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## A Hierarchical Model for Optimal Supplier Selection in Multiple Sourcing Contexts

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**Abstract.** The paper addresses a crucial objective of the strategic purchasing function in supply chains, i.e., optimal supplier selection. We present a hierarchical extension of the Data Envelopment Analysis (DEA), the most widespread method for supplier rating in the literature, for application in a multiple sourcing strategy context. The proposed hierarchical technique is based on three levels. First, a modified DEA approach is used to evaluate the efficiency of each supplier according to some criteria proposed by the buyer. Second, the well known Technique for Order Preference by Similarities to Ideal Solution (TOPSIS) is applied to rank the maximally efficient suppliers given by the previous step. Third and finally, a linear programming problem is stated and solved to find the quantities to order from each maximally efficient supplier in the multiple sourcing context. The presented approach is able to straightforwardly discern between efficient and inefficient partners, avoid the confusion between efficient and effective suppliers, and split the supply in a multiple sourcing context. The hierarchical model is applied to the supply of a C class component to show its robustness and effectiveness, while comparing it with the DEA and TOPSIS approaches.

**Keywords.** Supply chain, Supplier Evaluation, Supplier Efficiency, Optimal Supplier Selection, Data Envelopment Analysis, Technique for Order Preference by Similarities to Ideal Solution, Linear Programming.

### 1. Introduction and motivation

A Supply Chain (SC) is a business network interconnecting independent manufacturing and logistics companies that perform critical functions in the order fulfilment process (Dotoli *et al.*, 2006). The extended enterprise strategic and tactical planning refers to the SC network design, a complex decision process (see Biswas and Narahari, 2004, for a discussion on the topic). In the new global business environment purchasing is becoming one of the most significant and strategic decision areas of the physical SC design, because external suppliers now exert a major influence on a company's success or failure (Karpak *et al.*, 2001). In the purchasing management domain, the

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3 supplier selection process has started to receive considerable attention in the business management  
4 literature, especially with reference to the private sector (de Boer *et al.*, 2001). Indeed, incorrect  
5 decisions about supplier selections may lead to serious profit losses up to the exit from a product's  
6 market, as shown by numerous examples of problems suffered by the SC of leading world  
7 enterprises (Piramuthu, 2005).

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10 This paper focuses on optimal supplier evaluation and selection. Supplier rating systems identify the  
11 candidate partners that are best equipped to meet the SC expected level of performance and check  
12 them periodically. Typically, supplier selection is a multi-objective decision problem, including  
13 conflicting objectives such as, besides the obvious goal of (low) price, quality, quantity, delivery,  
14 performance, capacity, communication, service, geographical location, etc. (Degraeve *et al.*, 2000).  
15 The problem is further complicated by the possibility to consider either a single sourcing or a  
16 multiple sourcing solution.

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19 The wide literature connected to supplier evaluation and selection is synonymous of the importance  
20 of such a choice. However, a thorough enumeration and discussion of the many techniques for  
21 supplier rating available in the related literature is beyond the scope of this paper: the interested  
22 reader is referred to the comprehensive reviews by de Boer *et al.* (2001) and Ho *et al.* (2010) for an  
23 in-depth discussion on this topic.

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26 Broadly, the numerous multi-criteria decision making approaches suggested in the literature to  
27 solve the supplier evaluation and selection problem may be classified into individual approaches  
28 and integrated ones. The most widespread individual methods are (Ho *et al.*, 2010): the Data  
29 Envelopment Analysis (DEA), mathematical programming, the Analytic Hierarchy Process (AHP),  
30 case-based reasoning, fuzzy decision making, genetic algorithms, the Analytic Network Process  
31 (ANP), the Simple Multi-Attribute Rating Technique (SMART) and many more. The so-called  
32 integrated approaches join together different techniques (e.g., integrated AHP, DEA, and artificial  
33 neural networks, integrated AHP and goal programming, etc.). Individual approaches are more  
34 popular than integrated ones, with the most widespread individual technique being DEA, due to its  
35 robustness (Ho *et al.* 2010) and its ability to be implemented also considering qualitative criteria: as  
36 an example, Talluri *et al.* (2006) extend the classical DEA technique considering risk evaluation.  
37 Two examples of DEA integrated approach are proposed by Sevkli *et al.* (2007), presenting the  
38 DEAH method and by Wu and Blackhurst (2009), proposing an augmented DEA approach.  
39 However, DEA presents the drawback that its efficient alternatives are by definition equally optimal  
40 and no difference can be singled out with respect to their effectiveness. Moreover, the method  
41 cannot be straightforwardly applied to multiple sourcing supplier selection.

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3 The motivation of this paper is to propose a novel formulation of the most widespread method for  
4 supplier selection in the literature, namely DEA, with the aim of overcoming some of its recalled  
5 drawbacks: in particular, assuming a given number of pre-existing suppliers, we wish to evaluate  
6 and rank them, so as to choose only the most efficient ones to cooperate with and determine the  
7 product quantities to order from such suppliers. To this aim, we propose a novel three-level  
8 hierarchical method that overcomes the drawbacks of the single DEA method.  
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12 The presented hierarchical method for supplier evaluation and selection is structured as follows.

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14 First, the method uses a modified version, called DEA-P, of the well-known DEA method, to make  
15 a first distinction of suppliers into two categories: efficient and inefficient ones. More precisely, the  
16 DEA-P approach, presented by the authors in Dotoli *et al.* (2010), personalizes DEA to evaluate the  
17 weights of input and output criteria in terms of percentages.  
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20 In the second step, we apply the so-called Technique for Order Preference by Similarities to Ideal  
21 Solution (TOPSIS) (Hwang and Yoon, 1981) to rank the maximally efficient suppliers determined  
22 by DEA. Although in many cases methods such as AHP, TOPSIS and Linear Weighting (LW) lead  
23 to similar results (Costantino *et al.*, 2006), here we adopt TOPSIS because it groups the optimal and  
24 worst performances of the alternatives, respectively, showing them in the so-called Best Ideal  
25 Solution (BIS) and Worst Ideal Solution (WIS), providing a clear idea of how close (far) an optimal  
26 solution is from the BIS (WIS).  
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29 Third, after ranking the maximally efficient suppliers by TOPSIS, a linear programming problem is  
30 solved to calculate the quantities of product to require from each such supplier in the multiple  
31 sourcing context.  
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34 Summing up, the paper provides a novel decision support tool for supplier business intelligence,  
35 i.e., for ranking suppliers and providing the buyer with a simple and flexible instrument for  
36 determining the quantities to order from each maximally efficient supplier in a multiple sourcing  
37 strategy context.  
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40 The remainder of the paper is organized as follows: Section 2 presents a review of the related  
41 literature on DEA focusing particularly on the multiple sourcing context; Section 3, after recalling  
42 the DEA traditional approach, presents the hierarchical method based on DEA, TOPSIS and linear  
43 programming; Section 4 reports a numerical example to demonstrate the application of the method  
44 and its effectiveness; finally, Section 5 presents the conclusions and further research suggestions.  
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## 48 **2. Related Literature on DEA in a Multiple Sourcing Context**

