of contractor performance, the logistic model will describe a probability of getting a good (or poor) contractor with the cut of value of 0.5 (Fig. 1). The predicted contractor performance will fall between the good or poor group regardless of the types and values of independent variables.

To summarize, LR analysis in this study enables:

- the prediction of contractor performance, which lies in the range between good and poor groups;
- the demonstration of the (combined) effect of input variables on dichotomous dependent variables; and
- ultimately to produce a contractor performance prediction model.

A good source of review on the LR technique is given by Hosmer and Lameshow (1989). For brevity, the following sections discuss the LR analysis results based on the study of 68 completed construction projects.

Logistic Statistics

The LR analysis begins with the selection of statistically significant independent variables to be included in the analysis via a stepwise procedure. The outputs given in Table 4 shows the stepwise LR results of Group A data. It shows the stepwise selection process for the LR model with all of the selected independent variables from Steps 1 to 3. Three evaluation criteria were identified in the analysis: suitability of the equipment; past performance in similar project cost; and contractor relationship with local authority. During the Step 1 selection process, the independent variable with highest chi-square score (17.004) that meets the *p* value criterion (significant at 0.05) is selected in the model. This process is repeated until there are no further independent variables with a significant *p* value. The whole process stopped and the final LR model consists of three independent variables. At Step 1, 79% of 48 cases were correctly predicted. This shows that the first selected variable proves to be the highest prediction power compared to the second and the third selected variables. The combination of the second and third variables only contributed 15% of the overall cases that were correctly predicted. Details of entire cases that were correctly classified computed from Group A data are shown in Table 5. As can be seen, 94% the total cases were found to be correctly predicted. Only three out of 48 cases were wrongly predicted. This indicates that the developed LR model is reasonably good in prediction of contractor performance.

Coefficients for Logistic Regression

Table 6 shows the estimated coefficients (under column heading B) and related statistics of the developed LR model. The table also shows the combination of a constant and the variables that statistically significant identified in the developed LR model, i.e., suitability of the equipment; past performance in similar project cost; and contractor relationship with local authority.

Given these coefficients, Eq. (1) can be written as

Table 4. Stepwise Logistic Regression Statistics

Step	Chi-Sq.	df	Sig[a]	Chi-Sq.	df	sig	Class %	Variable
1	17.004	1	0.000	17.004	1	0.000	79.17	IN: SUITABIL
2	13.140	1	0.000	30.144	2	0.000	85.42	IN: P_COST
3	8.754	1	0.003	38.898	3	0.000	93.75	IN: LOCAL_A

[a]*P* value significant at 0.05 level.

Table 6. Coefficients of Logistic Regression

Variable	*B*	S.E.	Wald	df	Sig[a]	*R*	Exp (*B*)
SUITABIL	−2.5208	0.9081	7.7051	1	0.0055	−0.3138	0.0804
P_COST	−3.6619	1.3090	7.8263	1	0.0051	−0.3171	0.0257
LOCAL_A	−1.3409	0.5719	5.4981	1	0.0190	−0.2457	0.2616
Constant	19.8438	6.4335	9.5138	1	0.0020		

[a]Significant at 0.05 level.

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Table 7. External Validation of Group B Data

Group-B (20 cases)					Cut value =0.5	
SUITABIL	P_COST	LOCAL_A	Y scores[a]	Original	Probability[b]	Prediction[c]
2	2	2	4.796	Poor	0.992	Poor
3	2	1	3.616	Good	0.974	Poor
4	2	4	−2.928	Good	0.051	Good
4	2	3	−1.587	Good	0.170	Good
5	2	4	−5.449	Good	0.004	Good
4	3	5	−7.930	Good	0.000	Good
3	2	4	−0.407	Good	0.400	Good
3	3	4	−4.069	Good	0.017	Good
3	2	4	−0.407	Good	0.400	Good
1	3	1	4.996	Good	0.993	Poor
4	2	4	−2.928	Good	0.051	Good
3	2	2	2.275	Poor	0.907	Poor
3	3	5	−5.409	Good	0.004	Good
4	2	3	−1.587	Poor	0.170	Good
3	1	3	4.596	Poor	0.990	Poor
1	1	4	8.297	Poor	1.000	Poor
4	2	4	−2.928	Poor	0.051	Good
3	2	4	−0.407	Poor	0.400	Good
3	2	1	3.616	Poor	0.974	Poor
3	2	3	0.934	Poor	0.718	Poor

[a]$Y = 19.844 - 2.521$ (SUITABIL)-3.662 (P_COST)-1.341 (LOCAL_A).

[b]Probability $= 1/(1+e^{-(Y)})$.

[c]Five cases were wrongly classified, therefore 75% (15/20) of Group B correctly classified.

$$Y = 19.844 - 2.521(\text{SUITABIL}) - 3.662(\text{P\_COST}) - 1.341(\text{LOCAL\_A}) \qquad (5)$$

By substituting Group B (20 new case) into Eq. (5) and incorporating it into Eq. (4), it was found that 75% of the 20 cases were correctly predicted. Results of the external validation are shown in Table 7.

