New way to select multiple suppliers for a supply chain

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Abstract

Supplier selection has received extensive attention in supply chain management. This investigation assumes that K candidates are being considered using a given set of independent performance evaluation indices. Each candidate can either be selected or excluded. The total number of possible supplier composites that can be selected is 2^K, and the sum of the values of an assessment index of the suppliers in a composite is the index value of that composites. Data Envelopment Analysis (DEA) is applied to assess all 2^K composites. This investigation presents a novel procedure for selecting 'efficient' composites from the 2^K composites. Sensitivity analysis is also performed on each supplier index value. This result captures differences in the competition indices of suppliers that allow them to rapidly respond to the dynamic environment. In their tolerance, the managers will change the to-be-minimized values or to-be-maximized values to realize all the suppliers that are too unstable. These results can be used to enhance and alter decisions.

Keywords : *Data envelopment analysis (DEA), decision-making unit (DMU), decision composite unit (DCU), sensitivity analysis.*

1. Introduction

The increasingly competitive global business environment not only requires more efficient use of supply chain resources to coordinate

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geographically dispersed manufacturing and marketing activities, but also makes supply chain efficiency. Suppliers in a supply chain perform interactively rather than independently, as the output of one organization can be the input of another. Consequently, all decisions should be integrated by trading off the performances of different suppliers at each supply chain stage.

Assume that a firm wishes to select several suppliers from a pool of K candidates. A *composite supplier* (CS) composes a subset of suppliers. Supply performance was divided into two distinct categories, indices-to-be minimized and indices-to-be-maximized. For each of these areas, particular performance dimension was subjectively selected for comparison. The performance increases in all of the to-be-maximized indices; that is, a higher measure value indicates superior performance for the dimension being under consideration. Unlike the to-be-maximized indices, for the to-be-minimized indices a lower value translates into superior performance for the dimension being considered. No preference weights exist among the indices.

For a CS, the value of an index equals the sum of the values of the suppliers of which the CS composed. This investigation employs Data Envelopment Analysis (DEA) to assess the relative (not absolute) performance of each CS against all of the others. DEA identifies efficient and inefficient CSs' and allowing an efficient CS to be selected based on further analysis. This investigation also performed sensitivity analysis to obtain the lower and upper bounds for each candidate index value given that the obtained set of efficient CS remained unchanged.

The rest of this paper is organized as follows. Relevant literature on supplier selection criteria is reviewed, along with multiple criteria decision-making methods. The six-process procedure for supplier selection is illustrated and a numerical example provided. The following section then identifies the extent to which the perturbations in each index value of candidate suppliers can be tolerated before any efficient DMU is not changed as inefficient. Conclusions of this study are finally drawn.

2. Literature review

2.1 *Supplier selection criteria*

Vendor selection has been extensively studied along with how just-in time (JIT) manufacturing strategies affect vendor selection. Dickson's

23 criteria were used, and it was found that net price, delivery, and quality were discussed in 80%, 59%, and 54% of the 74 articles, respectively [1, 2]. Management experts determined logistical capabilities that measured the logistical performance of a firm in the key areas of cost, quality, delivery, flexibility, and innovation [3]. Identifying these capabilities is difficult because many different criteria for a good partner exist and trust and coordination play a major role are very important in achieving price reductions, quality improvement, reduced production development time and flexibility [4, 5, 6]. The criteria for developing a partnership with a supply chain member organization are typically driven by expectations regarding quality, cost, delivery, flexibility and customer service [7]. The ultimate goal of leading firms ultimately aim to manage their suppliers throughout the entire supply chain for fast delivery, shorter production lead-time, reduced cost and increased quality. Specific requirements regarding vendor evaluation differ among companies. For instance, in the Consumer Electronics Division of Philips Electronics Industries (Taiwan) Ltd., the requirements for vendor selection include quality, cost, delivery, flexibility and response [8].

Activity Based Costing (ABC) focuses on the activities involved in the manufacturing process of suppliers [9, 10]. Some authors applied an ABC approach for supplier selection and evaluation [11]. Management experts consider the economic aspects of vendor evaluation, and focus on the direct costs (price) and indirect costs (quality) of materials supplied by vendors [12]. However, since suppliers in a supply chain perform interactively, some cost-based mathematical models in the literature appear insufficient for delineating such key supply chain characteristics as multi-objective and responsive requirements [13, 14].