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50 In a recent contribution, Ho *et al.* (2010) provide a thorough overview of the literature addressing  
51 the supplier selection problem in the last decade. The so-called individual approaches are a little  
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3 more popular than the integrated techniques, with the most accepted individual approach being  
4 DEA, apparently due to its robustness and straightforwardness. DEA, first proposed by Charnes *et*  
5 *al.* (1978), is a linear programming-based technique for determining the efficiency of different  
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7 decision making units. Currently, in the related literature there exist numerous approaches that,  
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9 starting from the traditional DEA technique, are personalized by the authors to better fit their own  
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11 case study (see for instance the recalled paper by Talluri *et al.*, 2006 and the work by Saen, 2007).

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13 As regards the application of DEA to supplier selection, the strong point of this technique is its  
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15 straightforwardness in practical implementation: the DEA approach does not require the decision  
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17 maker to pre-define the criteria weights but these are endogenously determined. A further strength  
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19 of the approach lies in the distinction between input and output performance measures. The input  
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21 performance is given by the amount of resource used by the supplier to carry out the supply process  
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23 (for instance, the purchasing price), while output parameters express how good the service is  
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25 (examples are the quality of the purchased product or the timeliness of deliveries).

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27 Although DEA is by far the most widespread technique for supplier selection, some remarks are in  
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29 order. First, while in the past this method was typically used only on quantitative data, nowadays it  
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31 is implemented also considering qualitative criteria. Second, although price is generally the chosen  
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33 criterion against which to rank suppliers (particularly using DEA), additional criteria are nowadays  
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35 being used, the most popular one being quality. Third, DEA presents the drawback of making a  
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37 confusion between efficient suppliers and effective suppliers (Ho *et al.* 2010). As a matter of fact,  
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39 DEA simply classifies suppliers into two categories (efficient and inefficient ones), while other  
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41 approaches (e.g., AHP, TOPSIS, and LW) simply rank suppliers, disregarding their efficiency level.  
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43 In the private sector, the buyer addresses the supplier selection problem choosing between a single  
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45 or multiple sourcing approach. On the one hand, single sourcing is defined as the fulfillment of all  
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47 corporate requirements for a particular product by a selected supplier. On the other hand, multiple  
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49 sourcing is the splitting of an order among multiple sellers. Obviously, each solution presents  
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51 advantages and drawbacks (Costantino and Pellegrino, 2010).

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53 The problems connected to single sourcing are related to the disruption risk, while those connected  
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55 to the multiple sourcing strategy can involve higher managing costs due to dealing with more than  
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57 one contract/supplier. The most important advantage presented by the former approach is the  
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59 cooperation between buyer and seller in improving quality, due to their long term relationship; the  
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61 latter type of sourcing, on the contrary, presents as an advantage the increasing competition among  
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63 partners that often lead to improvements in the supply quality.

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In this paper the application of DEA in the multiple sourcing context is analyzed, i.e., we assume that the buyer has already chosen the set of partners to provide a certain component by a multiple sourcing.

As it is common in the literature, the spare parts in inventory are divided into three classes (A, B, and C) according to their money usage (corresponding respectively to 80%, 15%, and 5% of money usage and 20%, 30% and 50% of the items, see Krajewski and Ritzman, 2002).

Typically, for A and B components a strategic partnership between buyer and seller is created. Hence, all suppliers can roughly satisfy the buyer's requirements of demand, quality, delivery, etc., so that the buyer only needs to make one decision, i.e., which supplier is the best (Xia and Wu, 2007). On the contrary, C components are such that an increasing competition among several suppliers can allow the buyer to obtain a better price. In other words, the buyer needs to purchase some part of the demand from a supplier and the other from other ones, e.g., to compensate for shortage of capacities, or low quality of some suppliers.

Summing up, in general any supplier selection technique has to consider the sourcing strategy chosen by the buyer, so that it results in being generally influenced by three fundamental decisions that the buyer has to take (Burke and Vakharia, 2004): the criteria for identifying potential suppliers, the criteria for choosing the appropriate or *efficient* suppliers (a subset of the potential ones), and the optimal quantity of goods to order to each selected supplier.

DEA alone, although widespread for its simplicity, cannot answer to all the above questions. Some authors in the related literature proposed several contribution on the subject. In particular, Weber *et al.* (2000) developed an optimization approach that uses multi-objective programming to select suppliers and then evaluate their efficiency on multiple criteria using DEA. However, the approach does not consider the limitations on suppliers capacity nor answer to the question of which quantities to order from which supplier. Later, Talluri and Baker (2002) presented a comprehensive model for effectively designing the entire SC by considering not only the efficiency and capacity of participating candidates, but also location and transportation issues. However, the technique addresses too many strategic problems simultaneously, resulting in a complex procedure. Later on, Talluri and Narasimhan (2004) proposed a framework for strategic sourcing using a combination of DEA models for effectively discriminating supplier performance. However, the method requires numerous data and utilizes statistical techniques that make the overall approach quite complex. Further, Ha and Krishnan (2008) used DEA and neural networks to measure supplier performance efficiency more accurately. Similarly, Wu (2009) proposed a hybrid model using DEA, decision trees and neural networks to assess supplier performance. However, both these techniques are

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3 hindered by the use of advanced soft computing methods that will not be straightforward for most  
4 users and make the process quite cumbersome.  
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7 In conclusion, all the cited works either result in complex techniques, often requiring numerous  
8 parameters that are not straightforward to determine for the buyer, or do not explicitly consider the  
9 optimal supplier selection problem in a multiple sourcing context. On the contrary, the presented  
10 approach uses three different techniques, i.e., DEA, TOPSIS, and linear programming, to obtain a  
11 simple and yet effective method in order to measure supplier performance efficiency (DEA),  
12 determine a ranking (TOPSIS) and calculate the quantities to order (linear programming). Since  
13 these techniques can complement each other, using the three of them is helpful to effectively  
14 discriminate among suppliers in a multiple sourcing strategy, while avoiding the typical pitfalls  
15 associated with traditional DEA models, and straightforwardly answering the buyers questions:  
16 which suppliers are the best, which suppliers should be selected, and how much should be  
17 purchased from each selected supplier.  
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### 27 28 **3. Methodology**

