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A two-stage data envelopment analysis model for measuring performance in three-level supply chains

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A B S T R A C T

Data Envelopment Analysis (DEA) has been widely used to evaluate supply chain performances. In conventional DEA, supply chains are represented as black boxes where only the initial inputs and final outputs are considered to measure their efficiency. However, an integrated model measuring both the efficiency of the entire supply chain and that of all its components at all levels is essential for a comprehensive evaluation. This study presents a two-stage DEA method to evaluate the performance of a three-level supply chain including suppliers, manufacturers and distributors. The proposed model can be used both under the constant returns to scale and the variable returns to scale assumptions and can be easily implemented for comprehensive analysis of multi-level supply chains. We present a numerical example to demonstrate applicability of the proposed model and exhibit the efficacy and effectiveness of the proposed algorithms and procedures. In particular, the numerical results demonstrate that the entire supply chain is "comprehensively" efficient only if efficient supplier–manufacturer and manufacturer–distributor relationships are established.

1. Introduction

In the era of globalization, supply chains play a fundamental role in the development of an organization and in its goal of profit maximization. Competitive forces in today's business environment require organizations and companies to rely on organized methods to manage their processes more systematically. This is what allows an organization to achieve competitive advantages and gain more share from the market. Therefore, activities such as supply and demand planning, preparing materials, producing and planning products, controlling the stock, distributing, delivering and serving the customers are managed within the context of an integrated supply chain as opposed to just at a company level. Supply Chain Management (SCM) manages, controls and coordinates these activities so that the customers can receive reliable and fast services and quality products at a low cost. The activities of a supply chain begin with the customer's order and continue until he/she pays for the purchased good or received

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service. SCM must manage the flows between the various stages and within each single stage of the chain in order to maximize the total profit.

In classic Data Envelopment Analysis (DEA) the supply chain is represented as a black box where only the initial inputs and the final outputs are considered in order to measure the efficiency. That is, intermediate products are neglected. On the other hand, in SCM, all possible efficiency measures play an essential role in achieving the twofold goal of reducing the cost and enhancing the profit. In this regard, note that an independent decision maker in any component of the supply chain maximizes his/her own technical efficiency ignoring the other components and the whole chain. For this reason network models are useful to model the processes of the entire chain and hence represent the content of the black box. For supply chains consisting of a supplier, a manufacturer and a distributor, the supplier's outputs are the manufacturer's inputs and the manufacturer's outputs are, in turn, the distributor's inputs.

The DEA technique was first proposed to estimate the efficiency in nonparametric models where the efficiency values were determined for one input and one output [13]. Afterwards, Charnes et al. [3] presented the CCR model which could measure the efficiency with several inputs and outputs. Finally, the BCC model was proposed by Banker et al. [1]. Over the years, DEA has become a well-known method to deal with performance measurement problems (see among others, Emrouznejad et al. [11]; Cook et al. [9]; Kaviani and Abbasi [16]; Maghbouli et al. [21]; Matin and Azizi [22]).

Seiford and Zhu [26] proposed a standard two-stage DEA model consisting of 55 commercial banks that utilized the workforce and capital to gain profit and revenue and then produce market value, efficiency, and productivity of the stocks so that they could measure the efficiency at each stage. However, they did not assume any serial relationship between the two stages.

Kao and Hwang [15] introduced a two-stage process of DEA, i.e. profit making and premiums, for 24 non-life insurance companies in Taiwan. In the first stage, the customers interested in paying direct premiums and receiving premiums from other insurance companies were considered. In the second stage, the premiums were taken into account in the portfolio to gain investment profits. Kao and Hwang [15] modified the standard model of DEA so as to include the serial relationship between the processes of the two stages, and defined the efficiency of the whole process as a function of the efficiencies of the two separate stages.

In their two-stage DEA model, Kao and Hwang [15] assumed constant returns to scale (CRS) for the efficiency measures and proposed to evaluate the efficiency of a two-stage process as the product of the efficiencies of the two single stages. In order to also allow for variable returns to scale (VRS), Chen et al. [5] proposed to model the efficiency of a whole two-stage process as the mean weighted efficiency of the two separate stages. Finally, Wang and Chin [32], generalized the combined model of Chen et al. [5] introducing relative weights for the two separate stages.

A considerable amount of attention has been given to combining the fields of supply chain management and marketing. However, the use of DEA has been introduced in SCM only recently [31,30,6]. A supply chain is defined so as to include all the activities related to the process of converting the product from the initial input into the final product together with the analysis of all the information used in this process. SCM integrates these activities by improving the relations among the chain loops in order to achieve reliable and sustainable competitive advantages [14]. According to this definition, SCM is a set of actions that aims to integrate the chain components (i.e. suppliers, manufacturers, distributors, retailers and final customers) in order to reduce the system costs and increase the level of service provided for the customers. Other definitions of supply chain are available in Levi et al. [20] and Chopra and Meindl [8].

Two-stage DEA models can be used to analyze the inner relationships among the chain components of a supply chain, but they must be design in a suitable manner. Indeed, in many real-life examples, production processes (DMUs) comprise subunits that are connected to each other through a network: the output of a subunit may be the input of another subunit, and these interactions ultimately result in the final output production. Therefore, in many cases it may be necessary to examine the inefficiency that a DMU inherits from its subunits, which requires the use of suitable serial, parallel or network models. The basics of network modeling are illustrated by Fare et al. [12], identifying three models whose combination allows us to evaluate the efficiency of a production process by "looking inside the black box". The first model examines the distribution of different products among farms providing a general structure that can be utilized in allotting the budget or resources among all the units. The second model is an explicit one for evaluating the intermediate products, i.e. those products obtained within the technologies or industries forming the system. Finally, the third model proposes a network formulation of a dynamic DEA where some of the outputs at a period t become the inputs for the next period $t + 1$.

1.1. Contribution

A literature review on supply chains and SCM shows that so far most of the supply chain processes have been modeled using two-stage DEA models. Please, refer to Table 1 for an outline of the literature we refer to.

However, despite the fact that supply chains usually consist of more than two components, supply chains with three or more components, such as for example a supplier–manufacturer–distributor chain, have never been evaluated using a two-stage DEA. This evaluation should consist of determining whether or not the whole supply chain is managed by an integrated strategy that is profitable for all the components.

In two-stage DEA models, such as those reviewed above [5,32], the overall efficiency score is usually modeled first and, subsequently, used to calculate the first and/or second stage efficiency values. One of the two minor efficiencies is enough to obtain the other, giving place to the so-called

Table 1
A review of the DEA applications to SCM.