2.2 *Method of multi-criteria decision analysis*

Many real world problems involve multiple objectives, and decision-makers must assess solution alternatives according to using multiple criteria. In fact, subjective measurement is the only concept widely applied in multi-criteria decision analysis for dealing with multi-criteria problems. Various works have considered the results of employing the multi-objective approach with DEA to design benchmarks and strategies for firms to incorporate into negotiations with various vendors regarding criteria performances [15, 16, 17].

The Analytic Hierarchy Process (AHP) procedures are conducted based on the results of pair-wise comparison among the factors. This approach provides a framework to deal with multiple criteria situations with intuitive, rational, qualitative and quantitative aspects [18]. AHP is designed for multi-criteria decisions, such as allocating order quantity among vendors based on price, quality, lead-time and service [19].

DEA is a set of methods and models based on mathematical programming and used for characterizing the efficiencies and inefficiencies of decision-making units (DMUs) with the same multiple to-be-minimized and to-be-maximized indices. DEA is a relative efficiency measurement and calculates weights by comparing performance. The efficiency index of DEA is thus the ratio of best-practice performance to actual performance. Three powerful DEA models exist, the Additive model [20], BCC model [21], and a classical model known as the CCR model [22]. To compare overall supplier performance, they proposed a novel approach based on DEA, and also provided benchmarks which poorly performing suppliers could use to improve their service. Their study employed a supplier capability questionnaire and supplier performance assessment questionnaire to gather data on to-be-minimized and to-be-maximized variables [23, 24].

In management contexts, mathematical programming is generally used to assess a group of possible alternative courses of action *en route* and select the best. In this capacity, mathematical programming serves as a planning aid to management. DEA reverses this approach and applies mathematical programming to obtain *ex post facto* assessments of the relative efficiency of management accomplishments, regardless of how they are planned or executed. While each of these approaches offers advantages under particular conditions, none provides a general methodology for combining multiple criteria or attributes into a single measurement of supplier performance.

3. Six-process procedure

The proposed six-process procedure for selecting suppliers is illustrated below a numerical example.

3.1 *Process* 1: *Supplier definition*

Define the group of suppliers being evaluated. The suppliers being evaluated should be supplying same goods or services, and several of them should be chosen. The illustrative example considers five candidate suppliers.

3.2 *Process* 2: *Definition of evaluation indices*

The evaluation indices should be well defined and collectable. The example presented here defines four indices for assessment. The first index *cost* is the lowest total cost required to achieve the logistics through efficient operations, technology and/or scale economies. The costs include those related to order fulfillments, material acquisition (production materials), total inventory carrying, logistics-related finance and management information systems, and production labor and inventory overhead costs. Meanwhile, the second index *delivery* measures the ability of the firm to respond to customer demands. In other words, how long is the time lapse between customer authorization of a purchase and the product becoming available to the user? Delivery metrics are critical to maintaining buyer/seller relationships. Most leading firms recognize and acknowledge the contribution of logistics-driven customer service. Lower cost and on time delivery scores are desirable.

The third index *quality* describes the ability to meet product and service quality requirements, and permits the customer to weigh the specific categories of each quality component using individualized overall satisfaction ratings. The tabulation of properly designed and administered questionnaires will result in a customer-focused measure of quality performance. The data will reflect which areas of quality are highly rated by customers, and which are perceived as unsatisfactory. Meanwhile, the fourth index *flexibility* is the ability to handle difficult, non-standard orders to meet special customer specifications and supply products characterized by numerous features, options, service requests, colors, order size and/or volume or composition during logistics. Flexibility also frees partner firms from rigid, engaging, and long-term agreements, enhancing their freedom to adapt to changing circumstances. Higher values are desirable for the quality and flexibility indices. This study uses the four indices of quality, flexibility, cost, and delivery, but other indices could also be added, such as *financial stability* and *supplier attitude*. Suppliers should not be assessed based solely on quantitative criteria, and intangible factors such as creativity, innovation, cooperativeness and so on could also be considered.

