Int J Adv Manuf Technol
DOI 10.1007/s00170-010-2697-0

ORIGINAL ARTICLE

A supplier selection and order allocation model with multiple transportation alternatives

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Received: 31 March 2009 / Accepted: 21 April 2010

Abstract Numerous analytical methods ranging from simple weighted scoring to complex mathematical programming approaches have been proposed to solve supplier selection and order allocation problems. However, the traditional methods too often fail to consider: (1) situations in which goods are transported from a supplier to a receiver using different transportation alternatives (TAs) and (2) a finite planning horizon consisting of multiple discrete time periods. We present a structured framework with two separate but dependent phases. In the selection phase, we use a data envelopment analysis model to determine the relative efficiency of the suppliers and the TAs. In the allocation phase, we use a multi-objective mixed integer programming model with two objectives for minimizing the total costs and maximizing the overall efficiencies. The contribution of this paper is threefold: (1) It provides a comprehensive and systematic framework that embraces both quantitative and qualitative criteria; (2) it addresses the need in the supplier evaluation literature for methods that considers different TAs in the supplier selection and order allocation decisions encompassing multiple discrete time periods; and (3) it uses a real-world case study to demonstrate the applicability of the proposed framework and exhibit the efficacy of the procedures and algorithms.

Keywords Supplier selection · Order allocation · Data envelopment analysis · Transportation alternative

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1 Introduction

The constant pressure for globalization and competitive advantage has forced organizations to search for effective supplier selection strategies [1, 7, 13]. The purpose of supplier selection is to determine the optimal supplier who can offer the best products or services for the customer and become a part of the organization's supply chain [21, 24]. Supplier selection and evaluation is a strategic problem with the emerging trend to select suppliers where a long-term relationship is desired and supplier involvement in product development is essential [2]. As a supplier becomes a part of the established supply chain, it will have a lasting effect on the efficiency and effectiveness of the entire supply chain [11]. Effective supplier evaluation and selection strategies can directly impact supply chain performance, resulting in organizational productivity and profitability.

Supplier selection is a multi-criteria problem which includes both tangible and intangible criteria [21]. Ho et al. [27] have provided an excellent review of the literature in multi-criteria decision-making approaches for supplier evaluation and selection. Their research not only provides evidence that the multi-criteria decision-making approaches are better than the conventional cost-based approach but also aids the researchers and decision makers in applying the multi-criteria approaches effectively. In order to select the best suppliers, it is necessary to make a trade-off between these tangible and intangible criteria, some of which may conflict [16, 17, 45]. Numerous analytical techniques ranging from simple weighted scoring to complex mathematical programming approaches have been proposed to solve these problems. However, traditional supplier selection models too often fail to consider the vital role of the transportation alternatives (TAs) in the evaluation and allocation process. Although the transportation, ordering, and storage costs are significantly important to the supplier evaluation and order allocation decisions, only a few mathematical programming models are developed to analyze such decisions [25, 30]. Dullaert et al. [20] have considered a combinatorial optimization methodology for determining the optimal mix of transportation alternatives to minimize total logistics costs when goods are shipped from a supplier to a customer. Their total logistics costs comprised the order costs, transportation costs, and inventory costs.

We present a structured framework for solving the supplier evaluation and order allocation problem. The proposed framework consists of two separate but dependent phases. In the selection phase, we determine the quantitative and qualitative criteria values for each supplier and TA and calculate the relative efficiency of the suppliers and the TAs. In the allocation phase, we develop a multi-objective mixed integer programming with two objectives for minimizing the total costs and maximizing the overall efficiencies subject to a set of capacity, demand, storage, and lead time constraints.

The remainder of the paper is organized as follow. In Section 2, we review the literature in supplier evaluation and order allocation. In Section 3, we introduce the mathematical notations and definitions used throughout the paper. Section 4 describes the two-phase framework proposed in this study for optimal order allocation. In Section 5, we use a real-world case study to demonstrate the applicability of the proposed framework and exhibit the efficacy of the procedures and algorithms. Finally, in Section 6, we sum up our conclusions and future research directions.

2 Literature review

2.1 Supplier evaluation criteria and order allocation

Supplier selection decisions affect various functional areas from procurement of raw materials and components to production and delivery of the end products. The criticality of supplier selection is evident from the significant attention in the literature and its impact on organizational performance [4, 19, 37]. Most supplier selection frameworks in the literature include multiple phases [1, 13, 35]. As reported by Aissaoui et al. [1], several decision-making steps make up the vendor selection process: At first, a preparation step is achieved by formulating the problem and the different decision criteria. After that, prequalification of potential suppliers and final choices are successively elaborated. Chou and Chang [13] have identified four distinct phases in the purchasing and supply literature, namely, defining the problem, formulation of criteria, qualification, and final selection. Sarkar and Mohapatra [35] developed a systematic framework for carrying out the supply base reduction process. They considered two dimensions of performance and capability. Performance of a supplier represents short-term effects and supplier capability indicates long-term effects on the supply chain. They proposed a multiphase fuzzy set approach to rank a potential list of suppliers against their performance and capability.

