SUBCONTRACTOR SELECTION BASED ON DATA ENVELOPMENT ANALYSIS

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Abstract
In today's construction market, subcontractors execute significant portions of construction work. Subcontractors lessen resource requirements faced by general contractors and provide specialized expertise to construction projects. The reliance of general contractors on subcontractors to execute major portions of construction work makes the success of construction projects highly susceptible to the performance of these subcontracting organizations. As a result, subcontractors' selection decisions are of crucial importance to general contractors bearing in mind that such decisions are exercised by general contractors multiple times in every single project. This paper contributes a Data Envelopment Analysis (DEA) model to guide general contractors in their subcontractor selection decisions.

Keywords
Subcontractor selection; Decision Support system; Performance measurement; Benchmarking; Data envelopment analysis.

INTRODUCTION

For almost the last two decades, subcontracting has been utilized extensively in the construction industry. Several researchers indicate that it is common to subcontract the majority of construction work to subcontractors (Hinze and Tracey, 1994; Kumaraswamy and Matthews, 2000; Shash, 1998; Wang, 2000). It is expected for this trend to continue in the future (Ng et al., 2008 a, 2008 b; Arditi and Chotibhongs, 2005; Wang and Liu, 2005).

Subcontractors help general contractors to overcome problems related to the need for special expertise, shortage in resources, and limitation in finances (Elazouni and Metwally, 2000). The operations of the average general contractor are not sufficiently extensive to afford full-time employment of skilled craftsmen in each of the several trade classifications needed in the field (Arditi and Chotibhongs, 2005). Subcontracting allows general contractors to employ a minimum workforce in construction projects and promotes specialization. It capitalizes on the skills of trade specialists and copes with the fluctuating construction demand (Ng et al., 2003). Arditi and Chotibhongs (2005) advocate that the use of subcontracting has proved to be efficient and economical in the use of available resources. Subcontracting might improve quality and reduce project time and costs (Ng et al., 2003). Qualified subcontractors are usually able to perform their work specialty more quickly and at a lesser cost than can the general contractor (Arditi and Chotibhongs, 2005).

The reliance of general contractors on subcontractors to execute major portions of construction work makes the success of construction projects highly susceptible to the performance of the subcontracting organizations. As a result, researchers emphasize the importance of selecting appropriate subcontractors (Kumaraswamy and Matthews, 2000; Ng et al., 2008 a&b; Arditi and Chotibhongs, 2005; Arslan et al., 2008; Tserng and Lin, 2002).

Despite this almost two-decade practice of subcontracting significant portions of construction work and the realization of the vital impact of subcontractors' work on overall project success, little research has been conducted to aid general contractors in their selection of subcontractors. Literature review reveals only few models that address this important decision-making issue that is exercised by general contractors multiple times on every single project.

Albino and Gravelli (1998) propose a neural network approach for subcontractor selection. Ko et al. (2007) critique the approach proposed by Albino and Gravelli (1998) because of the difficulties associated with identifying network topology and membership functions. Okoroh and Torrance (1999) develop a knowledge-based expert system using fuzzy logic. Lin and Chen (2004) argue that limitations of the fuzzy logic include the fact that the membership function of natural language expression depends on the managerial perspective of the decision-maker. Lin and Chen (2004) add that another limitation is that the computations of a fuzzy-weighted average is still complicated and not easily appreciated by managers.

Tserng and Lin (2002) propose an Accelerated Subcontracting and Procuring (ASAP) model that is based on eXtensible Markup Language (XML) and portfolio theory in financial management. ASAP helps general contractors to select subcontractors by deciding on an appropriate tradeoff between risk (i.e., cash flow) and profit for different combinations of subcontractors. However, ASAP is based on the assumption that all considered subcontractors are recognized as qualified subcontractors.

Luu and Sher (2006) develop a case based reasoning procurement advisory system for subcontractor selection. In this system, subcontractor selection cases are represented by a set of attributes elicited from experienced construction estimators. Ko et al. (2007) develop Subcontractor Performance Evaluation Model (SPEM) based on an Evolutionary Fuzzy Neural Inference Model (EFNIM). Ko et al. (2007) indicate that a limitation of their model is that both quality and accuracy of training data are crucial to its performance.

Arslan et al. (2008) propose a web-based subcontractor evaluation system called WEBSES. WEBSES determines a weighted average score for considered subcontractors based on 25 evaluation criteria, which are assumed of identical importance. Generally, it is well-accepted that weighted average scores have an inherent weakness due to the biases introduced in the development of the weights and the additive assumptions utilized in the computations of the weighted score average.