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30 Optimal supplier selection may be defined as a multi-objective decision problem, including  
31 conflicting objectives such as, besides the obvious goal of (low) price, quality, quantity, delivery,  
32 performance, capacity, communication, service, geographical location etc. (Degraeve *et al.*, 2000).  
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34  
35 Generally, a supplier selection problem is defined by a set of bidding suppliers  $S = \{s_1, s_2, \dots, s_F\}$   
36 and a set of conflicting criteria  $C = \{c_1, c_2, \dots, c_n\}$ , according to which suppliers have to be ranked.  
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39 We assume that the criterion set is partitioned into  $C = C_I \cup C_O$ , with  $C_I = \{c_1, c_2, \dots, c_H\}$  and  
40  $C_O = \{c_{H+1}, c_{H+2}, \dots, c_{H+K}\}$  respectively representing the input and output criteria sets, with  $H+K=n$   
41 being the criteria number.  
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48 The input criteria may be defined as the supplier attributes considered *before* the supply takes place  
49 (e.g., price, geographical distance of the supplier, ICT integration, etc.), while the output criteria  
50 characterize the supplier *after* the goods arrive at the firm (e.g., quality, reliability, lead time, etc.).  
51 Although qualitative criteria may be addressed, to avoid confusion on subjective judgments only  
52 quantitative criteria are considered in this paper.  
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56 Figure 1 shows the presented hierarchical integrated approach to determine efficient suppliers and  
57 the optimal product quantities in the multiple sourcing context.  
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### Take in Figure 1.

Figure 1. The hierarchical model for supplier selection.

#### 3.1 The DEA Method

The founding method of the supplier selection approach in Fig. 1 is DEA (Charnes *et al.*, 1978). DEA is a linear programming-based technique for determining the efficiency of different Decision Making Units (DMUs). Efficiency is a function of some input values (which are the resources used by the DMUs) and output values (expressing the results of the DMUs activities). Efficient DMUs are the vertices of a Pareto face: based on this, other DMUs efficiencies are calculated.

In the traditional DEA approach for supplier selection, the efficiency of the generic supplier  $s_f \in S$  is defined as follows:

$$E_f = \frac{\sum_{k=1}^K u_k \cdot y_{kf}}{\sum_{h=1}^H v_h \cdot x_{hf}} \quad \text{with } f=1, \dots, F, \quad (1)$$

where  $y_{kf}$  ( $x_{hf}$ ) is the  $k$ -th ( $h$ -th) output (input) performance value for the  $f$ -th supplier and  $u_k$  ( $v_h$ ) is its weighting coefficient.

The efficiency of each alternative is obtained by determining the set of coefficients  $u_k$  with  $k=1, \dots, K$  and  $v_h$  with  $h=1, \dots, H$  which maximizes such a value, taking into account that for each supplier  $s_f \in S$  it holds by definition  $E_f \leq 1$ . Hence, the measure of supplier efficiency is obtained solving the following optimization problem for each considered supplier:

$$\max E_f \quad \text{with } f=1, \dots, F, \quad (2)$$

subject to (s.t.):

$$\frac{\sum_{k=1}^K u_k \cdot y_{kg}}{\sum_{h=1}^H v_h \cdot x_{hg}} \leq 1 \quad \text{with } g=1, \dots, F, \quad (3)$$

$$u_k, v_h \geq 0 \quad \text{for } k=1, \dots, K; h=1, \dots, H. \quad (4)$$

The optimization problem (2)-(3)-(4) can be linearized by maximizing the outputs and keeping fixed input values, obtaining the so-called *output-oriented method* (Wang and Chin, 2010). Hence, the problem is modified into a linear programming problem as follows:

$$\max E_f = \sum_{k=1}^K u_k \cdot y_{kf} \quad \text{with } f=1, \dots, F, \quad (5)$$

s.t.:

$$\sum_{k=1}^K u_k \cdot y_{kg} - \sum_{h=1}^H v_h \cdot x_{hg} \leq 0 \quad \text{with } g=1, \dots, F, \quad (6)$$

$$\sum_{h=1}^H v_h \cdot x_{hg} = 1 \quad \text{with } g=1, \dots, F, \quad (7)$$

and (4).

Summing up, the efficiency of the analyzed suppliers can be found solving problem (5)-(6)-(7)-(4) for each  $f$ -th supplier with  $f=1, \dots, F$ . Obviously, the  $f$ -th supplier is maximally efficient if it holds  $E_f=1$ . Therefore, suppliers can be rated based on their efficiency value  $E_f$ .

### 3.2 The First Level of the Hierarchical Supplier Selection: The DEA-Percentage (DEA-P) Method to Single out Maximally Efficient Suppliers

The first level of the supplier selection approach in Fig. 1 employs the DEA-Percentage (DEA-P) method, a novel formulation of the DEA technique proposed by the authors in Dotoli *et al.* (2010) to single out the potential suppliers.

DEA-P allows the buyer to compare the different supplier evaluation criteria by assigning a percentage index, which expresses the importance of each criterion. Hence, the approach can find a useful application to choose one or more suppliers for a product or service on the basis of past performance evaluations or of offered quotations.

DEA-P evaluates the efficiency of a supplier by measuring the difference between weighted input values and weighted output values. Such an index of the usage of input resources is minimized and imposed to be non-negative for each analyzed supplier. A normalization constraint for weighting coefficients allows us to obtain a non-zero optimum for each supplier. The solution of the resulting linear programming problem provides the purchasing manager with a set of values for the criteria weights that can be compared with each other. These values express the percentages of the relevance of each criterion (a feature of the DEA-P technique that is instead not directly apparent in the DEA traditional technique).

Hence, defining the efficiency as in (1), in DEA-P a Performance Evaluation Index (PEI) for each supplier  $s_f \in S$  is defined as the difference between weighted input and output performance values:

$$PEI_f = \sum_{h=1}^H v_h \cdot x_{hf} - \sum_{k=1}^K u_k \cdot y_{kf} \quad \text{with } f=1, \dots, F. \quad (8)$$

Obviously, using the difference as a novel measure of comparison, the  $f$ -th supplier is maximally efficient (i.e.,  $E_f = 1$ ) if  $PEI_f = 0$ . Indeed, this means that all the resources used by the supplier in the supply process are returned as an output. Hence, in this case, the  $PEI_f$  index for each  $f$ -th supplier with  $f=1, \dots, F$  is determined by minimizing  $PEI_f$  while imposing that such a value is non-negative:

$$\min PEI_f \quad (9)$$

s.t.:

$$\sum_{h=1}^H v_h \cdot x_{hg} - \sum_{k=1}^K u_k \cdot y_{kg} \geq 0 \text{ with } g=1, \dots, F, \quad (10)$$

$$\sum_{h=1}^H v_h + \sum_{k=1}^K u_k = 1, \quad (11)$$

and (4).