There are four major decisions that are related to the supplier selection problem: What product or services to order, from which suppliers, in what quantities, and in which time periods? In an attempt to provide reasonable answers to the first question, some authors have studied supplier evaluation in multiproduct environments. For example, Rajan et al. [34] developed a multiphase decision-making model to evaluate a set of suppliers for a set of products with respect to product prioritization and customer expectations. In the first phase, they use profit ratio analysis to obtain the profitability rank order for the set of products. Then, they prioritize customers using the analytic hierarchy process (AHP) in the second phase. In the third phase, they employ critical value analysis to prioritize the products based on profitability rank order and customer expectations. Next, they evaluate the set of suppliers for the set of products using AHP in the fourth phase. Finally, they use an assignment model to allocate the specified supplier for each product based on priority. Even though Rajan et al. [34] considered a single product problem, their model could be extended to solve multi-product problems.

The next decision concerns with which suppliers and in what quantities? The answers to these questions require identification and evaluation of the relevant supplier evaluation criteria [14]. Dickson [18] distributed a questionnaire among 273 purchasing agent and managers from the USA and Canada and identified 23 different criteria relative to the supplier evaluation and selection decisions. Among these criteria, price, delivery, and quality objectives of the buyer, as well as the ability of the vendors to meet those objectives, are particularly important factors in deciding how much to order from the available suppliers. Although the evolution of the industrial environment has modified the relative importance of the supplier selection criteria since the 1960s, the 23 ones presented by Dickson [18] still cover the majority of those presented in the literature [1]. The supplier evaluation and selection literature has traditionally held that quality, delivery, service, and cost comprise the choice criteria utilized by business customers to evaluate their suppliers [39]. Therefore, these four criteria are assumed to provide an appropriate set of major performance measures for supplier evaluation.

Another complicating factor in supplier evaluation is the decision to buy from a single source or multiple sources. In single sourcing, all the suppliers can fully meet the buyer's price, quantity, quality, and delivery requirements. Consequently, the only decision concerns the selection of the "best" supplier. In contrast, multiple sourcing is adopted when either none of the suppliers can satisfy the buyer's total demands or when purchasing strategies aim at avoiding dependency on a single source. A useful approach to ensure the reliability of a manufacturer's supply stream is to follow a multiple sourcing policy [1]. Hong and Hayya [28] have argued that the use of multiple sourcing, in a majority of cases especially in a just-in-time environment, reduces the overall inventory and purchasing costs. In those situations, a buyer purchases the same item from more than one supplier by splitting total demand among them. Sometimes, for reasons such as price discount offers or possible limitations on capacity, quality, delivery, or price, a supplier may not be able to satisfy the assigned demand. Therefore, in multiple sourcing, we could have a shipment or order allocation phase where the buyer may want to split the order quantity among multiple suppliers for a variety of reasons including creating a constant environment of competitiveness. In other words, we have to determine the optimal order quantity from the chosen suppliers considering vendor capacity constraints and demand requirements.

Liu and Hai [31] attempted to provide a simple method for computing the total ranking of the suppliers and presented a novel weighting procedure in place of AHP's paired comparison for selecting suppliers. They proposed a method called voting AHP that does not lose the systematic approach of deriving the weights to be used for scoring the performance of suppliers. The technique for order performance by similarity to ideal solution is a well-known multi-criteria method; recently, Chen et al. [11] extended its concept to develop a methodology for solving supplier selection problems in fuzzy environments. To assess the criteria weights and the alternative ratings, linguistic variables are used for group decision-making processes with fuzzy decision data. Finally, a closeness coefficient is defined to determine the ranking order of the alternatives. In another study, Chou and Chang [13] presented a strategy-aligned fuzzy simple multi-attribute rating technique for solving the supplier selection problem in fuzzy environments. The proposed system utilizes operations management/supply chain strategy to identify and utilize quantitative and qualitative supplier selection criteria in a judgmental decision-making procedure.

The final decision concerns the time period in which the product should be ordered. There are a few studies in the literature that address this question [5, 6, 8, 40]. In reality, while multiple planning period considerations contribute to the problem complexity, inventory management considerations yield a more robust procurement plan. This balances the ordering costs and the holding costs and allows for the selection of the supplier with a low ordering cost when frequent ordering is necessary due to inventory management reasons (e.g., perishable inventory). In addition, the flexibility in the purchasing schedule may significantly reduce ordering and purchasing costs especially when the buyer can take advantage of discounted prices. Our method addresses these four decisions using a systematic and structured framework. Several authors have proposed similar frameworks in the literature [20, 25, 26, 30, 33]. As is shown in Table 1, our framework covers a broader range of decisions compared with the five competing frameworks in the supply selection and order allocation literature.

2.2 Data envelopment analysis and supplier evaluation

Data envelopment analysis (DEA) is a mathematical programming technique that measures the relative efficiency of multiple decision-making units (DMUs) based on multiple inputs and outputs [22]. The efficiency of a DMU is defined as the ratio of the weighted sum of its outputs (i.e., performance) to the weighted sum of its inputs (i.e., resources utilized). For each DMU, DEA finds the most favorable set of weights, i.e., the set of weights that maximizes the DMU efficiency rating without making its own or any other DMUs rating >1. The concept of frontier analysis suggested by Farrell [23] forms the basis of DEA, but the recent series of discussions started with the article by Charnes et al. [10]. Modifying the DEA model of Charnes et al. [10], Banker et al. [3] proposed the DEA model (BCC model) to handle cases of variable returns to scale. A general description of the model may be found in several studies [36, 43], and a detailed explanation is given in Cooper [15] and Charnes et al. [9]. Weber [41],

Table 1 Comparison between our framework and the competing frameworks in the literature