Author	Study
Easton et al. [10]	DEA method was utilized in supply chain and a DEA model was proposed for comparing the efficiency of companies' logistics in the oil industry. This model provided the manager with information so that they could evaluate the process of decision making
Talluri and Baker [28]	A three-phase DEA framework was proposed in order to help the process of decision making when selecting a series of competent and efficient partners for designing the supply chain
Troutt et al. [31,30]	DEA technique was applied in a multistage (serial) process, and the relationships between two stages were taken into consideration with the help of the conducted modeling. The efficiencies of different stages of a supply chain were measured
Ross and Drog [25,24]	DEA methodology was employed to evaluate the efficiency of homogeneous distribution centers using a large scale network. The distribution centers with the possibility of increasing efficiency were identified
Narasimhan et al. [23]	Using a multistage DEA model, a method was proposed for measuring the flexible efficiency in a supply chain model
Casteli et al. [2]	Modeling was conducted in a two-stage hierarchical structure consisting of a series of parallel units, and the efficiency was measured
Chen et al. [6]	A model was proposed to analyze the decision making processes of the supply chain components and provide the best efficiency strategy The relationships among the efficiencies of the supply chain components were analyzed using a Supply-Chain-DEA-Game model
Chen et al. [4]	Using DEA, the efficiency of the supply chain was measured an analyzed in a network mode with common characteristics
Yang et al. [33]	Two equivalent definitions were provided for the possible set of supply chain, and the technical efficiency of the whole supply chain was measured using a DEA model. The proposed model was presented as pattern units in order to improve the efficiency of inefficient supply chains
Chen [7]	A systematic methodology was proposed to select and evaluate the supplier using DEA and TOPSIS in the supply chain
Khalili-Damghani and Taghavifard [17]	A three stage DEA under fuzzy environment was utilized for agile supply chain performance measurement. The conceptual model was applied in a case study of dairy supply chains
Khalili-Damghani and Tavana [18]	A fuzzy network DEA method was proposed for performance measurement of agility in supply chains. The interval efficiency of the sub-processes and the overall process of agile supply chains was calculated by measuring the performance of the sourcing, making and delivery processes
Tavana et al. [29]	A network DEA model which extended the epsilon-based measures of efficiency was proposed for supply chain performance evaluation. The proposed DEA model considered radial and non-radial inputs and outputs simultaneously and was applied in a case study in the semiconductor industry
Shafiee et al. [27]	A hybrid network DEA and BSC approach was used for Supply chain performance evaluation. First a combined balanced scorecard and DEMATEL was applied to obtain a network structure. Then network DEA was utilized to evaluate the efficiency of a supply chain
Khodakarami et al. [19]	New methodologies are proposed to rectify shortcomings of two-stage DEA models and evaluate sustainability of SCM. Shortcomings derive from model improvements leading to conventional DEA models without dealing with their backstage network structure. An ordered ternary (input; intermediate; output) is utilized in place of two ordered pairs (input; intermediate) and (intermediate; output), which allows to determine not only the optimal amount of initial inputs and final outputs but also the optimal amount of the intermediate output/inputs

efficiency decomposition of the overall efficiency which is not necessarily unique. As a consequence, the problem becomes to find a set of multipliers allowing to obtain the largest efficiency value for the first (or second) stage while maintaining the overall efficiency score.

In this paper, we consider the efficiency performance evaluation problem from a completely different viewpoint. We focus on the problem of calculating the overall efficiency of a multi-level supply chain in a way that the efficiency score of the whole process reflects the efficiency values of all the lower-level sub-chains composing it.

We build on the model proposed by Wang and Chin [32] and, hence, indirectly on the one introduced of Chen et al. [5] to design a performance maximizing procedure that allows to measure both the efficiency of the entire supply chain and that of all its components at all levels providing a comprehensive evaluation of the supply chain. Our method can be implemented to obtain such a comprehensive evaluation for multi-level supply chains when working with both CRS and VRS efficiencies.

We introduce a new overall efficiency-like notion and analyze in detail the case of a three-level supply chain. The proposed method consists of converting the two-level sub-chains in one-level processes, while guaranteeing a coherent evaluation of the whole chain as well as of each of its two-stage sub-chains. This method can be easily extended to analyze any multi-level supply chain. A numerical example is provided to show the effectiveness of this method for three-level supply chains.

The rest of the paper is organized as follows. In Section 2, we review the two-stage DEA model and the existing extensions on which we build our model. In Section 3, we present a three-step method for a comprehensive evaluation of the performance of a three-level supply chain and outline its extension to evaluate the "comprehensive" efficiency of any n-level supply chain. A numerical example showing the effectiveness of the proposed model is discussed in Section 4. Finally, Section 5 presents our conclusions.

2. Existing extensions of two-stage DEA modeling

Suppose there are n decision making units (DMUs) each of which uses m inputs to produce s outputs. Also, let each type of input and output to be assigned a weight. The following notations will be used to formalize these assumptions:

- DMU_j, with $j = 1, 2, \ldots, n$, denotes the j-th DMU;
- x_{ij}, with $i = 1, 2, \ldots, m$ and $j = 1, 2, \ldots, n$, denotes the i-th input of the j-th DMU;
- y_{rj}, with $r = 1, 2, \ldots, s$ and $j = 1, 2, \ldots, n$, denotes the r-th output of the j-th DMU;
- v_i, with $i = 1, 2, \ldots, m$, denotes the weight of the i-th input; and
- u_r, with $r = 1, 2, \ldots, s$, denotes the weight of the r-th output.

Further notations will be added as we proceed with our analysis.

The classic approach to the problem of evaluating the CRS efficiency score of a fixed DMU, conventionally indicated by DMU_0, consists of using the CCR model, that is:

$$\begin{aligned} & Z_0 = Max \sum_{r=1}^{s} y_{r0} u_r \\ & s.t. \\ & \sum_{i=1}^{m} x_{i0} v_i = 1 \\ & \sum_{r=1}^{s} y_{rj} u_r - \sum_{i=1}^{m} x_{ij} v_i \leqslant 0 \quad (j = 1, 2, \ldots, n) \\ & v_i,\ u_r \geqslant 0 \quad (i = 1, \ldots, m;\ r = 1, \ldots, s) \end{aligned} \tag{1}$$

In the standard applications of these types of models, the whole system is represented as a black box and the inner relationships among the units and subunits forming the system completely overlooked. Two-stage DEA models address this issue in network terms and generally allow for reasonable solutions.

A DMU has a two-stage structure if it consists of a two-stage process with intermediate values located in between the two stages. In the first stage, inputs are used to make outputs which are at first only considered as intermediate values. In the second stage, the intermediate values are then utilized to produce the final outputs. A critical assumption is that the outputs of the first stage are the only inputs of the second stage.

Fig. 1 presents a two-stage DEA model where:

- DMU_j, with $j = 1, 2, \ldots, n$, denotes the j-th two-stage structured DMU;
- x_{ij}, with $i = 1, 2, \ldots, m$ and $j = 1, 2, \ldots, n$, denotes the i-th input of the j-th DMU in the first stage;
- z_{dj}, with $d = 1, 2, \ldots, D$ and $j = 1, 2, \ldots, n$, denotes the d-th output of the j-th DMU in the first stage and the d-th input of the j-th DMU in the second stage;
- y_{rj}, with $r = 1, 2, \ldots, s$ and $j = 1, 2, \ldots, n$, denotes the r-th output of the j-th DMU in the second stage;
- v_i, with $i = 1, 2, \ldots, m$, denotes the i-th input coefficient in the first stage;
- η_d^1, with $d = 1, 2, \ldots, D$, denotes the d-th output coefficient in the first stage;
- η_d^2, with $d = 1, 2, \ldots, D$, denotes the d-th input coefficient in the second stage; and
- u_r, with $r = 1, 2, \ldots, s$, denotes the r-th output coefficient in the second stage.