3.3 *Process* 3: *Data collection*

The data of each index is either subjective or non-subjective. Subjective data is collected through surveys or questionnaires of individuals who participated in the supply activities, while non-subjective data is obtained from historical records. In the illustrative example presented here, the values of cost, delivery and quality of each supplier are the category of non-subjective data. For the delivery time of each supplier, the function reaches its minimum value (i.e. that is, zero) if the orders are delivered on time. Otherwise, a penalty is imposed (at different rates) according the delay and early delivery time. Let α, β and γ denote three given constants. For supplier j, D_j represents the planned delivery time, d_j is the actual delivery time, and the penalty cost function $C(D_j)$ (buyer's delivery lost cost) is defined as follows: The notation $C(D_j)$ must be defined.

$$C(D_j) = \begin{cases} 0 & \text{if } D_j = d_j \\ \alpha C_j & \text{if } D_j < d_j \\ \beta C_j & \text{if } D_j > d_j \,. \end{cases} \tag{1}$$

The same definition as above is applied to the quality index. Q_j denotes the standard quality level, q_j represents the actual quality level, and the penalty cost function $C(Q_j)$ (buyer's quality lost cost) is defined as follows:

$$C(Q_j) = \begin{cases} 0 & \text{if } Q_j \leq q_j \\ \gamma C_j & \text{if } Q_j > q_j \,. \end{cases} \tag{2}$$

Supplier flexibility is a subjective index in the perspective of the manufacture. Managers may ask their colleagues to answer questionnaires to rate the flexibility of each supplier. Table 1 lists the example for rating the subjective index, where the lower and upper bounds are predetermined. The average rating can be taken as the data for each supplier. Since flexibility should be maximized, the least-favorable candidate is assigned the smallest value and the most-favorable candidate is assigned the largest value. Meanwhile, for to-be-minimized indices that are to be minimized, the least-favorable candidate is assigned the largest value and the most-favorable candidate is assigned the smallest value. In the illustrative example presented here, the range of subjective indices is set between 1 and 5. Table 2 lists the collected raw data.

In this process, these subjective and non-subjective data are quantitative and qualitative, respectively. Qualitative indices could be translated into numerical ratings using different methods, such as questionnaire, AHP and so on.

Table 1
Rating scale of subjective indices

Very dissatisfied (*Lower bound*)	(*Scores*)	*Very satisfied* (*Upper bound*)
Much worse than competition	*About the same as competition*	*Superior to competition*

Table 2
Collected data of indices

Supplier	To-be-maximized		To-be-minimized	
k	q_k	f_k	c_k	d_k
1	1053	3.9	30000	2400
2	1250	3.1	40000	3000
3	1538	2.8	35000	1500
4	1887	4.7	22000	900
5	2632	4.2	29000	2100

3.4 *Process* 4: *Correspondence of DCU and DMU*

Let the binary variable w_k denote the selection for supplier k. If supplier k is selected, $w_k = 1$, otherwise $w_k = 0$. A composite, say j, of the selection of the five suppliers is denoted by $\boldsymbol{w}_j = (w_{1j}, w_{2j}, w_{3j}, w_{4j}, w_{5j})$, and is termed a Decision Composite Unit (DCU) throughout this investigation [25].

A possible total of 32 DCUs exist $(2 \times 2 \times 2 \times 2 \times 2 = 2^5)$. In the illustrative example, for DCU-j, the corresponding decision-making unit (DMU-j) $(y_{qj}, y_{fj}, x_{cj}, x_{dj})$ is obtained using the following equations. Intuitively, each attribute of a DMU is the sum of the value of the index of the selected suppliers. Table 3 lists the 32 DCUs and DMUs.