Relevant research	Consideration			
	Multiple horizons	Supplier selection	Order allocation	Transportation alternatives
Dullaert [20]	√	–	–	√
Ghodsypour and O'Brien [25]	√	√	√	–
Ho and Emrouznejad [26]	–	–	–	√
Kawtummachai and Hop [29]	√	√	√	–
Quariguasi Frota Neto et al. [32]	–	–	√	√
This article	√	√	√	√

Weber et al. [42], Weber and Desai [43], and Weber and Ellram [44] have discussed the application of DEA in supplier selection problems in several studies. Narasimhan et al. [32] first used DEA to evaluate the effectiveness of the suppliers and classified them on this basis for the purpose of supply base rationalization. Talluri and Baker [38] presented a multiphase mathematical programming approach for effective supply chain design based on: (1) evaluation of supplier, manufacturer, and distribution candidates; (2) identification of the optimal number of suppliers; and (3) identification of optimal routing decisions. Recently, the DEA is used to solve multi-criteria assignment problems. Chen and Lu [12] have articulated the limitations of DEA in solving assignment problems with multiple costs or profits and presented a procedure to resolve these deficiencies. They used the BCC model and defined a composite efficiency index to serve as the performance measurement for each possible assignment in the problem formulation. Then, they used these measurements in an integer programming model in order to achieve the maximum efficiency in resource utilization.

2.3 Procurement lot sizing and transportation alternatives

Many studies have been conducted on various optimization aspects in supply chains. Supply chains are typically large and hard to study in their entirety. Consequently, many researchers have focused their attention on smaller subsets rather than the entire supply chain system. The problem of how to allocate orders to the proper suppliers tends to be an important topic, especially in the case of the multiple-supplier environment [30]. However, as noted by Ghodsypour and O'Brien [25], very little attention has been paid in the supply chain literature to decisions concerning the appropriate selection of suppliers. Ghodsypour and O'Brien [25] have proposed a mixed integer nonlinear programming model to solve multiple supplier evaluation and allocation problems by taking into account the total cost of logistics and buyer limitations. Moreover, their model provided a schedule for deliveries, which tells the buyer when and how much to buy from each supplier.

In another paper, Kawtummachai and Hop [30] studied the effects of an order allocation procedure in a supply chain. Their supply chain consisted of a firm that can order products from multiple suppliers. At any time of an order, decisions have to be made by the firm concerning the allocation of products to the suppliers and the respective order quantities so that the total purchasing cost is minimized while a specified service level is maintained. Dullaert et al. [20] have suggested a new methodology for determining the optimal mix of TAs to minimize the total logistics costs when goods are shipped from a supplier to a buyer. Their total logistics costs comprised order costs, transportation costs, and inventory costs. They assumed that only a limited number of TAs are capable of shipping the products from the supplier to the buyer. Moreover, if a certain TA is selected to ship the products, then its entire capacity is used. Considering these assumptions, Dullaert et al. [20] implied that the number of possible order quantities is finite and that the problem can be formulated as a combinatorial optimization problem.

3 Mathematical notations

Let us introduce the following mathematical notations and definitions used throughout this paper:

D_t Product demand in period t.
h_t Product holding cost in period t
O_{ij} Ordering costs for supplier i using the transportation alternative j
CT_{ij} Transportation costs for supplier i using the transportation alternative j
P_{it} Capacity of supplier i in period t

CP_j Capacity of transportation alternative j
CP_T Overall storage capacity of the buyer
E_{ij}^{OV} Overall efficiency for supplier i using the transportation alternative j
C_{it} Product purchase price for supplier i in period t
n_j Number of transportation alternatives j
L_{ij} Product delivery lead time for supplier i using the transportation alternative j
X_{ijt} Number of products ordered from supplier i by using transportation alternative j in period t
S_{ijt} Binary variable for allocating the transportation alternative j to supplier i in period t
I_t Product inventory carried over from period t to period $t+1$ (it is assumed that $I_0=0$)

where $i=1,2,\ldots,n$; $j=1,2,\ldots,m$; and $t=1,2,\ldots,T$.

4 Supplier selection and order allocation framework

In this paper, we formulate the supplier selection problem as a multi-criteria assignment problem and allocate orders to the selected suppliers for each period in the planning horizon while integrating some of the order splitting and TA concepts proposed by Dullaert et al. [20]. The proposed framework depicted in Fig. 1 is divided into two distinct but dependent phases, namely, the evaluation phase and the allocation phase. In the evaluation phase, we consider the problem of assigning the most appropriate set of TAs to the suppliers. Similar to the method proposed by Chen and Lu [12], we calculate the relative efficiency of each TA to each supplier. Next, we determine the relative efficiency of each supplier to each TA. Finally, we develop a composite efficiency index that incorporates the two former relative efficiencies for each assignment cell (assignment of the ith TA to the jth supplier). In the allocation phase, we develop a multi-objective mixed integer programming model with two objectives for minimizing the total costs and maximizing the overall efficiencies (from the evaluation phase) subject to capacity, demand, storage, and lead time constraints. The proposed optimization model allocates a set of optimal order quantities to the selected suppliers for each time period in the planning horizon.