As shown in Fig. 1, in the first stage, each of the nDMUs is evaluated for producing D output units starting with m input units. These D output units become inputs for the next stage and are called intermediate units. Thus, in the second stage, each DMU is evaluated for transforming the D intermediate units into r final outputs.

For every $j = 1, 2, \ldots, n$, the CRS efficiency of the j-th DMU, DMU_j, in the first and second stage is given, respectively, by:

$$\theta_j^{1*} = \sum_{d=1}^{D} \eta_d^1 z_{dj} \Big/ \sum_{i=1}^{m} v_i x_{ij} \text{ and } \theta_j^{2*} = \sum_{r=1}^{s} u_r y_{rj} \Big/ \sum_{d=1}^{D} \eta_d^2 z_{dj}.$$

Due to the serial relationship between the two stages, Kao and Hwang [15] have defined the total CRS efficiency of a fixed DMU, DMU_0, as the product of the first and second stage efficiencies, that is, $\theta_0^* = \theta_0^{1*} \times \theta_0^{2*}$, and assumed that $\eta_d^1 = \eta_d^2 = \eta_d$ for every $d = 1, 2, \ldots, D$. Kao and Hwang's model for evaluating the total CRS efficiency of DMUs in two-stage DEA is described by Eq. (2) below:

$$\begin{aligned} & \theta_0^* = Max \sum_{r=1}^{s} y_{r0} u_r \\ & s.t. \\ & \sum_{i=1}^{m} x_{i0} v_i = 1 \\ & \sum_{d=1}^{D} \eta_d z_{dj} - \sum_{i=1}^{m} v_i x_{ij} \leqslant 0 \quad (j = 1, 2, \ldots, n) \\ & \sum_{r=1}^{s} u_r y_{rj} - \sum_{d=1}^{D} \eta_d z_{dj} \leqslant 0 \quad (j = 1, 2, \ldots, n) \\ & \eta_d,\ v_i,\ u_r \geqslant 0 \quad (i = 1, \ldots, m;\ r = 1, \ldots, s;\ d = 1, \ldots, D) \end{aligned} \tag{2}$$

Once the total efficiency θ_0^* has been calculated, the efficiencies of the first and second stages $(\theta_0^{1*}, \theta_0^{2*})$ can be measured using LP models. Clearly, knowing the total efficiency

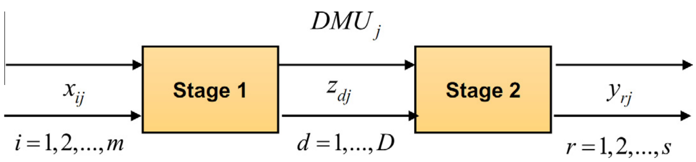

Fig. 1. Two-stage DEA model.

and one of the two minor efficiencies allows us to calculate the remaining minor efficiency using the equation $\theta_0^{1*} = \theta_0^*/\theta_0^{2*}$ and $\theta_0^{2*} = \theta_0^*/\theta_0^{1*}$. Eqs. (3) and (4) below provide the LP models to calculate the minor efficiency of the first and second stage, respectively.

$$\begin{aligned}
&\theta_0^{1*} = Max \sum_{d=1}^{D} \eta_d z_{d0} \\
&s.t. \\
&\theta_0 = \sum_{r=1}^{s} u_r y_{r0} \\
&\sum_{i=1}^{m} x_{i0} v_i = 1 \\
&\sum_{d=1}^{D} \eta_d z_{dj} - \sum_{i=1}^{m} v_i x_{ij} \leqslant 0 \quad (j = 1, 2, \ldots, n) \\
&\sum_{r=1}^{s} u_r y_{rj} - \sum_{d=1}^{D} \eta_d z_{dj} \leqslant 0 \quad (j = 1, 2, \ldots, n) \\
&\eta_d,\ v_i,\ u_r \geqslant 0 \quad (i = 1, \ldots, m;\ r = 1, \ldots, s;\ d = 1, \ldots, D)
\end{aligned} \tag{3}$$

$$\begin{aligned}
&\theta_0^{2*} = Max \sum_{r=1}^{s} u_r y_{r0} \\
&s.t. \\
&\sum_{d=1}^{D} \eta_d z_{d0} = 1 \\
&\sum_{r=1}^{s} u_r y_{r0} - \theta_0^* \sum_{i=1}^{m} v_i x_{i0} = 0 \\
&\sum_{d=1}^{D} \eta_d z_{dj} - \sum_{i=1}^{m} v_i x_{ij} \leqslant 0 \quad (j = 1, 2, \ldots, n) \\
&\sum_{r=1}^{s} u_r y_{rj} - \sum_{d=1}^{D} \eta_d z_{dj} \leqslant 0 \quad (j = 1, 2, \ldots, n) \\
&\eta_d,\ v_i,\ u_r \geqslant 0 \quad (i = 1, \ldots, m;\ r = 1, \ldots, s;\ d = 1, \ldots, D)
\end{aligned} \tag{4}$$

Chen et al. [5] re-examined the whole process by assigning a weight to each of the stages of the model. They utilized the data of Kao and Hwang's [15] study to measure the total efficiency through a weighted sum of the efficiencies of the single stages. The results of the Spearman test indicated that there was no significant difference between the efficiency values obtained by applying the method proposed by Kao and Hwang [15] and those obtained by Chen et al. [5], thus allowing Chen et al. [5] to propose the weighted sum method as a valid one. In their study, Chen et al. [5] also show that the two methods are equivalent under the constant returns to scale (CRS) assumption. In general, the method of Chen et al. [5] is preferable to the one of Kao and Hwang [15]. Indeed, Theorem 1 in Wang and Chin [32], proves that $\theta_0^{*c} \geqslant \theta_0^{*k}$, where θ_0^{*c} and θ_0^{*k} are the CRS efficiencies evaluated by the two-stage DEA models of Chen et al. [5] and Kao and Hwang [15], respectively. Moreover, Kao and Hwang's model cannot be applied to evaluate the efficiency when variable returns to scale (VRS) is assumed since, in this case, the model becomes nonlinear. On the other hand, Chen et al.'s model remains linear even when it is extended to a VRS setting. Thus, Chen et al.'s [5] method has a wider applicability than the one of Kao and Hwang [15].

Another variant of Kao and Hwang [15] method was proposed by Wang and Chin [32]. In Wang and Chin's model two relative weights of $\lambda_1 \geqslant 0$ and $\lambda_2 \geqslant 0$, with $\lambda_1 + \lambda_2 = 1$, are assigned to the two stages of Kao and Hwang's model and the total efficiency is defined as $\theta_0^* = \lambda_1 \theta_0^{1*} + \lambda_2 \theta_0^{2*}$.