For a specific DCU-j,

$$\begin{aligned}
y_{qj} &= 1053w_{1j} + 1250w_{2j} + 1538w_{3j} + 1887w_{4j} + 2632w_{5j} \\
y_{fj} &= 3.9w_{1j} + 3.1w_{2j} + 2.8w_{3j} + 4.7w_{4j} + 4.2w_{5j} \\
x_{cj} &= 30000w_{1j} + 40000w_{2j} + 35000w_{3j} + 22000w_{4j} \\
&\quad + 29000w_{5j} \\
x_{dj} &= 2400w_{1j} + 3000w_{2j} + 1500w_{3j} + 900w_{4j} + 2100w_{5j}\,. \qquad (3)
\end{aligned}$$

Table 3
Value of DCU and DMU

j	DCU$_j$					DMU$_j$				j	DCU$_j$					DMU$_j$			
	w_{1j}	w_{2j}	w_{3j}	w_{4j}	w_{5j}	y_{qj}	y_{fj}	x_{cj}	x_{dj}		w_{1j}	w_{2j}	w_{3j}	w_{4j}	w_{5j}	y_{qj}	y_{fj}	x_{cj}	x_{dj}
1	0	0	0	0	0	—	—	—	—	17	0	0	0	0	1	2632	4.2	29000	2100
2	1	0	0	0	0	1053	3.9	30000	2400	18	1	0	0	0	1	3685	8.1	59000	4500
3	0	1	0	0	0	1250	3.1	40000	3000	19	0	1	0	0	1	3882	7.3	69000	5100
4	1	1	0	0	0	2303	7.0	70000	5400	20	1	1	0	0	1	4935	11.2	99000	7500
5	0	0	1	0	0	1538	2.8	35000	1500	21	0	0	1	0	1	4170	7.0	64000	3600
6	1	0	1	0	0	2591	6.7	65000	3900	22	1	0	1	0	1	5223	10.9	94000	6000
7	0	1	1	0	0	2788	5.9	75000	4500	23	0	1	1	0	1	5420	10.1	104000	6600
8	1	1	1	0	0	3841	9.8	105000	6900	24	1	1	1	0	1	6473	14.0	134000	9000
9	0	0	0	1	0	1887	4.7	22000	900	25	0	0	0	1	1	4519	8.9	51000	3000
10	1	0	0	1	0	2940	8.6	52000	3300	26	1	0	0	1	1	5572	12.8	81000	5400
11	0	1	0	1	0	3137	7.8	62000	3900	27	0	1	0	1	1	5769	12.0	91000	6000
12	1	1	0	1	0	4190	11.7	92000	6300	28	1	1	0	1	1	6822	15.9	121000	8400
13	0	0	1	1	0	3425	7.5	57000	2400	29	0	0	1	1	1	6057	11.7	86000	4500
14	1	0	1	1	0	4478	11.4	87000	4800	30	1	0	1	1	1	7110	15.6	116000	6900
15	0	1	1	1	0	4675	10.6	97000	5400	31	0	1	1	1	1	7307	14.8	126000	7500
16	1	1	1	1	0	5728	14.5	127000	7800	32	1	1	1	1	1	8360	18.7	156000	9900

In the process, the total number of possible DCUs n equals 32 when the examples involve five suppliers (candidates). n exponentially increases with the number of candidates under consideration, $n = 2^K$. Suppose a supplier, say k, is selected before the selection process, then $w_k = 1$ is set. Meanwhile, half of n DCUs, namely those with $w_k = 0$, are not assessed.

3.5 *Process* 5: *Data scaling*

To provide a consistent basis for scaling the individual index from Table 3, each index of the data is scaled to minimize the collected value for a value of 0.0 and maximize the collected value for a value of 1.0, except for quality data which are collected based on penalty cost. For the quality index, the standardized evaluation value for DCU-j is calculated as

$$y'_{qj} = (\mathrm{Max}_{qj} - y_{qj})/(\mathrm{Max}_{qj} - \mathrm{Min}_{qj})\,. \tag{4}$$

For the other three indices, the standardized evaluation values are calculated as

$$y'_{fj} = (y_{fj} - \mathrm{Min}_{fj})/(\mathrm{Max}_{fj} - \mathrm{Min}_{fj}) \tag{5}$$

$$x'_{ij} = (x_{ij} - \mathrm{Min}_{ij})/(\mathrm{Max}_{ij} - \mathrm{Min}_{ij})\,. \tag{6}$$

x'_{ij} denotes the standardized value for DCU-j's data in index i, $i = c$ and d. Meanwhile, $\mathrm{Max}_{ij}(\mathrm{Min}_{ij})$ is the largest (smallest) value in index i, $i = q$, f, c and d. Table 4 lists the DCUs and their corresponding DMU with scaled data.