The constraint (10) is imposed to avoid negative PEI values. In addition, constraint (11) is added to avoid the trivial solution in which all the coefficients  $u_k$  for  $k=1, \dots, K$  and  $v_h$  for  $h=1, \dots, H$  are equal to zero. Moreover, such a constraint allows to compare the different criteria weights with each other forcing the coefficients to be percentage contributions of input and output performance values. In this way, the minimization admits non-zero solutions only.

The problem (9)-(10)-(11)-(4) is a linear programming problem to be solved  $F$  times; consequently, and remarkably, there is no need for linearization. Moreover, in the presented approach the input and output values are introduced in an already normalized fashion. In this way, input and output coefficients are not affected by different orders of magnitude among input and output values, but are only the expression of the contribution of every attribute to the overall effectiveness of the alternative.

In Dotoli *et al.* (2010), the authors demonstrate that DEA-P leads to the same efficiency results as the traditional DEA approach, but with different criteria weight values. Moreover, the DEA-P model exhibits the same computational complexity of the traditional DEA. Indeed, the two methods are both linear programming problems, sharing the same number of variables  $u_k$  with  $k=1, \dots, K$  and  $v_h$  with  $h=1, \dots, H$  and the same number of constraints equal to  $F+1$ . The main advantage of DEA-P with respect to DEA is that it provides the weights of the input and output criteria directly in percentages. In this way, it is possible to overcome the problem of aggressive values for these attributes, focusing only on the contribution of each input and output criterion to the overall efficiency. In order to limit the often large number of efficient suppliers, we add to the DEA-P optimization problem some constraints related to the importance of one or more criteria, as follows:

$$u_k \geq \alpha_k \text{ with } k=1, \dots, K, \quad (12)$$

$$v_h \geq \beta_h, \text{ with } h=1, \dots, H, \quad (13)$$

where  $\alpha_k$  and  $\beta_h$  are coefficients assigned by the buyer for each  $k$ -th ( $h$ -th) output (input) criterion,

with  $k=1, \dots, K$  ( $h=1, \dots, H$ ) such that  $\alpha_k, \beta_h \in [0; 1]$  and  $\sum_{k=1}^K \alpha_k + \sum_{h=1}^H \beta_h \leq 1$ .

Constraints (12) and (13) are related to the buyer judgments on criteria and enable him to assign the range in which a criterion weight can vary depending on how strategic it is in the supplier evaluation. In this way, it is possible to determine a subset of efficient suppliers satisfying the buyer requirements. Hence, constraints (12)-(13) play a role similar to that of assurance regions (Thompson *et al.*, 1990) in traditional DEA. These allow to rank the different weights of the DEA input and output criteria and can be useful when dealing with components of different typologies (e.g., A, B or C class component) in the multiple sourcing context. The advantage of DEA-P with respect to the assurance regions approach is that by the former technique the buyer can indicate in an absolute way how much a given criteria weighs on the overall set of criteria weights. Instead, the assurance regions approach only allows to compare in a pairwise manner the relative importance of input and/or output criteria.

Summing up, the first level of the hierarchical supplier selection uses the DEA-P procedure to provide as a solution to problem (9)-(10)-(11)-(4)-(12)-(13) a subset of the suppliers set  $S$  collecting the  $m$  maximally efficient suppliers (i.e., the partners showing the maximum efficiency level) with the corresponding performance values against the  $H+K=n$  criteria.

### 3.3 The Second Level of the Hierarchical Supplier Selection: The TOPSIS Method to Rank the Maximally Efficient Suppliers

The second level of the supplier selection approach in Fig. 1 employs TOPSIS to rank the potential suppliers obtained by the first level and select the most efficient ones according to the given criteria. TOPSIS, developed by Hwang and Yoon (1981), is a multi-objective decision technique for ranking a set of alternatives according to a set of conflicting criteria of various degrees of importance. This decision technique is based on simple geometric concepts: the best alternative exhibits the shortest distance from the BIS and the farthest distance from the WIS in a Euclidean sense. Defining the decision matrix  $\mathbf{D}$  of dimensions  $m \times n$  where  $m$  is the number alternatives (the maximally efficient suppliers), with the generic element  $d_{ij}$  with  $i=1, \dots, m$  and  $j=1, \dots, n$  the corresponding performance values against the  $j$ -th criterion, the TOPSIS technique consists of the following six steps.

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### 1. Constructing the normalized decision matrix.

The generic element  $n'_{ij}$  of the  $m \times n$  normalized decision matrix  $\mathbf{N}'$  is determined as follows:

$$n'_{ij} = \frac{d'_{ij}}{\sqrt{\sum_{i=1}^m d'^2_{ij}}}, \quad i=1, \dots, m, j=1, \dots, n \text{ (with } n=H+K\text{)}. \quad (14)$$

### 2. Constructing the weighted normalized decision matrix.

Assigning a vector  $\mathbf{W}=[w_1 \dots w_n]$  with  $\sum_{j=1}^n w_j = 1$  as the vector of criteria weights, the  $m \times n$

weighted normalized decision matrix  $\mathbf{W}'$  is determined, where  $w'_{ij} = n'_{ij} \cdot w_j$ , for  $i=1, \dots, m$  and  $j=1, \dots, n$ .

### 3. Determining the best and worst ideal solutions.

The BIS is determined as the ideal solution with performance indices given by the row vector  $\mathbf{G}=[G_1 \dots G_n]$ , where  $G_j = \text{opt}(n'_{1j}, \dots, n'_{mj})$  with  $j=1, \dots, n$  is obtained applying function *opt* defined by the buyer to the normalized decision matrix  $j$ -th column. Hence, each element of  $\mathbf{G}$  is the optimum performance value of all suppliers with respect to the  $j$ -th criterion: as an example, *opt* may be the minimum function if a performance index - such as price - is to be minimized. As a result, vector  $\mathbf{G}$  is composed by the best performance values of the suppliers against all the criteria. Similarly, the WIS is determined as the ideal solution associated to performance indices of the row vector  $\mathbf{P}=[P_1 \dots P_n]$ , where  $P_j = \text{wor}(n'_{1j}, \dots, n'_{mj})$  with  $j=1, \dots, n$  and *wor* is a function providing the worst performance value for the  $j$ -th criterion (e.g., *wor* may be the maximum function if a performance index - such as price - is to be minimized). As a result, vector  $\mathbf{P}$  collects the worst performance values of the suppliers against all criteria.