Wang and Chin's model generalizes the two-stage DEA model of Chen et al. [5] and can be used to calculate both CRS and VRS efficiency scores. For the sake of completeness we report the LP models relative to both returns to scale assumptions. Eqs. (5)–(7) provide the LP models proposed by Wang and Chin [32] in order to calculate the CRS efficiency of the whole two-stage process, the first stage efficiency and the second stage efficiency, respectively. Eqs. (8)–(10) show the corresponding LP model for the VRS efficiency case.

$$\begin{aligned}
&\theta_0^* = Max \lambda_1 \sum_{d=1}^{D} \eta_d z_{d0} + \lambda_2 \sum_{r=1}^{s} u_r y_{r0} \\
&s.t. \\
&\lambda_1 \sum_{i=1}^{m} v_i x_{i0} + \lambda_2 \sum_{d=1}^{D} \eta_d z_{d0} = 1 \\
&\sum_{d=1}^{D} \eta_d z_{dj} - \sum_{i=1}^{m} v_i x_{ij} \leqslant 0 \quad (j = 1, 2, \ldots, n) \\
&\sum_{r=1}^{s} u_r y_{rj} - \sum_{d=1}^{D} \eta_d z_{dj} \leqslant 0 \quad (j = 1, 2, \ldots, n) \\
&\eta_d,\ v_i,\ u_r \geqslant 0 \quad (i = 1, \ldots, m;\ r = 1, \ldots, s;\ d = 1, \ldots, D)
\end{aligned} \tag{5}$$

$$\begin{aligned}
&\theta_0^{1*} = Max \sum_{d=1}^{D} \eta_d z_{d0} \\
&s.t. \\
&\sum_{i=1}^{m} x_{i0} v_i = 1 \\
&(\lambda_1 - \lambda_2 \theta_0^*) \sum_{d=1}^{D} \eta_d z_{d0} + \lambda_2 \sum_{r=1}^{s} u_r y_{r0} = \lambda_1 \theta_0^* \\
&\sum_{d=1}^{D} \eta_d z_{dj} - \sum_{i=1}^{m} v_i x_{ij} \leqslant 0 \quad (j = 1, 2, \ldots, n) \\
&\sum_{r=1}^{s} u_r y_{rj} - \sum_{d=1}^{D} \eta_d z_{dj} \leqslant 0 \quad (j = 1, 2, \ldots, n) \\
&\eta_d,\ v_i,\ u_r \geqslant 0 \quad (i = 1, \ldots, m;\ r = 1, \ldots, s;\ d = 1, \ldots, D)
\end{aligned} \tag{6}$$

$$\theta_0^{2*} = Max \sum_{r=1}^{s} u_r y_{r0}$$
$$s.t.$$
$$\sum_{d=1}^{D} \eta_d z_{d0} = 1$$
$$\lambda_2 \sum_{r=1}^{s} u_r y_{r0} - \lambda_1 \theta_0^* \sum_{i=1}^{m} v_i x_{i0} = \lambda_2 \theta_0^* - \lambda_1$$
$$\sum_{d=1}^{D} \eta_d z_{dj} - \sum_{i=1}^{m} v_i x_{ij} \leqslant 0 \quad (j = 1, 2, \ldots, n)$$
$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{d=1}^{D} \eta_d z_{dj} \leqslant 0 \quad (j = 1, 2, \ldots, n)$$
$$\eta_d,\ v_i,\ u_r \geqslant 0 \quad (i = 1, \ldots, m;\ r = 1, \ldots, s;\ d = 1, \ldots, D) \tag{7}$$

$$\theta_0^* = Max\ \lambda_1 \left(\sum_{d=1}^{D} \eta_d z_{d0} + \sigma_1 \right) + \lambda_2 \left(\sum_{r=1}^{s} u_r y_{r0} + \sigma_2 \right)$$
$$s.t.$$
$$\lambda_1 \sum_{i=1}^{m} v_i x_{i0} + \lambda_2 \sum_{d=1}^{D} \eta_d z_{d0} = 1$$
$$\sum_{d=1}^{D} \eta_d z_{dj} - \sum_{i=1}^{m} v_i x_{ij} + \sigma_1 \leqslant 0 \quad (j = 1, 2, \ldots, n)$$
$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{d=1}^{D} \eta_d z_{dj} + \sigma_2 \leqslant 0 \quad (j = 1, 2, \ldots, n)$$
$$\eta_d,\ v_i,\ u_r \geqslant 0 \quad (i = 1, \ldots, m;\ r = 1, \ldots, s;\ d = 1, \ldots, D)$$
$$\sigma_1 \text{ and } \sigma_2 \text{ free in sign.} \tag{8}$$

$$\theta_0^{1*} = Max \sum_{d=1}^{D} \eta_d z_{d0} + \sigma_1$$
$$s.t.$$
$$\sum_{i=1}^{m} x_{i0} v_i = 1$$
$$(\lambda_1 - \lambda_2 \theta_0^*) \sum_{d=1}^{D} \eta_d z_{d0} + \lambda_1 \sigma_1 + \lambda_2 \sum_{r=1}^{s} u_r y_{r0} + \lambda_2 \sigma_2 = \lambda_1 \theta_0^*$$
$$\sum_{d=1}^{D} \eta_d z_{dj} - \sum_{i=1}^{m} v_i x_{ij} + \sigma_1 \leqslant 0 \quad (j = 1, 2, \ldots, n)$$
$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{d=1}^{D} \eta_d z_{dj} + \sigma_2 \leqslant 0 \quad (j = 1, 2, \ldots, n)$$
$$\eta_d,\ v_i,\ u_r \geqslant 0 \quad (i = 1, \ldots, m;\ r = 1, \ldots, s;\ d = 1, \ldots, D)$$
$$\sigma_1 \text{ and } \sigma_2 \text{ free in sign.} \tag{9}$$

$$\theta_0^{2*} = Max \sum_{r=1}^{s} u_r y_{r0} + \sigma_2$$
$$s.t.$$
$$\sum_{d=1}^{D} \eta_d z_{d0} = 1$$
$$\lambda_2 \sum_{r=1}^{s} u_r y_{r0} + \lambda_2 \sigma_2 - \lambda_1 \theta_0^* \sum_{i=1}^{m} v_i x_{i0} + \lambda_1 \sigma_1 = \lambda_2 \theta_0^* - \lambda_1$$
$$\sum_{d=1}^{D} \eta_d z_{dj} - \sum_{i=1}^{m} v_i x_{ij} + \sigma_1 \leqslant 0 \quad (j = 1, 2, \ldots, n)$$
$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{d=1}^{D} \eta_d z_{dj} + \sigma_2 \leqslant 0 \quad (j = 1, 2, \ldots, n)$$
$$\eta_d,\ v_i,\ u_r \geqslant 0 \quad (i = 1, \ldots, m;\ r = 1, \ldots, s;\ d = 1, \ldots, D)$$
$$\sigma_1 \text{ and } \sigma_2 \text{ free in sign.} \tag{10}$$