3.6 *Process* 6: *Evaluation of the DMUs through DEA models*

Let $P = \{j \mid j = 2 \sim n\}$ represent the set of DCUs and/or DMUs. Every DMU-r is assessed to use the following two-phase BCC input-oriented prime model [26].

$$\begin{aligned}
\text{Phase I:}\quad & \operatorname{Min}\theta_r \\
& \text{subject to } \sum_{j\in P} y'_{qj}\lambda_j - s_q = y'_{qr} \\
& \sum_{j\in P} y'_{fj}\lambda_j - s_f = y'_{fr} \\
& \theta_r x'_{cr} - \sum_{j\in P} x'_{cj}\lambda_j - s_c = 0 \\
& \theta_r x'_{dr} - \sum_{j\in P} x'_{dj}\lambda_j - s_d = 0 \\
& \sum_{j\in P} \lambda_j = 1 \\
& s'_q, s_f, s_c, s_d, \lambda_j\ (\forall_{j\in P}) \geq 0\,.
\end{aligned} \tag{7}$$

Table 4
Correspondence of DCU and DMU from scaling data

	DCU$_j$					DMU$_j$					DCU$_j$					DMU$_j$			
j	w_{1j}	w_{2j}	w_{3j}	w_{4j}	w_{5j}	y'_{qj}	y'_{fj}	x'_{cj}	x'_{dj}	j	w_{1j}	w_{2j}	w_{3j}	w_{4j}	w_{5j}	y'_{qj}	y'_{fj}	x'_{cj}	x'_{dj}
1	0	0	0	0	0	—	—	—	—	17	0	0	0	0	1	0.801	0.132	0.066	0.143
2	1	0	0	0	0	1.000	0.114	0.074	0.176	18	1	0	0	0	1	0.669	0.365	0.287	0.407
3	0	1	0	0	0	0.975	0.066	0.147	0.242	19	0	1	0	0	1	0.644	0.317	0.360	0.473
4	1	1	0	0	0	0.843	0.299	0.368	0.505	20	1	1	0	0	1	0.512	0.551	0.581	0.736
5	0	0	1	0	0	0.939	0.048	0.110	0.077	21	0	0	1	0	1	0.608	0.299	0.324	0.308
6	1	0	1	0	0	0.806	0.281	0.331	0.341	22	1	0	1	0	1	0.475	0.533	0.544	0.571
7	0	1	1	0	0	0.782	0.234	0.404	0.407	23	0	1	1	0	1	0.450	0.485	0.618	0.637
8	1	1	1	0	0	0.649	0.467	0.625	0.670	24	1	1	1	0	1	0.318	0.719	0.838	0.901
9	0	0	0	1	0	0.895	0.162	0.015	0.011	25	0	0	0	1	1	0.564	0.413	0.228	0.242
10	1	0	0	1	0	0.763	0.395	0.235	0.275	26	1	0	0	1	1	0.431	0.647	0.449	0.505
11	0	1	0	1	0	0.738	0.347	0.309	0.341	27	0	1	0	1	1	0.407	0.599	0.522	0.571
12	1	1	0	1	0	0.605	0.581	0.529	0.604	28	1	1	0	1	1	0.274	0.832	0.743	0.835
13	0	0	1	1	0	0.702	0.329	0.272	0.176	29	0	0	1	1	1	0.370	0.581	0.485	0.407
14	1	0	1	1	0	0.569	0.563	0.493	0.440	30	1	0	1	1	1	0.238	0.814	0.706	0.670
15	0	1	1	1	0	0.544	0.515	0.566	0.505	31	0	1	1	1	1	0.213	0.766	0.779	0.736
16	1	1	1	1	0	0.412	0.749	0.787	0.769	32	1	1	1	1	1	0.081	1.000	1.000	1.000