4.1 Evaluation phase

The first step in the evaluation phase is the identification of the input and output criteria. Numerous studies have addressed supplier evaluation criteria. Among the mentioned criteria, cost, quality, delivery, and service constitute the most repetitive criteria in the supplier evaluation literature [29, 39]. In addition, each TA has special "logistics characteristics": loading capacity, order and transportation costs, average lead time, and variance of lead time [20]. As depicted in Fig. 2, in this phase, we have an assignment problem with n suppliers and m transportation alternatives. We solve this problem with the BCC model and calculate the relative efficiencies of the suppliers for each TA (say E_{ij}^{TA} for supplier i and TA j) and relative efficiencies of the TAs for each supplier (say E_{ij}^{SU} for supplier i and TA j). Finally, the

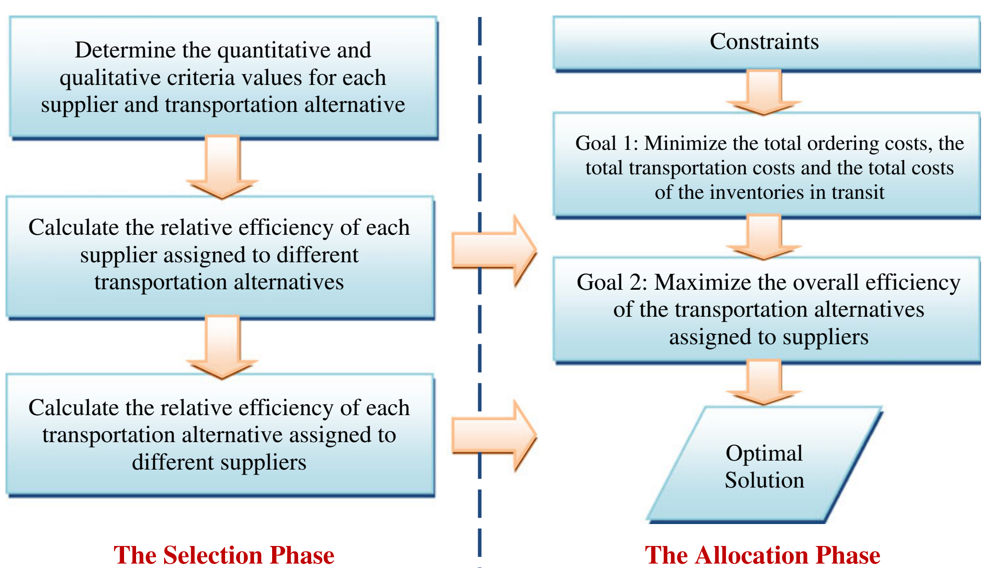

Fig. 1 Supplier evaluation and order allocation framework

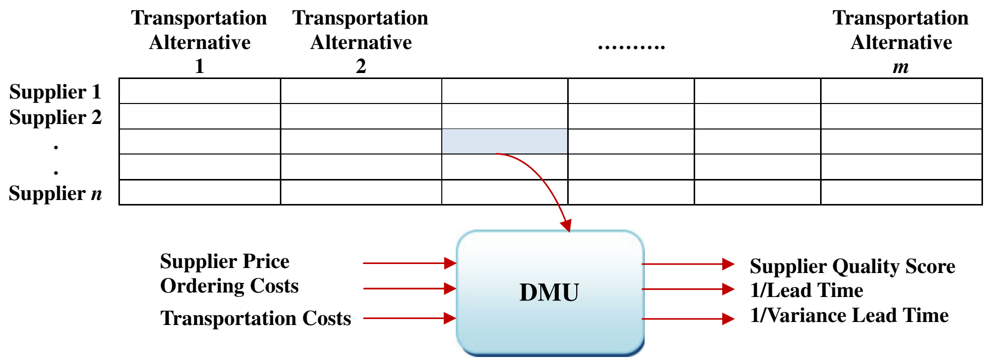

Fig. 2 Supplier evaluation problem as a multi-criteria allocation problem

overall efficiency of assigning supplier i to TA j, E_{ij}^{OV}, is calculated as a product of E_{ij}^{TA} and E_{ij}^{SU} ($E_{ij}^{\mathrm{OV}} = E_{ij}^{\mathrm{TA}} \times E_{ij}^{\mathrm{SU}}$). The details of the DEA model used in the evaluation phase are presented in Appendix 1.

4.2 Allocation phase

In this phase, we want to answer three questions: (1) What order quantity should be allocated to each supplier; (2) which TAs should be assigned to each supplier; and (3) which period in the planning horizon should be used. While one goal is to maximize the overall efficiency of each assignment, we must simultaneously minimize three different logistics costs including total ordering costs, total transportation costs, and total costs of the inventories in transit [20]. The overall efficiency of each assignment is the product of the respected relative efficiencies calculated in the evaluation phase: $E_{ij}^{\mathrm{OV}} = E_{ij}^{\mathrm{TA}} \times E_{ij}^{\mathrm{SU}}$. The formulation of the aforementioned costs are as follows: The total ordering costs are calculated by multiplying the costs per order by the number of orders placed, i.e., the number of TAs that are used. The total transportation costs are calculated by multiplying the transportation costs per TA by the number of times that TA is used. The total costs of the inventories in transit are calculated by multiplying the average lead time per TA by the number of TAs used which is multiplied by the value of the product and by holding cost. Therefore, we construct the multi-objective mixed integer programming model presented in Appendix 2. This model can be solved by linear programming commercial software such as Microsoft Excel Solver.