Existing models of subcontractor selection are useful in guiding contractors in their selection decisions. However, new methods are still needed as they offer new insights to both researchers and practitioners. Additionally, it is recommended that a general contractor utilizes multiple methods when exercising selection decisions.

This paper contributes a Data Envelopment Analysis (DEA) model to guide general contractors in their subcontractor selection decisions. The proposed DEA model is highly flexible. It can be easily tailored to reflect a general contractor's criteria for subcontractor selection. This flexibility includes number and type of factors considered in the analysis. More importantly, the proposed approach provides a framework for selection decisions at

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large. The DEA model is well-suited to guide organizations that are exercising selection decisions.

DATA ENVELOPMENT ANALYSIS MODEL FOR SUBCONTRACTOR SELECTION

This section discusses selection criteria for subcontractors, DEA background, methodology, and mathematical form. The section concludes with an example to illustrate the proposed DEA model for subcontractor selection.

Identifying the selection criteria

In making selection decisions of subcontractors, construction researchers call for an evaluation that is based on a set of criteria. Several researchers have isolated factors that impact the selection decision. Examples on these factors include: number of years in business, highest value of relevant subcontracted work completed in the past, number of relevant projects completed, previous relationship with the contractor, financial capacity, completion of job within time, standard of workmanship, quality of materials used, delay in payment to labor, failure to adhere to subcontract provisions, safety record (incident rate), and non adherence to relevant environmental regulations (Ng and Luu, 2008; Ng et al., 2008a, 2008b; Arslan et al., 2008; Ko et al., 2007).

Table 1 shows variables that are considered in the proposed DEA model for subcontractor selection along with their method of measurement.

Table 1: *Variables that are considered in the DEA model for subcontractor selection*

Variable	Method of measurement	Input/Output
Number of relevant projects completed	Number of projects	O1
Highest value of relevant subcontracted work completed in the past	Dollar amount	O2
Financial capacity	Subjective scale of 1 (lowest) to 10 (highest)	O3
Completion of job within time		O4
Quality of workmanship		O5
Failure to adhere to subcontract provisions		I1
Delay in making payment to labor		I2
Non adherence to relevant environmental regulations		I3
Safety record	Incident rate	I4

Data envelopment analysis (DEA)

DEA was developed by Charnes et al. (1978, 1979, 1981). Nowadays, DEA is well-deployed in other industries with many papers published on its utilization for performance measurement and decision making. DEA deployment in construction is still limited. Examples on construction-DEA research include the work of El-Mashaleh (2003, 2010), El-

Mashaleh et al. (2001, 2005, 2007, 2010), McCabe et al. (2005), Pilateris and McCabe (2003), and Vinter et al. (2006), Cheng et al. (2007), Chiang et al. (2006), and Xue et al. (2008).

DEA is a non-parametric linear programming approach that is designed to compare and evaluate the relative efficiency of a number of Decision Making Units (DMUs) (Charnes et al., 1978). These DMUs can be organizations, business units, universities, etc. For the purposes of this research, DMU refers to a subcontractor.

Thamassoulis (2001) explains that DEA is non-parametric because it allows efficiency to be measured without any assumptions regarding the functional form of the production function or the weights for the different inputs and outputs. Charnes et al. (1978) realize the difficulty in seeking a common set of weights to determine relative efficiency. As a result, DEA allows each DMU to adopt a set of weights to determine its relative efficiency compared to other DMUs. Each DMU is allowed to adopt a set of weights, which shows it in the most favorable light in comparison to the other DMUs. Consequently, McCabe et al. (2005) argue that a DMU that is inefficient with even the most favorable weights cannot argue that the weights are unfair.

DEA is based on an input-output framework, where inputs are minimized and/or outputs are maximized. Cooper et al. (2000) provide the following data selection criteria for inputs and outputs:

- Numerical data are available for each input and output;
- The items (inputs, outputs and choice of DMUs) should reflect an analyst's or a manager's interest in the components that will enter into the relative efficiency evaluations of the DMUs; and
- The measurement units of the different inputs and outputs need not be congruent. Some may involve number of persons, or areas of floor space, money expended, etc.

Bearing in mind the above input/output selection criteria and the fact that inputs are minimized and outputs are maximized, we categorize the first five variables in Table 1 as outputs. To the contrary, the last four variables of Table 1 are classified as inputs.

DEA makes use of linear programming to determine which of the set of DMUs under study form an envelopment surface. This envelopment surface is called the efficient frontier. The efficient frontier is "made up" of efficient DMUs. Figure 1 shows an example of an efficient frontier for a simple one input-one output case with only 5 subcontractors under consideration. The slope of the line connecting each point to the origin corresponds to the output per input. The highest slope is for the line connecting the origin through Sub2. This line is called the efficient frontier. Note that the efficient frontier touches at least one point and all points are therefore on or below this line. The frontier "envelops" all the data points suggesting the name data envelopment analysis.