Table 5

Solutions for evaluating all DMUs

r	s_q^*	s_f^*	s_c^*	s_d^*	θ_r^*	Status	r	s_q^*	s_f^*	s_c^*	s_d^*	θ_r^*	Status
1	—	—	—	—	—	—	17	0.094	0.030	0	0.022	0.227	I
2	0	0	0	0	1	E	18	0	0	0	0.063	0.671	I
3	0	0.029	0	0	0.561	I	19	0.047	0	0	0.039	0.407	I
4	0	0	0	0.007	0.486	I	20	0	0	0	0.054	0.623	I
5	0	0	0	0	1	E	21	0.106	0	0.013	0	0.445	I
6	0	0	0.011	0	0.409	I	22	0.006	0	0	0	0.654	I
7	0.018	0	0.001	0	0.190	I	23	0.059	0	0	0	0.502	I
8	0	0	0.019	0	0.500	I	24	0.030	0	0	0.026	0.668	I
9	0	0	0	0	1	E	25	0	0	0	0	1	E
10	0	0	0	0	1	E	26	0	0	0	0	1	E
11	0	0	0.003	0	0.602	I	27	0.044	0	0	0	0.787	I
12	0	0	0	0	1	E	28	0	0	0	0	1	E
13	0	0	0.106	0	0.978	I	29	0	0	0	0	1	E
14	0	0	0	0	1	E	30	0	0	0	0	1	E
15	0	0	0.082	0	0.727	I	31	0.059	0	0	0	0.839	I
16	0	0	0	0	1	E	32	0	0	0	0	1	E

E : Efficient ; I : Inefficient

The optimal solution θ_r^* of Phase I is then taken to Phase II as a constant.

Phase II:

$$\begin{aligned}
&\text{Min } z_r = -s_q - s_f - s_c - s_d \\
&\text{subject to } \sum_{j\in P} y'_{qj}\lambda_j - s_q = y'_{qr} \\
&\sum_{j\in P} y'_{fj}\lambda_j - s_f = y'_{fr} \\
&\sum_{j\in P} x'_{cj}\lambda_j + s_c = \theta_r^* x'_{cr} \\
&\sum_{j\in P} x'_{dj}\lambda_j + s_d = \theta_r^* x'_{dr} \\
&\sum_{j\in P} \lambda_j = 1 \\
&s_q, s_f, s_c, s_d, \lambda_j\ (\forall_{j\in P}) \geq 0\,.
\end{aligned} \tag{8}$$

The scalar variable θ_r^* denotes the proportional reduction applied to all to-be-minimized indices of DMU-r to improve efficiency. Meanwhile, s_i represents the slack variable of index i, where $i = q, f, c$ and d. Finally, λ_j is the weight of DMU-j , $(j \in P)$ in determining the efficiency of DMU-r. DMU-r is efficient if and only if the optimal solution of the two-phase model, $\theta_r^* = 1$ and $z_r^* = 0$. Each DMU-r, $r = 2, \ldots, 32$, as listed in Table 4. The solutions for evaluating all DMUs are listed in Table 5.

At this point a further observation can be made. If s_q^*, s_f^* have any positive components then the associated to-be-maximized values in the levels of these slack variables can be increased without altering any of the λ_j^* values or violating any constraints. Similarly, if s_c^* and s_d^* have positive components the to-be-minimized values can be reduced in an analogous manner. Notably, the weightings identified for this example, listed above, are objectively determined to obtain a (dimensionless) scalar measure of efficiency for any situation.

As shown in Table 5, DMU-10 is efficient, indicating that the associated DCU-10, $(1, 0, 0, 1, 0)$, in Table 4 where suppliers 1 and 4 are selected, is an efficient composite. Table 5 rearranges the 13 efficient DCUs according to the number of suppliers selected, as listed in Table 6.

Notably, in this process the efficient frontiers for the BCC and Additive models are identical, while if a DMU was characterized as efficient in the CCR model, it will also be characterized as efficient in the BCC model. The absence of the convexity constraint enlarges the feasible region for CCR prime model from the convex hull to be considered in the BCC prime model to the conical hull of the DMUs. Since the total number of DCUs is very large, the CCR model is used to obtain fewer efficient frontiers.