### 4. Calculating the separation measure.

The separation distance  $S_{G,i}$  from the BIS of each supplier  $s_i$  with  $i=1, \dots, m$  is calculated as follows:

$$S_{G,i} = \sqrt{\sum_{j=1}^n (n'_{ij} - G_j)^2}. \quad (15)$$

Moreover, the separation distance  $S_{H,i}$  of  $s_i$  with  $i=1, \dots, m$  from the WIS is as follows:

$$S_{H,i} = \sqrt{\sum_{j=1}^n (n'_{ij} - H_j)^2}. \quad (16)$$

Hence, the above two values respectively measure the relative distance of each alternative from the BIS and WIS ideal solutions.

##### 5. Calculating the relative closeness of alternatives to the ideal solution.

The overall performance index  $PI_{i\_TOPSIS}$ , measuring the closeness to the BIS of each maximally efficient supplier  $s_i$  is thus determined as follows:

$$PI_{i\_TOPSIS} = \frac{S_{H,i}}{S_{G,i} + S_{H,i}} \quad \text{for each } i=1, \dots, m. \quad (17)$$

##### 6. Ranking the alternatives.

Finally, the maximally efficient suppliers are ranked according to the values of the  $PI_{i\_TOPSIS}$  index with  $i=1, \dots, m$ . Obviously, the best supplier is the one showing the highest value obtained by (17).

Hence, the  $PI_{i\_TOPSIS}$  index can be considered as a buyer satisfaction priority to be maximized.

Summing up, the second level of the hierarchical supplier selection uses the TOPSIS approach to rank *only* the  $m$  maximally efficient suppliers in set  $S$  against the  $n$  conflicting criteria.

#### 3.4 The Third Level of the Hierarchical Supplier Selection: The Linear Programming Method to Split the Supply among the Maximally Efficient Suppliers

The third and final level of the technique employs linear programming to split the supply among the maximally efficient suppliers, as ranked by the second and higher level, and determine the quantities to order from them.

Linear programming is an optimization mathematical process: an objective function states what is being maximised, e.g., profit, or minimized, e.g., cost or scrap. To determine the quantities to require from the efficient suppliers, we define the Supply Evaluation Index (SEI) as follows:

$$SEI = \sum_{i=1}^m q_i \cdot PI_{i\_TOPSIS}, \quad (18)$$

that is an overall index measuring the efficiency of the supply by the  $m$  maximally efficient suppliers obtained by the first-level DEA optimization as ranked by the second-level TOPSIS optimization. In particular, variables  $q_i$  with  $i=1, \dots, m$  are the unknown quantities of product (expressed as percentage of the supply with values ranging from 0 to 1) to request from each optimal supplier.

Note that, for the sake of simplicity, we assume that the supply is fulfilled by a multiple sourcing procedure including all the maximally efficient suppliers. Obviously, the present third level

optimization may also be straightforwardly modified considering only a number  $\mu \leq m$  of maximally efficient suppliers assigned by the buyer.

Hence, the following problem is stated to fulfill the supply in an optimal way:

$$\text{Max}(SEI) \quad (19)$$

s.t.:

$$\sum_{i=1}^m q_i = 1 \quad (20)$$

$$q_i \leq \gamma_i \text{ with } 0 \leq \gamma_i \leq 1 \text{ and } i = 1, \dots, m \quad (21)$$

$$q_i \geq \delta_i \text{ with } \sum_{i=1}^m \delta_i \leq 1. \quad (22)$$

In particular,  $\delta_i$  with  $i=1, \dots, m$  is a parameter measuring the minimum percentage quantity of the overall supply (eventually equal to zero) that the buyer decides to buy from the  $i$ -th efficient supplier independently from its ranking to keep the long-term partnership. In addition,  $\gamma_i$  is the given production capacity (expressed in percentage values of the whole supply) of the  $i$ -th maximally efficient supplier with  $i=1, \dots, m$ .

Hence, constraint (20) guarantees that the whole requested quantity is supplied (note that it is possible to increase the unitary term in the right member of the equation in order to consider safety stocks), constraints (21) take into account the quantities that each supplier is able to deliver, and finally constraints (22) model the buyer will of requiring products from each efficient supplier independently from their ranking.

Summing up, the third level of the hierarchical optimal supplier selection uses linear programming to calculate the quantities to require from the set of efficient suppliers as obtained by the DEA-P first-level method and ranked through the TOPSIS approach in the second-level optimization.

#### 4. Case study

To show the effectiveness of the three step approach for optimal supplier evaluation and selection, we consider a simulated case study requiring the supply of C class components under multiple sourcing and assuming that the number of existing suppliers equals  $F=10$ .

The presented method is compared with DEA and TOPSIS in order to underline differences and similarities.

#### 4.1 The Case Study Data

Supplier efficiency is estimated using  $H=3$  input criteria and  $K=3$  output ones. In particular, the input criteria are price, ICT integration cost, and geographical distance. They are detailed as follows.

Price. This attribute measures the price offered by each supplier for the required product. Obviously, it is a very significant criterion, but nowadays its importance is becoming less and less central.

ICT integration cost. This criterion addresses the costs necessary for improving the intercommunication ability between buyer and supplier. A high performance value means that the two partners are not well integrated with each other from a managerial point of view.

Geographical distance. This criterion expresses the geographical distance of the buyer from the supplier. Obviously, the nearer the supplier, the lower the transportation costs; moreover, the flexibility in delivery generally grows in case of a closer partner.

The  $K$  output criteria considered for supplier efficiency evaluation are delivery on time, quality, and lead time. They are detailed as follows.

Delivery on time. This criterion can be related to numerous correlated indices, e.g., the appropriateness of the delivery date, the compliance with the due date, the degree of closeness, delivery, and location, and many more. In this paper a crisp or nonfuzzy measure of the reliability level is defined as the ratio between the amount of dispatched orders and the overall number of orders. This is a very important issue, because delays in deliveries can cause disruptions in the production chain.

Quality index. This criterion is strictly related to the number of accepted products among the verified ones: indeed, a high number of defects means high costs of repairs or maintenance. A crisp performance value is obtained for each supplier as the ratio between the percentage of accepted items and that of accepted lots.

Lead time. This criterion is strictly related to the manufacturing capability of the supplier and its flexibility. The lead time is defined as the span of time between the placing of an order and the receipt of goods. Obviously, the shorter it is, the better the supplier in term of flexibility, production capability, and internal organization.