DEA provides a comprehensive analysis of relative efficiency by evaluating each DMU and measuring its performance relative to the efficient frontier. DMUs that lie below the efficient frontier are considered inefficient compared to the DMUs that "determine" that frontier. As such, Sub1, Sub3, Sub4, and Sub5 in Figure 1 are considered inefficient compared to Sub2.

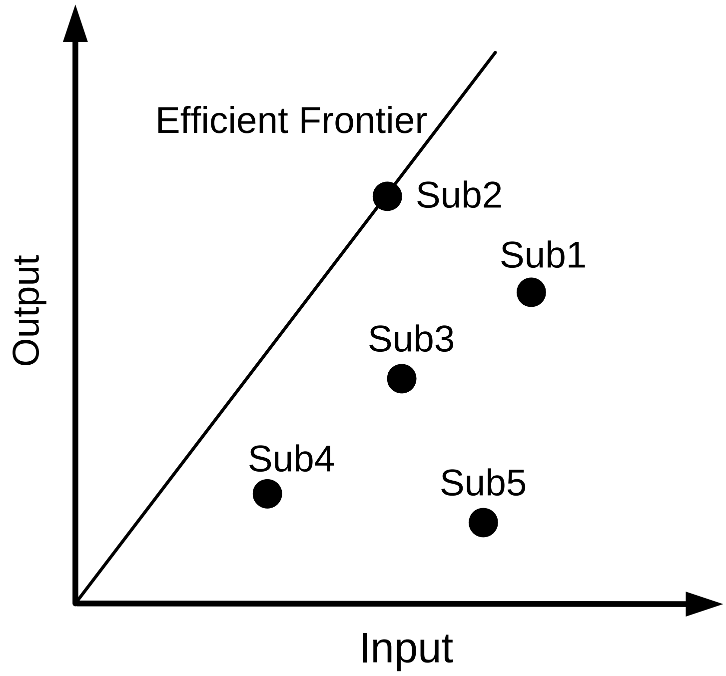

Figure 1: *Efficient frontier*

A limitation of DEA is the fact that its discriminatory power depends on the number of DMUs in comparison to the number of variables (inputs + outputs). A rule of thumb indicates that the minimum number of DMUs should be 3 times the number of variables (Charnes and Cooper, 1990). However, Ellis (2003), Wang (2002), and Cheng et al. (2007) relaxed this requirement by creating an "Ideal" DMU. An Ideal DMU has the lowest values of inputs and the highest values of outputs (Cheng et al., 2007).

The mathematical form of DEA

The mathematical form of DEA is shown below (Equations 1-4). For a detailed discussion, readers are referred to Thamassoulis (2001), Cooper et al. (2000), and Coelli et al. (1998).

Assume that we have *n* DMUs (*j=1,…, n*) with *m* input items and *s* output items. Let the input and output data for DMU_j be ($x_{1j}, x_{2j}, \ldots, x_{mj}$) and ($y_{1j}, y_{2j}, \ldots, y_{sj}$) respectively. Note that we measure the efficiency of each DMU once. As a result, we need *n* optimizations, one for each DMU_j to be evaluated.

$$\max\ \theta_0 = \frac{\sum_{r=1}^{s} u_r y_{r0}}{\sum_{i=1}^{m} v_i x_{i0}} \tag{1}$$

$$\text{subject to}\ \frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \leq 1 \tag{2}$$

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$i=1,\dots, m; \quad j = 1,\dots, n; \quad r=1,\dots, s$ (3)

$u_r, v_i \geq 0$ (4)

Where:
θ_0 = the measure of efficiency for DMU_0 (the DMU under evaluation), which is a member of the set $j = 1, \dots, n$ DMUs.
u_r = the output weight, which is determined by the solution.
v_i = the input weight, which is determined by the solution.
y_{r0} = the known amount of the *rth* output of DMU_0.
x_{i0} = the known amount of the *ith* input of DMU_0.
y_{rj} = the known amount of the *rth* output of DMU_j.
x_{ij} = the known amount of the *ith* input of DMU_j.

The objective function is to maximize the efficiency of DMU_0 (the DMU under evaluation). This is done by maximizing the sum of DMU_0's outputs divided by the sum of its inputs (Equation 1). Equation 2 means that the efficiency of all DMUs is ≤1.0. This implies that all DMUs are either on the efficient frontier or below it, and that the efficiency scores range between 0 and 1.0.

Therefore, in DEA terminology, efficient DMUs are given an efficiency score of 1.0. Inefficient DMUs have an efficiency score that falls in the following range: 0≤ efficiency < 1.0.