Table 6
Efficient supplier composites

Number of selected suppliers in SC	Efficient DCUs	Supplier composites
1	DCU-2, -5, -9	(1), (3), (4)
2	DCU-10, -25	$(1,4)$, $(4,5)$
3	DCU-12, -14, -26, -29	$(1,2,4)$, $(1,3,4)$, $(1,4,5)$, $(3,4,5)$
4	DCU-16, -28, -30	$(1,2,3,4)$, $(1,2,4,5)$, $(1,3,4,5)$
5	DCU-32	$(1,2,3,4,5)$

In the category of single suppliers, Suppliers 1 and 4, respectively, have the highest to-be-maximized performance quality and flexibility, while Supplier 4 has the lowest to-be-minimized performance cost and delivery. In the two supplier category, the pair of Suppliers 1 and 4 is not the only choice, and the pair of Suppliers 4 and 5 would be selected as SC partners if cost or flexibility was the key consideration. Meanwhile, if only one supplier is being selected, one DEA model can be directly chosen to assess the performance of each supplier and select one of the efficient suppliers. If the final decision permits multiple suppliers, the novel approach provides more alternative choices. For various reasons, selections can differ among firms.

When choosing betweens suppliers 1 and 4, Supplier 4 is selected if flexibility, cost and delivery are the key considerations, while Supplier 1 is the best choice if quality is the main concern. Consequently, this investigation identifies two optimal choices, namely supplier 1 and 4, or supplier 4 and 5. Table 7 lists the composites of the to-be-minimized and to-be-maximized indices of the two suppliers.

Table 7
The composites data of two suppliers

Supplier	To-be-maximized		To-be-minimized	
	Quality	*Flexibility*	*Cost*	*Delivery*
1 and 4	$(1053, 1887)$	$(3.9, 4.7)$	$(30000, 22000)$	$(2400, 900)$
4 and 5	$(1887, 2632)$	$(4.7, 4.2)$	$(22000, 29000)$	$(900, 2100)$

4. Sensitivity analysis on indices data

The data for each supplier, listed in Table 2, may be questioned. For example, investigators can examine the extent to which perturbation in the data can be tolerated before the current DEA efficiency is changed as inefficient. Sensitivity analysis was conducted for cost and delivery variations one at a time. For every supplier under consideration, cost and delivery were increased stepwise in 5% increments, while and flexibility and quality were decreased by 5% decrements. Processes 4, 5, and 6 were then performed at each step to check for changes in efficiency. This process was continued with $5\%+$ $(5\%-)$ cost and delivery increments (quality and flexibility decrements) up to $30\%+$ $(30\%-)$ [27].

Table 8 listed the step changes for the current DEA efficiency. For example, the first data of the Quality column, $\mathbf{.95}\boldsymbol{q_1}$ indicates that the downward perturbation of q_1 stops at the step of .95, since DMU-5 becomes an inefficient DMU. Furthermore, the final piece of data in the Quality column, $\mathbf{.9}\boldsymbol{q_3}$, indicates that as q_3 perturbed at the step of $.9$, DMU-13 becomes an efficient DMU.

In the management context, changes are made in upward and downward steps of $+5\%$ and -5%, respectively, a scale of change that can be accepted by managers. Upward and downward changes of any proportion for the to-be-minimized and to-be-maximized indices can also be examined. This result captures differences in the competition indices of suppliers that allow them to rapidly respond to the dynamic environment. The production functions derived can be used for forecasting and sensitivity analysis, providing useful insights into policy decisions. In their tolerance, the managers will change the to-be-minimized values or to-be-maximized values to realize all the suppliers. These results can be used to enhance and alter decisions.