The attributes or performance values of each supplier against each criterion are determined in a normalized fashion, by dividing each attribute by the highest performance value. In this way, normalization can be made only on coefficients and not on weights associated to input and output values. The considered input attributes of the  $f$ -th supplier with  $f=1, \dots, F$  are as follows:

normalized product price  $\bar{p}_f = \frac{p_f}{p_{\max}}$ , where  $p_{\max} = \max_{f=1,2,\dots,F} (p_f)$  is the maximum offered price;

normalized ICT integration cost  $\overline{cICT}_f = \frac{cICT_f}{cICT_{\max}}$ , where  $cICT_{\max} = \max_{f=1,2,\dots,F} (cICT_f)$  is the maximum

attribute;

normalized geographical distance  $\bar{d}_f = \frac{d_f}{d_{\max}}$ , where  $d_{\max} = \max_{f=1,2,\dots,F} (d_f)$  is the maximum distance.

In addition, the output attributes are as follows for the  $f$ -th supplier with  $f=1,\dots,F$ :

normalized delivery on time  $\overline{DT}_f = \frac{DT_f}{DT_{\max}}$ , where  $DT_{\max} = \max_{f=1,2,\dots,F} (DT_f)$  is the maximum value of

such an index and  $DT_f = \frac{NDO_f}{NO_f}$ , with  $NDO_f$  and  $NO_f$  representing the amount of dispatched orders

by such a supplier and the overall number of orders, respectively;

normalized quality index  $\overline{QI}_f = \frac{QI_f}{QI_{\max}}$ , where  $QI_{\max} = \max_{f=1,2,\dots,F} (QI_f)$  is the maximum quality index

and  $QI_f = \frac{pc_{a,f}}{pc_{v,f}} \cdot \frac{lot_{a,f}}{lot_{v,f}}$ , with  $pc_{a,f}$  ( $pc_{v,f}$ ) being the number of accepted (verified) items and  $lot_{a,f}$

( $lot_{v,f}$ ) being the amount of accepted (verified) lots of the  $f$ -th supplier;

normalized lead time index  $\overline{LTI}_f = 1 - \frac{LT_f}{LT_{\max}}$ , where  $LT_{\max} = \max_{f=1,2,\dots,F} (LT_f)$  is the maximum lead

time.

#### 4.2 Application of the Proposed Hierarchical Method to the Case Study

The normalized input performance values of each supplier are collected in Table 1 (columns 2, 3, and 4). Note that normalized prices (column 2) range from a value of 1.000 for supplier 2 (offering the highest price) to 0.467 for supplier 10 (the lowest price); second, ICT integration costs (column 3) range from 1.000 for supplier 5 (the highest cost) to 0.202 for supplier 9; third, geographical distances (column 4) vary from 1.000 for supplier 7 (the farthest one from the buyer firm) to 0.066 for supplier 5. Moreover, in columns 5, 6, and 7 of Table 1 the output indices are reported. In particular, the data in column 5 show that the most reliable supplier is supplier 9, while the less reliable one is supplier 10; based on the quality attribute only (column 6), the best supplier is supplier 9, while the worst one is supplier 1; finally, column 7 shows that the quickest partner in providing the required component is supplier 10, while the slowest one is supplier 5.

We apply the described first-level optimization procedure defining the optimization problem (9)-(10)-(11)-(4)-(12)-(13) with  $\alpha_k = 0$  for  $k=1,2,3$  and  $\beta_h = 0$   $h=1,2,3$  for each supplier, so that the results shown in Table 2 are obtained. In particular, the table reports in columns 2, 3, and 4 (5, 6, 7) the resulting input (output) weights obtained by the DEA-P optimization and in the second-last and last columns the resulting  $PEI_f$  and  $E_f$  indices, determining respectively the performance evaluation index and efficiency of each  $f$ -th supplier with  $f=1, \dots, F$ . Obviously, the efficiency values reported in the last column of Table 2 are determined by substituting in (1) the weights  $v_1, v_2, v_3, u_1, u_2$ , and  $u_3$  (reported in the previous columns of Table 2) that are the solution of the linear programming problem (9)-(10)-(11)-(4)-(12)-(13) for each supplier according to DEA-P. In the considered case study, for instance, the DEA-P procedure shows that, to obtain a maximum efficiency index equal to 1.000 for supplier 5, the normalized price weights for a percentage equal to 43.7%, the normalized geographical distance for 22.8%, the quality index for 30.2%, the lead time index for 3.3%, and the remaining criteria for a percentage equal to zero (see the results in Table 2).

We now consider a second case in which the buyer asks for a more severe requirement on the lead time: in particular, we solve problem (9)-(10)-(11)-(4)-(12)-(13) assuming that  $\beta_h = 0$   $h=1,2,3$  and  $\alpha_k = 0$  for  $k=1,2$ , while the last constraint in (13) is specified as follows:

$$u_3 \geq 0.300. \quad (23)$$

Hence, constraint (23) imposes that the weight of the lead time output criterion has to equal at least a percentage of 30%. Based on this further constraint, the first level optimization procedure now leads to the results shown in Table 3. The obtained results are analogous to the previous results reported in Table 2, but it is apparent that the number of efficient solutions decrease from five efficient suppliers (suppliers 3, 5, 6, 9, 10 in Table 2) to only three efficient partners (suppliers 3, 9, and 10 in Table 3). Such a reduction is expected, since the requirements of the buyer are in this case more severe and are not satisfied by all the first case efficient suppliers.

As an example, in this second case, according to the data in Table 3, supplier 3 is maximally efficient (i.e.,  $E_3=1$ ) by weighting the price criterion for 24.4%, ICT integration for 10.6%, geographical distance for 23.0%, reliability for 4.4%, quality for 5.2%, and lead time for 32.3% (that is obviously larger than 30%). On the contrary, it is worth underlining that supplier 5, which was maximally efficient in the previous case (see Table 2, showing  $E_5=1$ ), becomes totally inefficient (i.e.,  $E_5=0$ ) in the second case by applying constraint (23). Indeed, Table 3 shows that the lead time weight associated to this supplier equals zero (i.e., this supplier is the worst one with regard to this attribute only, which is coherent with the data in Table 1, reporting  $LT_5=0$ ).

Summing up, by the efficiency evaluation provided by DEA-P, the buyer has made the so called prequalification of the existent partners.

**Take in Table 1.**

THE DATA FOR THE DEA-P INPUT AND OUTPUT CRITERIA.

**Take in Table 2.**

THE RESULTS OF THE DEA-P FIRST LEVEL OPTIMIZATION (FIRST CASE).

**Take in Table 3.**

THE RESULTS OF THE DEA-P FIRST LEVEL OPTIMIZATION (SECOND CASE).

**Take in Table 4.**

THE RESULTS OF THE TOPSIS SECOND LEVEL OPTIMIZATION.

**Take in Table 5.**

THE DATA FOR THE LINEAR PROGRAMMING THIRD LEVEL OPTIMIZATION.

**Take in Table 6.**

THE RESULTS OF THE LINEAR PROGRAMMING THIRD LEVEL OPTIMIZATION.