5 Case study

The proposed model has been implemented at Pars Automotive Parts Company (PAPC), the largest supplier of automotive parts to Iran Khodro Company (IKCO). IKCO is the largest vehicle manufacturer in the Middle East, Central Asia, and North Africa. In Iran, it is the largest vehicle manufacturing company, having an average share of 65% of domestic vehicle production. PAPC designs, engineers, and manufactures a wide variety of components, integrated systems, and modules and is the largest and most diversified supplier of automotive parts in Iran. PAPC outsources over 75% of their products. In an attempt to improve the effectiveness of the company's supply, PAPC management has decided to implement a new supplier evaluation and allocation system. A committee of five managers, who are experts in supplier evaluation and purchasing, was formed to develop the supplier evaluation and order allocation system at PAPC. Four different TAs were considered as feasible options for shipping the parts from ten suppliers to the receiver. The four TAs are: small trucks, large trucks, small vessels, and large vessels. A general profile of the four transportation alternatives for the ten suppliers is presented in Table 2.

As is shown in Table 2, each supplier has its own price and quality score. For a particular supplier, a competitor with a lower quality score or a higher price may have a better order fulfillment or geographical position which could compensate for its lower quality score or higher price. This table also shows the ordering costs and the transportation costs per full load for different TAs. Furthermore, the means and the variances of the lead times for fully loaded TA shipments from a supplier to a manufacturer, reflecting the transportation time efficiencies, are also shown in Table 2. Finally, the available quantity and the loading capacity of each TA are shown in the last two rows of this table. These available quantities and loading capacities are a part of the order allocation model constraints.

Table 3 shows a general profile of the ten suppliers over six periods (months). The capacity and price forecasts for each supplier and each TA are provided in this table.

Table 2 General profile of the four transportation alternatives

Supplier	Price	Quality Score (1–10)	Transportation alternative															
			1				2				3				4			
			Small truck				Large truck				Small vessel				Large vessel			
			OC[a]	TC[b]	LT[c]	LTV[d]	OC	TC	LT	LTV	OC	TC	LT	LTV	OC	TC	LT	LTV
1	20	4	2,200.00	3,200.00	12.5	5.6	6,083.30	7,083.30	8.0	4.0	17,810.80	10,810.80	16.7	4.0	31,490.00	19,490.00	50.0	9.1
2	30	2	2,040.00	2,040.00	3.0	1.4	3,333.30	4,333.30	5.3	1.0	17,756.80	8,756.80	4.8	7.1	27,220.00	12,220.00	16.7	5.3
3	30	7	1,720.00	2,720.00	4.0	3.3	4,866.70	4,966.70	7.0	3.0	12,567.60	9,567.60	9.0	5.0	30,335.00	16,335.00	21.0	5.9
4	42	3	2,040.00	3,040.00	5.0	2.5	9,000.00	6,200.00	9.0	2.0	17,864.90	10,864.90	14.0	5.9	29,250.00	17,250.00	24.0	10.0
5	48	9	2,680.00	3,680.00	10.0	7.7	5,300.00	6,800.00	7.0	3.0	14,621.60	11,621.60	15.0	5.9	31,245.00	19,245.00	42.6	11.1
6	23	8	2,680.00	3,680.00	3.0	2.0	3,950.00	6,950.00	2.1	2.0	11,675.70	11,675.70	9.3	5.9	31,735.00	19,735.00	20.0	5.0
7	47	4	2,200.00	3,200.00	4.0	1.0	6,166.70	6,166.70	8.0	2.0	18,405.40	10,405.40	7.5	5.0	30,860.00	17,860.00	14.3	14.3
8	32	7	2,680.00	3,680.00	3.5	3.3	7,500.00	7,500.00	7.0	3.0	19,486.50	12,486.50	12.0	4.0	28,725.00	19,725.00	23.0	14.3
9	35	10	2,840.00	3,840.00	3.0	2.0	5,583.30	7,583.30	2.8	3.0	18,837.80	12,837.80	6.3	5.9	29,985.00	18,985.00	25.0	9.1
10	45	6	2,680.00	3,680.00	3.0	2.0	5,833.30	7,833.30	2.4	2.0	18,081.10	12,081.10	7.7	4.0	26,625.00	19,625.00	2.1	6.7
Available quantity			4				2				3				1			
Loading capacity			20				70				200				470			

A quality score 1 (very poor) is assigned to items with a defect rate ≥10% and a quality score 10 (excellent) is assigned to items with a defect rate ≤0.5%

[a] Ordering costs (US dollars)

[b] Transportation costs (US dollars)

[c] Lead time (days)

[d] Lead time variance (days)

Table 3 General profile of the suppliers

Supplier	Period (1-month duration)											
	1		2		3		4		5		6	
	Capacity	Price	Capacity	Price	Capacity	Price	Capacity	Price	Capacity	Price	Capacity	Price
1	350	20	350	22	350	20	350	25	350	18	350	18
2	500	30	500	30	500	30	500	30	500	30	500	30
3	400	32	400	32	400	32	400	30	400	33	400	30
4	470	32	470	32	470	32	470	42	470	42	470	42
5	480	38	480	28	480	28	480	48	480	48	480	48
6	490	23	490	23	490	23	490	19	490	19	490	19
7	410	47	410	47	410	34	410	34	410	47	410	47
8	520	35	520	30	520	30	520	30	520	30	520	35
9	500	35	500	29	500	29	500	30	500	30	500	35
10	400	45	400	40	400	35	400	35	400	40	400	45
Demand	2,900		3,300		3,500		3,500		3,500		3,000	
Holding costs	2		2		2		3		3		3	
Buyer storage capacity	1,800		1,800		1,800		1,800		1,800		1,800	

Generally, the suppliers can estimate their capacities and prices for the upcoming 6 months based on the manufacturer's growth or downsizing plans.