Table 8

Results of sensitive analysis

Status	DMU	DCU	Quality	Flexibility	Cost	Delivery
Efficient	2	$(1,0,0,0,0)$				
	5	$(0,0,1,0,0)$	$\mathbf{.95q_1}$, $.95q_5$ $.9q_4$, $1.05q_3$			$.95d_1$, $.9d_5$, $1.05d_4$
	9	$(0,0,0,1,0)$				
	10	$(1,0,0,1,0)$				
	12	$(1,1,0,1,0)$		$.7f_2$		
	14	$(1,0,1,1,0)$	$.85q_5$, $1.15q_3$	$.9f_3$, $1.1f_5$		$1.25d_3$
	16	$(1,1,1,1,0)$	$.85q_5$, $1.15q_3$	$.85f_3$, $1.15f_5$		
	25	$(0,0,0,1,1)$		$.8f_5$, $1.25f_1$		
	26	$(1,0,0,1,1)$				
	28	$(0,0,0,1,0)$	$.75q_3$	$.8f_2$, $1.15f_3$	$.7c_3$	
	29	$(0,1,0,1,1)$		$.85f_3$, $.8f_5$, $1.15f_1$		$.85d_1$, $1.15d_3$
	30	$(1,0,1,1,1)$				
	32	$(1,1,1,1,1)$				
Inefficient	3	$(0,1,0,0,0)$	$.8q_2$, $1.20q_1$		$.7c_2$	
	4	$(1,1,0,0,0)$	$.95q_2$, $1.05q_4$	$.95f_4$, $1.05f_2$		
	8	$(1,1,1,0,0)$		$.7f_4$		
	13	$(0,0,1,1,0)$	$.9q_3$, $1.1q_5$	$.95f_5$, $.9f_1$, $1.05f_3$		$.95d_3$, $1.05d_5$, $1.1d_1$
	17	$(0,0,0,0,1)$			$.75c_5$	

5. Discussion

Instead of measure the 2^K possible SCs by using DEA models (7) and (8), one may measure the performance of the K candidates directly. Then, in (7) and (8), $P = \{j \mid j = 1 \sim K\}$, and the data y'_{qj}, y'_{fj}, x'_{cj} and x'_{dj} are substituted by the data q_k, f_k, c_k and d_k in Table 2, respectively. Table 9 lists the evaluation results. Suppliers 1, 3 and 4 have three efficient alternatives, but top managers lack information and must decide among different suppliers in a competitive market that considers the core capability composites of individual suppliers. This approach will increase the opportunity for the company to achieve a win-win outcome. In the result, different composites of these suppliers could not be realized, except for one supplier.

Table 9
Efficient of suppliers

Supplier	s_q	s_f	s_c	s_d	θ_r	Status
1	0	0	0	0	1.000	E
2	0	0.989	0	62.59	0.703	I
3	0	0	0	0	1.000	E
4	0	0	0	0	1.000	E
5	745	0.5	0	693	0.759	I

E : Efficient ; I : Inefficient

The collected raw data are re-scaled in Process 5. Data with widely ranging values may be encountered, and one index may have values in the units, while another has values in the hundreds of thousands and millions. This wide range in the values of the indices can create computational difficulties, particularly for those using general-purpose mathematical programming software packages that do not have the ability to fine-tune the tolerance of the solution mechanism. Another problem is the wide variation in the scores for indices across the n DMUs, since each index value of a DMU is the sum of the value of the selected suppliers on that index. Generally, the to-be-minimized indices are defined because in their case lower values indicate better performance. Consequently, $(y'_{\max} - y'_t)$ can be used when defining data as to-be-maximized, and similarly the data attribute y'_t can be used to define the to-be-minimized indices. Conversely, the to-be-maximized indices can be defined because their larger values indicate a more favorable performance. $(x'_{\max} - x'_k)$ can then be used to define the data as to-be-minimized, and the data attribute x'_k is the same as the to-be-maximized indices.

6. Conclusion

This investigation presents a novel method for selecting suppliers. Suppliers of multiple types of products may be considered, and each candidate may supply multiple products, while each product can also be supplied by multiple suppliers. The performance indices may differ among each type of product supplier. One is to select a set of multiple suppliers for each product so that the overall index scores for the company would have the most efficiency.

Stepwise sensitivity analysis is performed in this investigation to identify the neighborhood of the change of each supplier index value. A one step approach can be used to obtain the precise change that is possible in each index value to preserve the existing set of efficient composite unchanged.

Finally, some additional research issues are summarized below.

1. The DCU method of selection could be extended to become a management and strategic tool, particularly in decisions combining various aspects such as mergers, alliances, and transportation networks.
2. Different constraints are added to the related model in real competition markets. Meanwhile, the supplier k must set $w_k = 1$ or else there will only be one choice between the specific two suppliers, m and n, and $w_m + w_n = 1$.
3. One can use fuzzy theory, utility function or other methods to integrate these composites data for alternative suppliers to assess performance of suppliers.

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