We now rank the  $m=3$  maximally efficient suppliers (i.e., suppliers 3,9,10) by determining their overall TOPSIS performance index (17) against the  $n=6$  conflicting criteria. In particular, the vector of input and output weights  $\mathbf{W}=[w_1\dots w_6]$  has to be assigned based on the buyer judgements and obviously satisfying constraints (12)-(13). In this case it holds  $\beta_h = 0$   $h=1,2,3$ ,  $\alpha_k = 0$  for  $k=1,2$  and  $\alpha_3 = 0.3$  by (23). Hence, we assign  $w_6 = \alpha_3 = 0.3$ . Considering that the supply regards a C class component, and supposing that price is twice as much important than quality and delivery on time, and finally that these last two attributes are twice as much important than ICT integration and geographical distance, the vector of weights  $\mathbf{W}$  with  $\sum_{j=1}^n w_j = 1$  is assigned as follows:

$$\mathbf{W}=[0.28 \quad 0.07 \quad 0.07 \quad 0.14 \quad 0.14 \quad 0.30]. \quad (24)$$

The results of the TOPSIS second level optimization are shown in Table 4. In particular, in columns 2 to 7 the performance values of the maximally efficient suppliers  $s_f$  with  $f=3,9,10$  against the conflicting criteria are reported (according to Table 1), while the third-last, second last, and last columns respectively show the novel supplier numbering index in the TOPSIS optimization, their overall performance value, and their ranking. It is apparent that the best supplier is  $s_{10}$ , showing the

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3 best lead time index (since this is the highest weight criterion) and the best offered price (the second  
4 highest weight criterion). Suppliers  $s_9$  and  $s_3$  follow in the ranking.

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6 Having ranked the maximally efficient suppliers, we apply the described third-level optimization  
7 procedure, i.e., we solve the linear programming problem (18), (19), (20), (21), and (22). The  
8 assigned supplier capacities and minimum requested quantities are reported in Table 5, in columns  
9 3 and 4, respectively. Table 6 shows the results of the linear programming problem solution,  
10 detailing the percentages according to which the supply is to be split. In particular, since  $s_{10}$  is  
11 evaluated as the best supplier both in terms of efficiency (according to DEA) and effectiveness  
12 (according to TOPSIS), the hierarchical technique suggests that the buyer should buy his whole  
13 capacity, while the remaining part of the supply should be bought by the second and third efficient  
14 suppliers, favouring the second and more effective supplier.  
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#### 24 *4.3 Comparison with DEA and TOPSIS and Discussion*

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26 In order to underline the efficacy of the presented approach, we apply the TOPSIS method alone to  
27 the case study, i.e., to the whole supplier set. For the sake of comparison, Table 7 reports in column  
28 2 the DEA ranking of all the suppliers obtained by the efficiency evaluation (according to the  
29 results in the last column of Table 3), in column 3 the TOPSIS supplier rating, and in the last and  
30 fourth column the results obtained by the proposed three level procedure. In particular, we remark  
31 that, although the best two suppliers ( $s_9$  and  $s_{10}$ ) are the same in the three approaches, the  
32 subsequent partners in the classification are not the same. Indeed, under the presented technique  
33 only  $s_3$  is evaluated, since it is the only remaining efficient partner, while for example in TOPSIS  
34 suppliers  $s_6$ ,  $s_8$  and  $s_7$  are valued better than  $s_3$  even though they are not efficient (as underlined by  
35 DEA).  
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44 We point out some general remarks. On the one hand, DEA alone cannot lead to a detailed ranking  
45 (because it usually leads to equally maximally efficient suppliers). On the other hand, the TOPSIS  
46 approach leads to a more accurate classification of suppliers but does not discriminate between  
47 efficient and inefficient partners. Conversely, the presented hierarchical model combines the DEA  
48 advantage of singling out inefficient suppliers with the TOPSIS ability of discerning among equally  
49 efficient partners, helping the buyer in the decision on how many suppliers to consider in the  
50 supply. In addition, the proposed model provides a simple procedure to determine the quantities to  
51 order from the suppliers based on their characteristics and the buyer priorities.  
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58 Summing up, the three-step integrated approach is a flexible and simple tool enabling the buyer to  
59 answer the main questions related to a supply in a multiple sourcing strategy context: which  
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suppliers are the best, which suppliers should be selected, and how much should be purchased from each selected supplier.

### Take in Table 7.

THE COMPARISON BETWEEN DEA, TOPSIS AND THREE LEVEL OPTIMIZATION.

## 5. Conclusions

The paper presents a novel three-step methodology for optimal supplier selection in a multiple sourcing context. The hierarchical model is based on the Data Envelopment Analysis (DEA) approach, the Technique for Order Preference by Similarities to Ideal Solution (TOPSIS), and linear programming. To the best of the authors' knowledge, no one in the related literature has ever joined these three approaches for supplier selection and evaluation in such a context.

The proposed integrated technique takes the best of each method: first, DEA is used to divide the suppliers into efficient and not efficient ones; second, TOPSIS is adopted to rank the efficient suppliers; and, finally, linear programming lets us calculate the quantities to order from each supplier. In such a way, the hierarchical approach avoids the drawbacks of individual methods: it overcomes the well-known DEA inability to discriminate between efficient and effective suppliers, as well as the TOPSIS difficulty to discern between efficient and inefficient partners, and finally overcomes the inability of the two said methods to split the whole supply among suppliers, guaranteeing the will of the buyer to adopt a multiple sourcing strategy.

A numerical case study is reported to show the effectiveness of the three step method for a C class component. The proposed methodology is compared to DEA and TOPSIS, showing its enhanced completeness and flexibility.

Future perspectives are making the technique recursive (e.g., to increase the number of involved suppliers in one or more levels of the methods if the obtained solution is not satisfactory for the buyer), identifying a real case study in order to further verify the approach flexibility and simplicity, and finally extending the approach considering fuzzy techniques to take into account qualitative criteria.