In the assignment phase, we constructed a model in Lingo 8.0 software based on the procedure described in the evaluation phase and determined the overall efficiency scores, $E_{ij}^{\mathrm{OV}} = E_{ij}^{\mathrm{TA}} \times E_{ij}^{\mathrm{SU}}$, presented in Table 4. All the required algorithms were implemented in Microsoft Excel Macros with Visual Basic programming. As is shown in Table 4, the overall efficiency score of using a particular TA for a particular supplier is calculated solving both the row-based DEA (all TAs compete or are compared according to their optimal shipping from a particular supplier) and the column-based DEA (all suppliers compete or are compared according to their optimal shipping by a particular TA). For instance, in

Table 4 Overall efficiency scores

Supplier	Transportation alternative							
	1		2		3		4	
	Small truck		Large truck		Small vessel		Large vessel	
	Efficiency score	Log	Efficiency score	Log	Efficiency score	Log	Efficiency score	Log
1	0.575	−0.24	0.575	−0.24	1.000	0.00	0.632	−0.20
2	1.000	0.00	1.000	0.00	1.000	0.00	1.000	0.00
3	1.000	0.00	0.828	−0.08	1.000	0.00	0.914	−0.04
4	0.669	−0.17	0.643	−0.19	0.667	−0.18	0.533	−0.27
5	0.939	−0.03	0.961	−0.02	0.940	−0.03	0.900	−0.05
6	1.000	0.00	1.000	0.00	1.000	0.00	1.000	0.00
7	1.000	0.00	0.714	−0.15	0.882	−0.05	0.474	−0.32
8	0.840	−0.08	0.786	−0.10	1.000	0.00	0.778	−0.11
9	1.000	0.00	1.000	0.00	1.000	0.00	1.000	0.00
10	1.000	0.00	1.000	0.00	1.000	0.00	1.000	0.00

order to compute the overall efficiency of assigning a *small truck* to *supplier 1*, we multiply supplier 1's efficiency score by the small truck's efficiency score ($E_{ij}^{\mathrm{OV}} = E_{ij}^{\mathrm{TA}} \times E_{ij}^{\mathrm{SU}}$). Moreover, the base 10 logarithm of the overall efficiency for assigning each TA to a particular supplier is represented in the "Log" column in Table 4 as suggested by Chen and Lu [12]. For example, using a *small truck* for shipping products from *supplier 1* has an efficiency score of 0.575 with a −0.24 logarithm in base 10.

In the allocation phase, we constructed a multi-objective mixed integer programming model presented in the Appendices 1 and 2 with two objectives for maximizing the overall efficiencies and minimizing the total costs subject to capacity, demand, storage, and lead time constraints. The model was constructed in Lingo 8.0 software to determine the number of parts to be transported by a TA from a certain supplier to the buyer in a specific time period. All the required algorithms were implemented in Microsoft Excel Macros with Visual Basic programming. The results for the first month (initial period) and the subsequent 5 months are presented in Table 5. As is shown in this table, except for the sixth month, the buyer's supply for more than 50% of suppliers should be handled by TA1 (small truck). The small truck alternative is a critical resource for the buyers' logistics.

Figure 3 shows the results of the sensitivity analysis on a number of different TAs and the costs of the buyer. We kept TA1 constant and increased TA2, TA3, and TA4; surprisingly, the change in the total cost was marginal. Conversely, purchasing another TA1 from 4 to 5 will result in \$50,832.26 − \$50,498.72 = \$333.54 reduction in the total costs of the supply chain (inventory, transportation, and logistic costs). This provides the buyer with a cost–benefit analysis on its transportation network development scenarios. If the TA1 purchase item is \$500,000, then it is advisable to purchase one TA1 which results in \$166,000 profit in 1 year.

6 Conclusions and future research directions

Supplier selection problems are inherently multi-criteria decision problems. Numerous analytical techniques

Table 5 Order quantities

Period	Transportation alternative	Supplier									
		1	2	3	4	5	6	7	8	9	10
1	1: Small truck	0	0	0	0	0	0	0	0	0	0
	2: Large truck	0	0	0	0	0	0	0	0	0	0
	3: Small vessel	0	0	0	0	0	0	0	0	0	0
	4: Large vessel	0	0	0	0	0	0	0	0	0	0
2	1: Small truck	192	0	0	0	480	456	0	0	500	204
	2: Large truck	0	0	400	0	0	0	0	0	0	0
	3: Small vessel	158	500	0	0	0	0	0	0	0	0
	4: Large vessel	0	0	0	0	0	0	410	0	0	0
3	1: Small truck	192	0	0	0	480	456	0	0	500	342
	2: Large truck	0	0	400	0	0	0	0	62	0	0
	3: Small vessel	158	500	0	0	0	0	0	0	0	0
	4: Large vessel	0	0	0	0	0	0	410	0	0	0
4	1: Small truck	192	0	0	0	480	456	0	0	500	342
	2: Large truck	0	0	400	0	0	0	0	62	0	0
	3: Small vessel	158	500	0	0	0	0	0	0	0	0
	4: Large vessel	0	0	0	0	0	0	410	0	0	0
5	1: Small truck	192	0	0	0	480	456	0	0	500	342
	2: Large truck	0	0	400	0	0	0	0	62	0	0
	3: Small vessel	158	500	0	0	0	0	0	0	0	0
	4: Large vessel	0	0	0	0	0	0	410	0	0	0
6	1: Small truck	192	0	0	0	0	456	0	0	500	0
	2: Large truck	0	0	400	0	0	0	0	0	0	0
	3: Small vessel	158	404	0	0	0	0	0	0	0	0
	4: Large vessel	0	0	0	0	0	0	410	0	0	0