Predictive Efficiency of Logistic Regression Model

There are various ways to assess the predictive efficiency (goodness-of-fit) of the LR model: for instance, to compare the prediction results to the observed outcomes (as detailed in Table 5) and external validation (Table 7). Another is by histogram of estimated probabilities (Norusis 1994). Fig. 2 shows the plot of

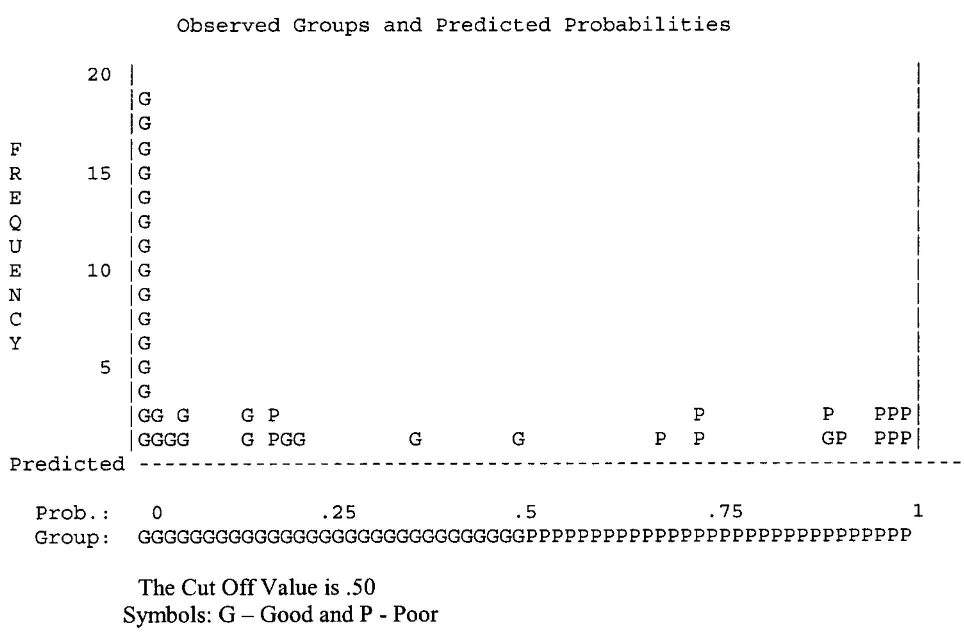

Fig. 2. Histogram of estimated probabilities

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observed groups and predicted probabilities of contractor performance from the observed 48 cases (Group A). The symbols (i.e., *G*-good and *P*-poor) used for each case specifies the group to which the case actually belongs. The histogram indicates that the cases predicted probabilities of belonging in Good (0) and Poor (1) divided into two by the cutoff value 0.5 at their respective ends of the plot. This plot indicates the accuracy of prediction is very high.

Discussion

The recent advances in contractor selection and evaluation methods indicate the need for diverse contractor assessment options due to increased project complexity and clients' demands. However, deciding what method to apply from a wide range of alternatives is crucial and difficult when the methods for evaluating a contractor performance are too sophisticated to understand and utilize by construction clients (as discussed in early sections). This could be more complicated if the evaluation process relies upon the interaction of a group of decision-makers' perceptions (e.g., selection preferences and subjectivity) and when there is a high risk associated with unknown evaluation consequences. Therefore, when deciding the most "suitable" selection method, the core to this decision problem will be the input variables (i.e., decision-makers' preferences and LIA of each evaluation criterion) and other factors such as project characteristics and client types.

This paper proposed a LR model that linked clients' evaluation preferences and contractor performance to predict the likelihood of project failure(s) to which the client may be exposed when awarding a contract to a "poor" contractor. It is shown that the LR technique is able to model the relationship between clients' evaluation preferences (i.e., LIA of each evaluation criterion) and contractor performance to achieve satisfactory accuracy in contractor performance prediction. The findings also show that the LR model can deal relatively easily with a mixture of qualitative and quantitative independent variables to demonstrate the dichotomous outcome, whereas other multivariate statistics have difficulty with predicted values or group memberships which are constrained to binary results (i.e., fall in the interval between 0 and 1). Based on the findings it seems that the LR technique has the advantage and offers the potential for contractor performance prediction.

The proposed LR model could be further refined beyond the analysis of dichotomous prediction; for instance, the use of polychotomous prediction of contractor performance. However, in this study the relationship of client's evaluation preferences and contractor performance being modeled often represents a "casual" relationship, in which the contractor performance is believed to be an effect of the client's evaluation preferences. In the LR statistic the emphasis is on predictive rather than "causal" relationship when describing a dependent "related" to an independent. In practice, it is almost impossible to "relate" the dependent (effect) to an independent (cause) in order to achieve a perfect prediction, i.e., perfect casual relationship. Therefore, the investigation of client evaluation relationship and its impact on contractor performance in this study should be addressed as "prediction" rather than "casual" relationship in nature.

Conclusion

This paper provides the scope for a rationalization of the contractor selection process by assigning contractor performance into good and poor groups. The LR has the ability to construct a "causal" function where the qualitative and quantitative independent variables can be described in a predictable and explanatory way. The independent variables for the LR modeling process can be the combination of ordinal data and ratio variables. It requires fewer statistical assumptions than other multivariate analyses and the produced dichotomous outcome is easily interpreted by decision-makers. Future research of contractor selection in multivariable attributes analysis will be focused on the use of other multivariate statistics and its in-depth study of its application, which allows the direct prediction of group membership and classification of contractor performance to provide retrospective and predictive application to the selection problem.

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