Illustrative example

To illustrate the proposed DEA model for subcontractor selection, let's consider the data shown in Table 2. Ten subcontractors are considered for selection with 5 outputs (O1-O5) and 4 inputs (I1-I4). Outputs and inputs refer to the ones shown in Table 1. For the sake of demonstration, we limited the number of DMUs to 10 and the number of variables to 9. However, note that DEA can handle tens of variables and thousands of DMUs.

Table 2: *Example data*

Subcontractor	O1	O2 ($)	O3	O4	O5	I1	I2	I3	I4
Sub1	7	279,520	7	5	2	6	9	2	9.4
Sub2	4	267,615	4	2	5	5	8	9	8.3
Sub3	6	225,688	6	5	8	5	8	3	12.0
Sub4	4	199,461	4	6	9	6	7	8	11.1
Sub5	2	232,589	2	9	8	6	9	2	8.8
Sub6	3	287,398	3	2	4	5	2	1	7.4
Sub7	1	213,333	1	4	3	4	1	3	7.3
Sub8	2	241,576	2	6	7	6	7	8	7.6
Sub9	3	143,244	3	5	1	5	4	3	9.0
Sub10	4	215,815	4	6	7	5	2	1	8.2
Ideal Sub	7	287,398	10	10	10	1	1	1	7.3

Given the fact that we have 9 variables, this means that at least 27 DMUs are needed to keep the discriminatory power of DEA. Since we only have 10 DMUs, we need to create an Ideal Sub. As indicated earlier, an Ideal DMU has the most favorable outputs and inputs. Starting with O1, an examination of number of relevant projects that are completed by a subcontractor in Table 2 indicates that Sub 1 completed 7 projects. This is the largest number of projects across all subcontractors. Consequently, O1 for the Ideal Sub equals 7 as shown in Table 2. Similarly, when considering O2, we notice that Sub 6 executed the highest value of relevant subcontracted work for a sum of $287,398. As a result, O2 for Ideal Sub is set at the same dollar amount of Sub 6 as shown in Table 2. For the remaining outputs, the value for every output for the Ideal Sub is 10, since this is the most favorable value. For inputs (I1-I3), the contrary is true. The value of these inputs is 1, since this is the most favorable value. The last input (I4) is calculated based on a formula, where different countries utilize different formulas. OSHA recordable incidence rate which is utilized in the US construction industry is a good example for such formula. It is shown below for demonstration purposes.

Incidence rate = No. of incidents * 200,000 hours / No. of hours worked

It is common knowledge that lower incident rates reflect better safety performance. Table 2 shows that Sub 7 has the lowest incident rate with a value equals 7.3. Consequently, this value is used for the Ideal Sub as shown in Table 2.

The DEA solver software of Cooper et al. (2000) is used to run the DEA model. Table 3 ranks all considered subcontractors (Sub1-Sub10) and shows their efficiency scores. Note that subcontractors (Sub1-Sub10) are rated in comparison to Ideal Sub, which has an efficiency score of 1.0. The rest of subcontractors (Sub1-Sub10) have efficiency scores that are less than 1.0.

Since Sub1 has the highest efficiency score (0.78) among all considered subcontractors, we consider this subcontractor as our first choice in executing relevant construction work.

Table 3: *DEA results*

Rank	DMU	Efficiency Score
1	Ideal Sub	1.0
2	Sub1	0.78
3	Sub5	0.75
4	Sub10	0.70
5	Sub8	0.67
6	Sub4	0.59
7	Sub3	0.51
8	Sub2	0.50
9	Sub6	0.43
10	Sub9	0.41
11	Sub7	0.40

The above example demonstrates how the proposed DEA model is utilized to select one subcontractor out of 10 potential subcontractors. The proposed DEA approach combines 9 criteria to aid in the selection process. The model results in efficiency scores rating every subcontractor in relation to the efficient frontier. The subcontractor with the highest efficiency score is selected to execute the relevant construction work. Consequently and based on DEA results, general contractors can exercise more informed decisions when considering subcontractors for executing construction work.

For demonstration purposes, the illustrative example is based on 10 subcontractors and 9 variables. However, note that DEA can handle tens of variables and thousands of DMUs.

CONCLUSIONS

Subcontractors' selection decisions are of prime importance to general contractors. These decisions are exercised by general contractors multiple times on every single project. This paper contributes a DEA model for subcontractors' selection. The proposed DEA model is highly flexible. It can be easily tailored to reflect any general contractor's criteria for subcontractor selection. This flexibility includes number of DMUs and number and type of factors that are considered in the analysis. More importantly, the proposed approach provides a framework for selection decisions at large. It is well-suited to guide organizations that are exercising selection decisions.

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