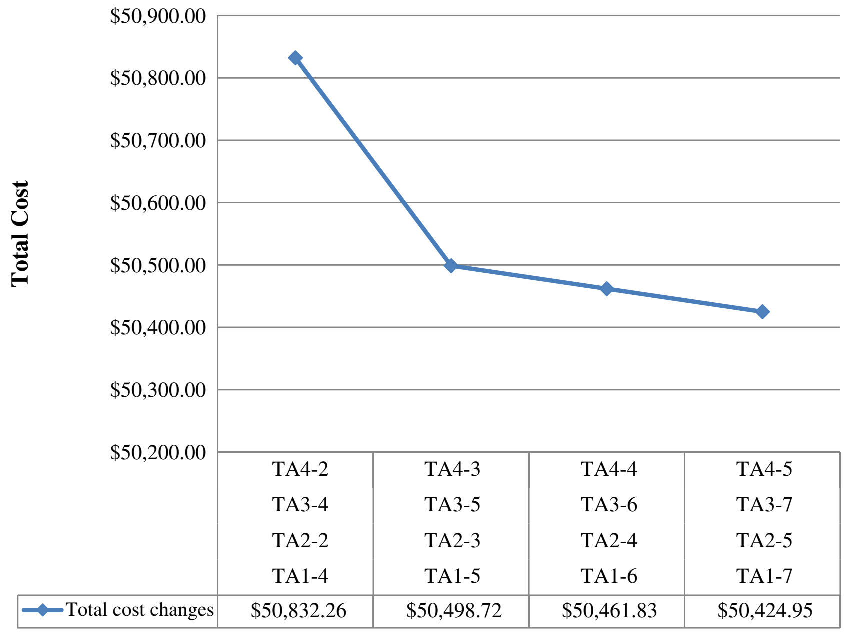

Fig. 3 Results of the sensitivity analysis on the number of transportation alternatives and its impact on the buyer's total cost

ranging from simple weighted scoring to complex mathematical programming approaches have been proposed to solve these problems. However, the traditional methods too often fail to consider: (1) situations in which goods are transported from a supplier to a receiver using different TAs and (2) a finite planning horizon consisting of multiple discrete time periods.

There are four major decisions that are related to the supplier selection problem: What product or services to order, from which suppliers, in what quantities, and in which time periods? We present a structured framework with two separate but dependent phases. In the selection phase, we use a DEA model to determine the relative efficiency of the suppliers and the TAs. In the allocation phase, we use a multi-objective mixed integer programming model with two objectives for minimizing the total costs and maximizing the overall efficiencies. Our method addresses these four questions using a systematic and structured framework.

The contribution of this paper is threefold: (1) We provide a comprehensive and systematic framework that embraces both quantitative and qualitative criteria; (2) we address the need in the supplier evaluation literature for methods that considers different TAs in the supplier selection and order allocation decisions encompassing multiple discrete time periods; and (3) we use a real-world case study and demonstrated the applicability of the proposed framework and exhibited the efficacy of the procedures and algorithms. We decompose the supplier selection and order allocation problem into manageable steps and integrate the results to arrive at a solution consistent with managerial goals and objectives. This decomposition encourages decision makers to carefully consider the elements of uncertainty.

The proposed structured framework does not imply a deterministic approach in supplier selection. While our approach enables decision makers to assimilate the precise data in a formal systematic approach, it should be used with care and in conjunction with management experience. There are a number of challenges involved in the proposed research. These challenges provide a great deal of fruitful scope for future research. In our framework, all the data assume some form of specific numerical values. However, the observed values of the input and output data in real-life problems are sometimes imprecise or vague. Imprecise evaluations may be the result of unquantifiable, incomplete, and non-obtainable information. A fuzzy DEA model can be developed to produce crisp efficiencies in the selection phase of our model. The application of the fuzzy DEA framework to hierarchical structures is an important area for future research. Many organizational problems tend to exhibit such a profile. The framework developed in this study can potentially be applied to the concepts and structures studied in the network DEA models.

Acknowledgment The authors would like to thank the anonymous reviewers and the editor for their insightful comments and suggestions.

Appendix 1

Table 6 DEA model used in the evaluation phase

Several relevant variables are considered during the item procurement process (i.e., time, cost, and quality). The time of procuring an item is a stochastic variable that makes it necessary to consider both the mean and the variance. The mean and variance of the lead time (the time between the ordering of an item until it arrives at the desired location) are output variables in the DEA model. Lower values of both the mean and variance of the lead time are desirable. Therefore, the reciprocal of the mean and variance of the lead time are used as output variables. In addition, quality is measured by a "supplier quality score," which is also considered as an output variable in the DEA model. Finally, both ordering costs and transportation costs occur in the procurement process. They are considered as input variables in the DEA model because they represent the financial resources necessary to carry out the supply process.