Remark 1. In Kao and Hwang [15] the assumption that $\eta_d^1 = \eta_d^2 = \eta_d$ is essential in order to convert their two-stage DEA model into a LP problem and calculate the efficiency scores of DMUs. Indeed, without this assumption, it is clearly not possible to cancel out the factors $\sum_{d=1}^{D} \eta_d^1 z_{d0}$ and $\sum_{d=1}^{D} \eta_d^2 z_{d0}$ in the objective function $\theta_0^* = \theta_0^{1*} \times \theta_0^{2*}$ of Model (2). Apart from this technical advantage, assuming that $\eta_d^1 = \eta_d^2 = \eta_d$ also links the two stages of the chain making it a unique process instead of the union of two independent one-stage processes to evaluate by using two independent CCR models. This is the reason why Chen et al. [5] and Wang and Chin [32] also assume the intermediate outputs to be assigned the same weights as they become intermediate inputs. More in general, assuming that the outputs from a stage have the same value when they are used as inputs in the following stage is a very natural and rational requirement that gives cohesion to the entire supply chain. Thus, we will work under this assumption as well. ■

Remark 2. Note that in the model of Chen et al.'s [5] the weights are defined and implemented so as to produce a fractional programming model which is, in turn, simplified as an LP problem where the objective function is the sum of the efficiencies of the two stages. That is, Chen et al.'s method results in using an equivalent LP problem where the initial weights disappear. On the other hand, in the generalized two-stage DEA model proposed by Wang and Chin [32] the relative importance weights of the two individual stages must be taken into consideration explicitly. This, Wang and Chin's model has the advantage that allows to account for the very real possibility that the two stages are not equally important within the whole process. ■

3. Proposed model: measuring performance in three-level supply chains

In a typical supply chain, raw materials are sent to factories by suppliers, the products produced by the factories are sent first to intermediate stocks and, subsequently, to distribution stocks, from where they are in turn delivered to retailers who will finally make them available to consumers or customers. In brief, the components of a supply chain usually are: stocks of raw materials, suppliers, manufacturing centers, distributors, retailers and, finally, customers. Fig. 2 provides a schematic representation of a typical supply chain process.

The model that we propose in the present study can be use for a comprehensive evaluation of the entire supply chain. We start by examining the initial three-level segment of a supply chain, that is, the part of the chain composed by suppliers, manufacturers and distributors. In order to do so, we need to formally introduce a new notion of overall efficiency accounting for both the efficiency of the entire supply chain and that of all its components. More precisely, we introduce introduces the notion of "comprehensive efficiency".

Definition 1. A DMU defining a multi-level supply chain is said to be "comprehensively efficient" if:

(a) every sub-chain of any length is efficient (efficiency score = 1) when considering only the corresponding initial inputs and corresponding final outputs;
(b) the whole supply chain is efficient (efficiency score = 1) when considering only the initial inputs and final outputs. ■

Based on this definition, the method we propose to measure the efficiency performance of the DMUs defining thee-level supply chains consists of following three steps:

Step 1. Evaluate the efficiency of two-level sub-chains.
1a. Analyzing the supplier–manufacturer sub-chain.
1b. Analyzing the manufacturer–distributor sub-chain.
We model both sub-chains using the two-stage DEA model of Wang and Chin [32] to measure their total efficiency. We use Eq. (5) for evaluating CRS efficiencies and Eq. (8) for VRS efficiencies.

Step 2. Evaluate the efficiency of the whole three-level supply chain, supplier–manufacturer–distributor. Building on the two-stage model of Wang and Chin [32], we define an LP model to measure the total efficiency of the three-level supply chain supplier–manufacturer–distributor. We use Eq. (11) for evaluating CRS efficiencies and Eq. (12) for VRS efficiencies.

Step 3. Decide on the comprehensive efficiency of the whole three-level supply chain.
We apply Definition 1.

Fig. 3 provides a graphical representation of the proposed three-step procedure.

The key idea of the proposed method is to measure the efficiency of the DMUs in a supply chain consisting of multiple stages by converting the long segments of the supply chain into shorter ones. The use of Eq. (5) or Eq. (8), according to the returns to scale setting being assumed, does in fact allow us to convert two-stage segments of supply chains into one-stage segments. Thus, to measure the efficiency in Step 2, we need a model that allows us to convert three-stage segments of supply chains into one-stage segments. As already mentioned, this model will be an extension of the one Wang and Chin [32].

The three-step method described above can be formalized as follows. Let:

- DMU_j, with $j = 1, 2, \ldots, n$, denote a three-stage structured DMU consisting of supplier–manufacturer–distributor;
- x_{ij}, with $i = 1, 2, \ldots, m$ and $j = 1, 2, \ldots, n$, denote the i-th input of the supplier in the j-th DMU;
- z_{dj}, with $d = 1, 2, \ldots, D$ and $j = 1, 2, \ldots, n$, denotes both the d-th output of the supplier and the d-th input of the manufacturer in the j-th DMU;
- w_{tj}, with $t = 1, 2, \ldots, T$ and $j = 1, 2, \ldots, n$, denotes both the t-th output of the manufacturer and the t-th input of the distributor in the j-th DMU;
- y_{rj}, with $r = 1, 2, \ldots, s$ and $j = 1, 2, \ldots, n$, denote the r-th output of the distributor in the j-th DMU;
- v_i $(i = 1, 2, \ldots, m)$, η_d $(d = 1, 2, \ldots, D)$, α_t $(t = 1, 2, \ldots, T)$ and u_r $(r = 1, 2, \ldots, s)$ be the coefficients of the corresponding inputs and outputs;
- $(\theta_j^*)_{S1a}$ stand for the overall efficiency of the two-stage supplier–manufacturer process of DMU_j in Step 1;
- $(\theta_j^*)_{S1b}$ stand for the overall efficiency of the two-stage manufacturer–distributor process of DMU_j in Step 1; and
- $(\theta_j^*)_{S2}$ stand for the overall efficiency of the three-stage process of DMU_j in Step 2.

3.1. CRS efficiency case

To obtain $(\theta_j^*)_{S1a}$ and $(\theta_j^*)_{S1b}$ we use Eq. (5). Considering Eqs. (6) and (7), and keeping in mind (as guide) Fig. 3d, we define the equations that allow us to measure the total CRS efficiency $(\theta_j^*)_{S2}$. The resulting model is the following:

$$(\theta_0^*)_{S2} = Max\ \lambda_1\left(\sum_{d=1}^{D}\eta_d z_{d0} + \sum_{t=1}^{T}\alpha_t w_{t0}\right) + \lambda_2\left(\sum_{r=1}^{s}u_r y_{r0} + \sum_{t=1}^{T}\alpha_t w_{t0}\right)$$

$s.t.$

$$\lambda_1\left(\sum_{i=1}^{m}v_i x_{i0} + \sum_{d=1}^{D}\eta_d z_{d0}\right) + \lambda_2\left(\sum_{t=1}^{T}\alpha_t w_{t0} + \sum_{d=1}^{D}\eta_d z_{d0}\right) = 1$$

Fig. 2. A typical supply chain.