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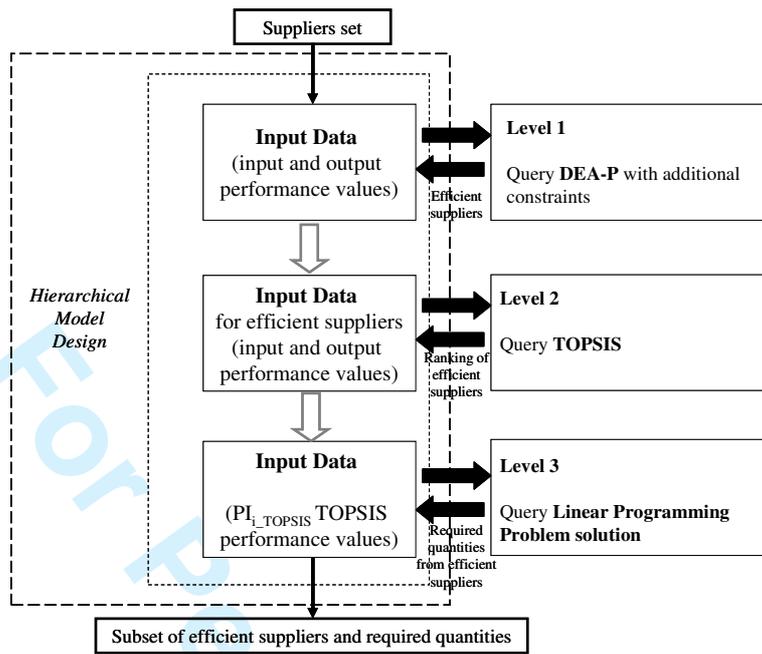


Figure 1. The hierarchical model for supplier selection.

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TABLE I  
THE DATA FOR THE DEA-P INPUT AND OUTPUT CRITERIA.

Supplier	Input 1 (h=1)	Input 2 (h=2)	Input 3 (h=3)	Output 1 (k=1)	Output 2 (k=2)	Output 3 (k=3)
$f$	$\bar{p}_f$	$\overline{cICT}_f$	$\bar{d}_f$	$\overline{DT}_f$	$\overline{QI}_f$	$\overline{LTI}_f$
1	0.689	0.913	0.456	0.938	0.894	0.237
2	1.000	0.656	0.538	0.888	0.998	0.347
3	0.798	0.234	0.192	0.978	0.985	0.521
4	0.790	0.912	0.594	0.879	0.946	0.125
5	0.589	1.000	0.066	0.778	0.902	0.000
6	0.487	0.500	0.987	0.969	0.945	0.568
7	0.897	0.711	1.000	0.892	0.976	0.625
8	0.657	0.480	0.456	0.837	0.928	0.544
9	0.984	0.202	0.732	1.000	1.000	0.875
10	0.467	0.600	0.897	0.764	0.910	0.935

TABLE II  
THE RESULTS OF THE DEA-P FIRST LEVEL OPTIMIZATION (FIRST CASE).

Supplier	Input weight 1 (h=1)	Input weight 2 (h=2)	Input weight 3 (h=3)	Output weight 1 (k=1)	Output weight 2 (k=2)	Output weight 3 (k=3)	Perform. Eval. Index	Efficiency
$f$	$v_1$	$v_2$	$v_3$	$u_1$	$u_2$	$u_3$	$PEI_f$	$E_f$
1	0.421	0.000	0.166	0.333	0.000	0.081	0.034	0.906
2	0.416	0.091	0.113	0.000	0.380	0.000	0.156	0.708
3	0.419	0.050	0.137	0.169	0.193	0.032	0.000	1.000
4	0.416	0.091	0.113	0.000	0.380	0.000	0.118	0.752
5	0.437	0.000	0.228	0.000	0.302	0.033	0.000	1.000
6	0.447	0.211	0.000	0.000	0.342	0.000	0.000	1.000
7	0.416	0.091	0.113	0.000	0.380	0.000	0.179	0.674
8	0.415	0.086	0.115	0.000	0.375	0.008	0.014	0.961
9	0.000	0.756	0.053	0.191	0.000	0.000	0.000	1.000
10	0.660	0.000	0.000	0.008	0.332	0.000	0.000	1.000

TABLE III  
THE RESULTS OF THE DEA-P FIRST LEVEL OPTIMIZATION (SECOND CASE).

Supplier	Input weight 1 (h=1)	Input weight 2 (h=2)	Input weight 3 (h=3)	Output weight 1 (k=1)	Output weight 2 (k=2)	Output weight 3 (k=3)	Perform. Eval. Index	Efficiency
$f$	$v_1$	$v_2$	$v_3$	$u_1$	$u_2$	$u_3$	$PEI_f$	$E_f$
1	0.293	0.000	0.273	0.133	0.000	0.300	0.130	0.599
2	0.280	0.000	0.294	0.000	0.126	0.300	0.208	0.523
3	0.244	0.106	0.230	0.044	0.052	0.323	0.000	1.000
4	0.293	0.000	0.273	0.133	0.000	0.300	0.277	0.392
5	0.036	0.000	0.664	0.000	0.000	0.300	0.065	0.000
6	0.271	0.353	0.000	0.076	0.000	0.300	0.235	0.790
7	0.231	0.225	0.135	0.109	0.000	0.300	0.404	0.567
8	0.280	0.000	0.294	0.000	0.126	0.300	0.038	0.879
9	0.095	0.502	0.099	0.003	0.002	0.300	0.000	1.000
10	0.665	0.000	0.000	0.011	0.012	0.312	0.000	1.000

TABLE IV  
THE RESULTS OF THE TOPSIS SECOND LEVEL OPTIMIZATION.

Supplier	Input 1 (h=1)	Input 2 (h=2)	Input 3 (h=3)	Output 1 (k=1)	Output 2 (k=2)	Output 3 (k=3)	TOPSIS index	Perform. Index	Position
$f$	$\bar{p}_f$	$\overline{cICT}_f$	$\bar{d}_f$	$\overline{DT}_f$	$\overline{QI}_f$	$\overline{LTI}_f$	$i$	$PI_{i\_TOPSIS}$	
3	0.798	0.234	0.192	0.978	0.985	0.521	1	0.387	3
9	0.984	0.202	0.732	1.000	1.000	0.875	2	0.445	2
10	0.467	0.600	0.897	0.764	0.910	0.935	3	0.690	1

TABLE V  
THE DATA FOR THE LINEAR PROGRAMMING THIRD LEVEL OPTIMIZATION.

Supplier $f$	Topsis Index $i$	Supplier Capacity $\gamma_i$	Minimum Quantity $\delta_i$
3	1	0.300	0.050
9	2	0.500	0.050
10	3	0.700	0.050

TABLE VI  
THE RESULTS OF THE LINEAR PROGRAMMING THIRD LEVEL OPTIMIZATION.

Supplier $f$	Topsis Index $i$	Required Quantity $q_i$
3	1	0.050
9	2	0.250
10	3	0.700

TABLE VII  
THE COMPARISON BETWEEN DEA, TOPSIS AND THREE LEVEL OPTIMIZATION.

Supplier	DEA Ranking Position	TOPSIS Ranking Position	Three Level Optimization Procedure
1	6	8	/
2	8	7	/
3	1	6	3
4	9	10	/
5	10	9	/
6	5	3	/
7	7	5	/
8	4	4	/
9	1	2	2
10	1	1	1