Definition	Formula
DEA model for the relative efficiencies of the suppliers for each TA	
Maximize the relative efficiency of the suppliers for each TA: Used to determine the weights that maximize the efficiency of the target unit.	$E_{ij}^{\mathrm{TA}} = \mathrm{Max}\,\frac{U_1 N_{ij1}+U_2 N_{ij2}+U_2 N_{ij2}}{V_0+V_1 M_{ij1}+V_2 M_{ij2}+V_3 M_{ij3}}$
Constraints: The value of this constraint for different supplier combinations (i = 1, 2,…, n) to TA (j is constant) should be <1.	$\frac{U_1 N_{ij1}+U_2 N_{ij2}+U_2 N_{ij2}}{V_0+V_1 M_{ij1}+V_2 M_{ij2}+V_3 M_{ij3}} \leq 1, \quad i = 1,2,..,n$
Parameters: M_{ij1}, M_{ij2}, and M_{ij3} are the supplier price, ordering costs and transportation costs if TA j is used for the shipment of the items from supplier i. In addition, N_{ij1},N_{ij2} and N_{ij3} are the supplier quality score, 1/lead time and 1/variance of the lead time, respectively, if TA j is used for the shipment of the items from supplier i.	$M_{ij1}, M_{ij2}, M_{ij3}, N_{ij1}, N_{ij2}, N_{ij3}$
Variables: The weights of the outputs and the inputs	$U_1, U_2, U_3, V_1, V_2, V_3 \geq \varepsilon > 0$ and V_0 is unrestricted
The DEA model for the relative efficiencies of the TAs for each supplier	
Maximize the relative efficiency of the suppliers for each TA: Used to determine the weights that maximize the efficiency of the target unit.	$E_{ij}^{\mathrm{SU}} = \mathrm{Max}\,\frac{U_1 N_{ij1}+U_2 N_{ij2}+U_2 N_{ij2}}{V_0+V_1 M_{ij1}+V_2 M_{ij2}+V_3 M_{ij3}}$
Constraints: The value of this constraint for different combinations of TAs (j = 1, 2,…, m) to supplier (i is constant) should be less than 1.	$\frac{U_1 N_{ij1}+U_2 N_{ij2}+U_2 N_{ij2}}{V_0+V_1 M_{ij1}+V_2 M_{ij2}+V_3 M_{ij3}} \leq 1, \quad j = 1,2,..,m$
Parameters: M_{ij1}, M_{ij2}, and M_{ij3} are the supplier price, ordering costs and transportation costs if TA j is used for shipment of the items from supplier i. In addition, N_{ij1}, N_{ij2}, and N_{ij3} are the supplier quality score, 1/lead time and 1/variance of the lead time, respectively, if TA j is used for shipment of the items from supplier i.	$M_{ij1}, M_{ij2}, M_{ij3}, N_{ij1}, N_{ij2}, N_{ij3}$
Variables: The weights of the outputs and the inputs	$U_1, U_2, U_3, V_1, V_2, V_3 \geq \varepsilon > 0$ and V_0 is unrestricted

Appendix 2

Table 7 Multi-objective mixed integer programming model used in the allocation phase

Definition	Formula
Objective functions	
Maximize the overall efficiency: The overall efficiency is the sum of the overall efficiency of the transportation alternative assignments to suppliers.	$f_2(S) = \sum_{j=1}^{m}\sum_{i=1}^{n}\sum_{t=1}^{T} S_{ijt} \times \left(E_{ij}^{\mathrm{OV}}\right)$
Minimize the total cost: The overall cost is comprised of the total ordering costs, the total transportation costs, and the total costs of the inventories in transit.	$f_1(X,Y) = \sum_{j=1}^{m}\sum_{i=1}^{n}\sum_{t=1}^{T}\left[\frac{O_{ij}+\mathrm{TC}_{ij}}{\mathrm{CP}_j} + L_{ij} \times (C_{it}+h_t)\right] \times X_{ijt} + I_t h_t$
Constraints	
Capacity constraints: Representing the limited capacity of each supplier.	$\sum_{j=1}^{m} X_{ijt} \leq P_{it},\ i = 1,2,..,n;\ t = 1,2,....,T.$
Demand constraint: The sum of the assigned order quantities of n suppliers and quantities carried from the preceding period should meet the buyer's demand.	$D_t \leq I_{t-1} + \sum_{j=1}^{m}\sum_{i=1}^{n} X_{ijt},\ t = 1,2,....,T.$
Product balance constraint	$I_t = I_{t-1} + \sum_{j=1}^{m}\sum_{i=1}^{n} X_{ijt} - D_t,\ t = 1,2,....,T.$
Buyer's storage capacity: The number of orders from the suppliers by using transportation alternatives should be smaller than the total storage capacity of the buyer.	$\sum_{j=1}^{m}\sum_{i=1}^{n} X_{ijt} \leq \mathrm{CP}_T,\ i = 1,2,..,n;\ t = 1,2,....,T.$
Lead time and the number of transportation alternative limitations.	$\frac{X_{ijt}}{\mathrm{CP}_j} \leq \frac{n_j}{L_{ij}},\ i = 1,2,..,n;\ j = 1,2,...,m;\ t = 1,2,....,T.$
The relationship between the supplier allocations, transportation alternatives, and the number of orders. M is a large positive constant.	$X_{ijt} \leq M \times S_{ijt}, X_{ijt} \geq S_{ijt}, i = 1,2,..,n;\ j = 1,2,...,m;\ t = 1,2,....,T.$

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