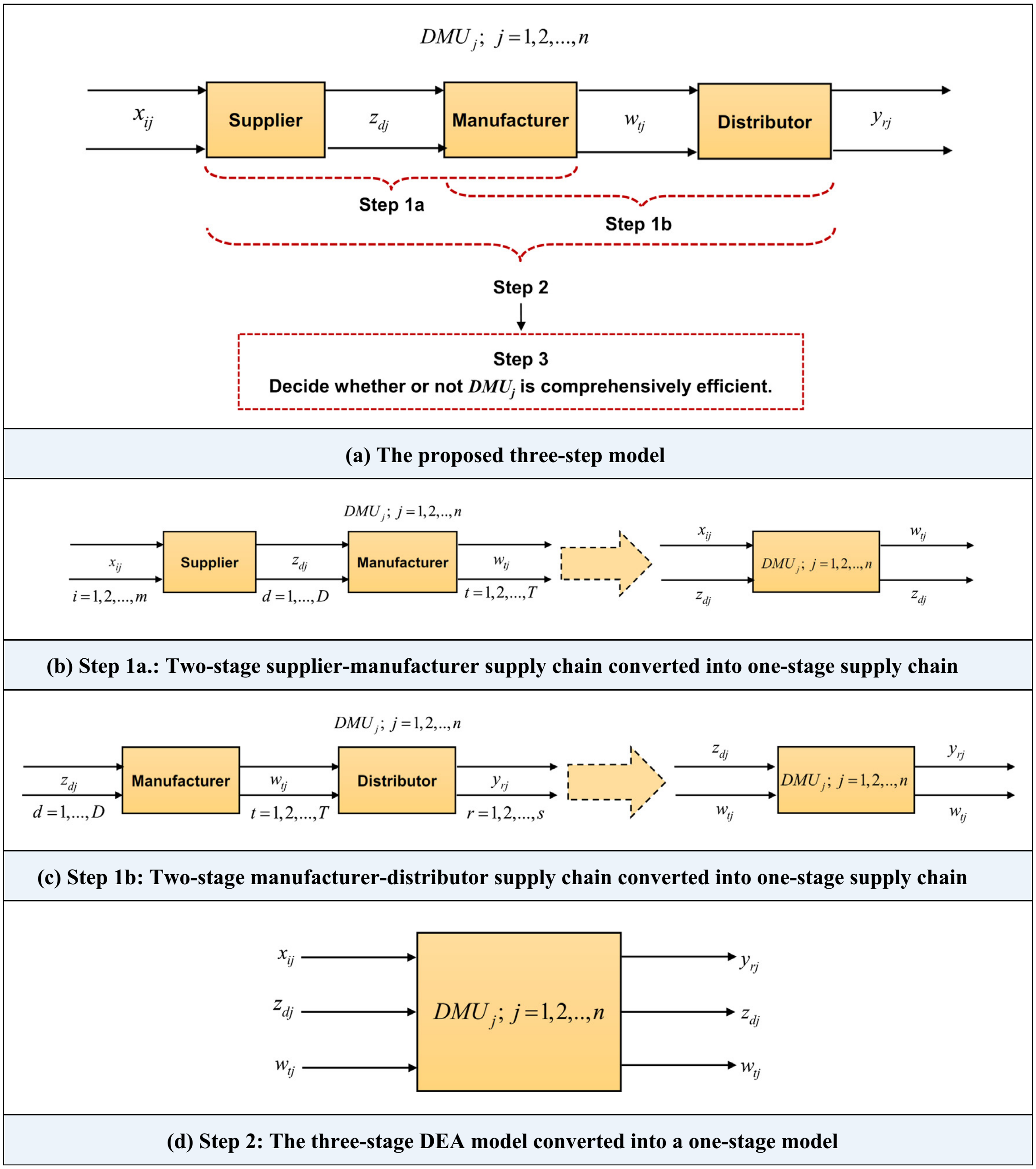

Fig. 3. Maximizing the total and each level efficiencies of three-level supply chains.

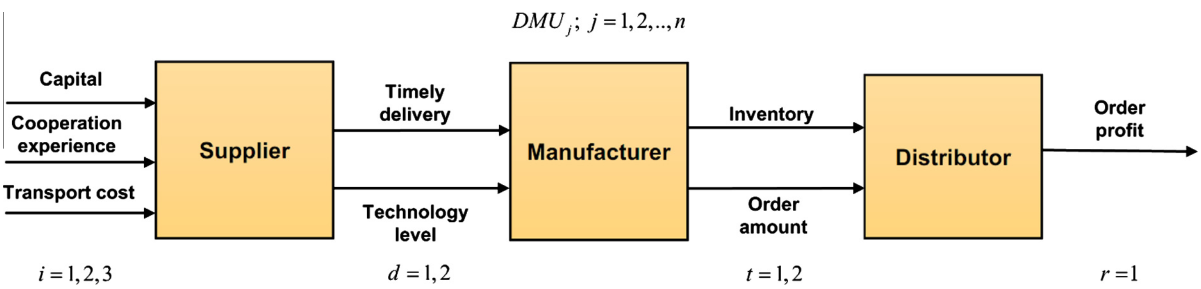

Fig. 4. Schematic view of the inputs and outputs used in the numerical example.

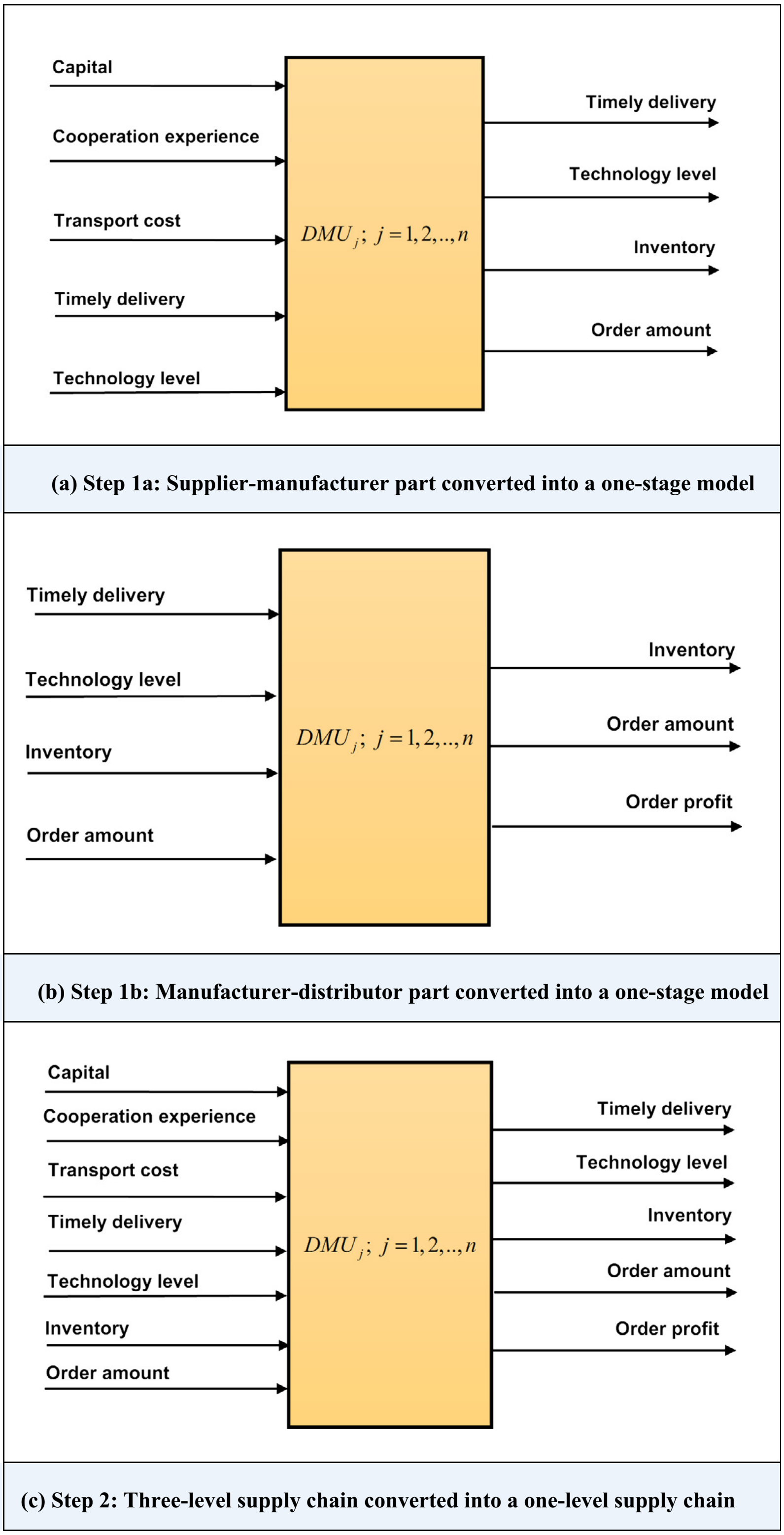

Fig. 5. Conversions to one-stage models in the proposed method.

$$\left(\sum_{d=1}^{D}\eta_d z_{dj}+\sum_{t=1}^{T}\alpha_t w_{tj}\right)-\left(\sum_{i=1}^{m}v_i x_{ij}+\sum_{d=1}^{D}\eta_d z_{dj}\right)\leqslant 0$$
$$(j=1,2,\ldots,n)$$
$$\left(\sum_{r=1}^{s}u_r y_{rj}+\sum_{t=1}^{T}\alpha_t w_{tj}\right)-\left(\sum_{t=1}^{T}\alpha_t w_{tj}+\sum_{d=1}^{D}\eta_d z_{dj}\right)\leqslant 0$$
$$(j=1,2,\ldots,n)$$
$$\alpha_t,\ \eta_d,\ v_i,\ u_r\geqslant 0\qquad (i=1,\ldots,m;\ r=1,\ldots,s;\ d=1,\ldots,D;\ t=1,\ldots,T) \tag{11}$$

3.2. VRS efficiency case

To obtain $(\theta_j^*)_{S1a}$ and $(\theta_j^*)_{S1b}$ we use Eq. (8). To measure the total VRS efficiency $(\theta_j^*)_{S2}$ we define the following model:

$$(\theta_0^*)_{S2}=Max\left[\lambda_1\left(\sum_{d=1}^{D}\eta_d z_{d0}+\sigma_1+\sum_{t=1}^{T}\alpha_t w_{t0}+\sigma_2\right)+\lambda_2\left(\sum_{r=1}^{s}u_r y_{r0}+\sigma_3+\sum_{t=1}^{T}\alpha_t w_{t0}+\sigma_2\right)\right]$$

s.t.

$$\lambda_1\left(\sum_{i=1}^{m}v_i x_{i0}+\sum_{d=1}^{D}\eta_d z_{d0}\right)+\lambda_2\left(\sum_{t=1}^{T}\alpha_t w_{t0}+\sum_{d=1}^{D}\eta_d z_{d0}\right)=1$$
$$\left(\sum_{d=1}^{D}\eta_d z_{dj}+\sum_{t=1}^{T}\alpha_t w_{tj}\right)-\left(\sum_{i=1}^{m}v_i x_{ij}+\sum_{d=1}^{D}\eta_d z_{dj}\right)+\sigma_1+\sigma_2\leqslant 0$$
$$(j=1,2,\ldots,n)$$
$$\left(\sum_{r=1}^{s}u_r y_{rj}+\sum_{t=1}^{T}\alpha_t w_{tj}\right)-\left(\sum_{t=1}^{T}\alpha_t w_{tj}+\sum_{d=1}^{D}\eta_d z_{dj}\right)+\sigma_3+\sigma_2\leqslant 0$$
$$(j=1,2,\ldots,n)$$
$$\alpha_t,\eta_d,v_i,u_r\geqslant 0\ \ (i=1,\ldots,m;r=1,\ldots,s;d=1,\ldots,D;t=1,\ldots,T)$$
$$\sigma_1,\sigma_2 \text{ and } \sigma_3 \text{ free in sign.} \tag{12}$$

where σ_1, σ_2 and σ_3 refer to the first, second and third stage, respectively.

The proposed three-step model results in a integrated model for measuring the comprehensive efficiency of the entire supply chain. This model not only optimizes the efficiency of every level of the supply chain but also maximizes the whole supply chain efficiency. In the next section we provide some numerical results attesting to the efficacy of this procedure.

The proposed method, illustrated in detail for three-level supply chains, can be easily implemented to evaluate any multi-level supply chain. For the sake of completeness, we provide a schema outlining the procedure extended to a n-level supply chain.

Step 1. Evaluate the efficiency of all the two-level sub-chains.
There are $n-1$ two-level sub-chains to evaluate. Convert every two-level sub-chains into a one-stage model. Use Eq. (5) for CRS efficiencies and Eq. (8) for VRS efficiencies.

Step 2. Evaluate the efficiency of all the three-level sub-chains.
There are $n-2$ three-level sub-chains to evaluate. Convert every three-level sub-chains into a one-stage model. Use Eq. (11) for CRS efficiencies and Eq. (12) for VRS efficiencies.

...

Step n-2. Evaluate the efficiency of the whole n-level supply chain.
There are two $(n-1)$-level sub-chains to evaluate. Convert every $(n-1)$-level sub-chains into a one-stage model. Adapt Eq. (11) for CRS efficiencies and Eq. (12) for VRS efficiencies.

Step n-1. Evaluate the efficiency of the whole n-level supply chain.
Convert the chain into a one-stage model. Adapt Eq. (11) for CRS efficiencies and Eq. (12) for VRS efficiencies.

Step n. Decide on the comprehensive efficiency of the whole n-level supply chain.
Apply Definition 1.

4. Numerical example

Suppose the inputs and outputs of each component of the supply chain in a cement company are as indicated in Fig. 4. The suppliers' inputs include capital (million dollars), cooperation experience (years), and transport cost (hundred thousand dollars). The suppliers' outputs that are accounted as the manufacturers' inputs include timely delivery (%) and technology level (%). Finally, it is assumed that the manufacturers deliver the amount of the order and the stock to the distributors in order to get the profit of the order. We have applied Eq. (5) twice, once to measure the DMUs' total efficiencies relative to the supplier–manufacturer part of the supply chain (Step 1a) and once to measure the DMUs' total efficiencies relative to the man ufacturer–distributor part (Step 1b). Subsequently, Eq. (11) has been applied to the whole supplier–manufacturer–distributor chain in order to measure the DMUs' total efficiencies (Step 2). Finally, we have identified the comprehensively efficient DMUs (Step 3). Fig. 5 shows the two-stage and three-stage DEA models already converted into one-stage models according to the proposed method.

We have solved the model for seven DMUs. Tables 2 and 3 report the data relative to the aforementioned indicators for the suppliers, manufacturers and distributors of the seven DMUs.

The numerical example was first solved for $\lambda_1=1/2$ and $\lambda_2=1/2$. The results obtained are shown in Table 4. Due to the small number of DMUs and also to the differ-

Table 2
Input values used in numerical example.

DMU	Capital (Million dollars)	Cooperation experience (year)	Transport cost (hundred thousand dollars)	Timely delivery (%)	Technology level (%)
1	14	3	9	90	86
2	12	2	14	63	75
3	10	3	32	86	73
4	1.6	2	15	75	83
5	10	2	25	69	90
6	7	3	52	78	84
7	3	3	37	82	90

Table 3
Output values used in the numerical example.

DMU	Profit (million dollars)	Timely delivery (%)	Technology level (%)	Inventory	Order amount
1	20	90	86	53	70
2	18	63	75	74	80
3	16	86	73	82	90
4	5	75	83	62	67
5	17	69	90	79	83
6	14	78	84	90	100
7	10	82	90	55	68

Table 4
Final model results for $\lambda_1 = 1/2$ and $\lambda_2 = 1/2$.

DMU	$(\theta_j^*)_{S1a}$	$(\theta_j^*)_{S1b}$	$(\theta_j^*)_{S2}$	Comprehensively efficient
1	1	0.869	0.832	No
2	1	1	1	Yes
3	1	1	0.969	No
4	1	0.861	0.852	No
5	1	0.963	0.943	No
6	0.992	1	0.976	No
7	0.992	0.844	0.955	No

ence in the relative importance of the indicators, we have included weights for inputs and outputs.

As can be observed in Table 4:

(a) The whole supply chain will be efficient if an efficient relationship is established both in the supplier–manufacturer part and in the manufacturer–distributor part. This is clearly expressed by the results obtained for DMU_2.
(b) The fact that both the supplier–manufacturer and the manufacturer–distributor relationships are efficient does not necessarily imply that the combined relationship is efficient. This is illustrated by the results obtained for DMU_3.
(c) As it would be intuitively expected, if either the supplier–manufacturer minor chain or the manufacturer–distributor minor chain, or both, are inefficient, then the whole chain is inefficient. The numerical results show that only the supplier–manufacturer chain is efficient for DMU_1, DMU_4, DMU_5, which are overall inefficient. Also, DMU_6 turns out to be efficient only in the manufacturer–distributor part, while DMU_7 exhibits all the inefficient relationships.

Table 5
Final model results for $\lambda_1 = 2/5$ and $\lambda_2 = 3/5$.

DMU	$(\theta_j^*)_{S1a}$	$(\theta_j^*)_{S1b}$	$(\theta_j^*)_{S2}$	Comprehensively efficient
1	1	0.80	0.99	No
2	1	1	1	Yes
3	1	0.95	0.95	No
4	1	0.9	0.975	No
5	1	1	0.979	No
6	1	1	0.954	No
7	1	0.85	0.96	No

The numerical example was also solved for $\lambda_1 = 2/5$ and $\lambda_2 = 3/5$. The results obtained are shown in Table 5.

As shown by Table 5, the efficiencies of DMU_6 and DMU_7 increase when performing Step 1 (i.e. considering the two-level sub-chains), while DMU_2 remains comprehensively efficient, illustrating the stability of the model with respect to changes in the relative weights of the minor chains.

5. Conclusion

In many applications, the DMUs must necessarily be structured as two-stage processes where the inputs of the first stage are used to produce outputs that are then employed as inputs to produce the outputs of the second stage.

The efficiency of these kind of DMUs is usually evaluated using two-stage DEA models as follows. The overall efficiency score of two-stage processes is evaluated first and, subsequently, used to calculate the first and/or second stage efficiency values, the real problem being to be able to find a set of multipliers allowing to obtain the largest efficiency value for the first (or second) stage while maintaining the overall efficiency score.

In this paper, we have considered the efficiency performance evaluation problem from a completely different viewpoint, focusing on the fact that the overall efficiency of a (multi-level) supply chain should reflect the efficiency values of all the (lower-level) sub-chains composing it. In line with this idea, a generalized two stage DEA model has been proposed and analyzed. The proposed model is an extension of the model of Wang and Chin [32]. In particular, following also Chen et al. [5], we have assumed different returns to scale (CRS and VRS) for the efficiency measures and assigned relative importance weights to each stage of the generalized two-stage DEA model.

We have focused our attention on the initial three-level segment of a typical supply chain, that is, the supplier–manufacturer–distributor supply chain. Our analysis of the efficiency performance of DMUs defining three-level supply chains consisted of three steps: first, we analyzed the supplier–manufacturer part and the manufacturer–distributor part separately; then, we measured the efficiency of the whole supply chain; finally, we established whether or not the whole chain is overall efficient according to the newly introduced definition of "comprehensively efficient". Both the supplier–manufacturer and the manufacturer–distributor minor chains have been modeled and evaluated using the two-stage DEA model of Wang and Chin [32]. In order to evaluate the whole chain efficiency we have defined and implemented an extended version of Wang and Chin's model. This model has been formulated for both CRS and VRS efficiencies.

The key idea of the proposed method was to convert the long segments of the supply chain into shorter ones. At the same time, the modeling procedure had to be complete enough to guarantee a coherent evaluation of the whole chain as well as of each of its two-stage sub-chains.

The numerical results show that our method allows us to achieve this twofold goal. In particular, the whole supply chain has been shown to be efficient only if the performances of both minor two-stage chains are also efficient.

Finally, we have shown how the proposed method, illustrated in detail using three-level supply chains, can be easily implemented to evaluate any multi-level supply chain.

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