Abstract

Effective supply chain management relies on information integration and implementation of best practice techniques across the chain. Supply chains are examples of complex multi-stage systems with temporal and causal interrelations, operating multi-input and multi-output production and services under utilization of fixed and variable resources as well as potentially environmental exposure. Acknowledging the lack of system’s view, the need to identify system-wide as well as individual effects, as well as the incorporation of a coherent set of performance metrics, the recent literature reports on an increasing, but yet limited, number of applications of frontier analysis models (e.g. DEA) for the performance assessment of supply chains or networks. The relevant models in this respect are multi-stage models with various assumptions on the intermediate outputs and inputs, enabling the derivation of metrics for technical and cost efficiencies for the system as well as the autonomous links. This note reviews the state of the art in two-stage or network DEA modeling, along with a discussion of reported applications and opportunities for further research.

Keywords: Supply chain management, Data envelopment analysis, Two-stage, Bi level programming.

1. Introduction

Supply chain management (SCM) was introduced as a common scientific and managerial term in 1982 (cf. Oliver and Webber, 1992) to describe a hierarchical control system for material, information and financial flows in a potentially multidirectional network of autonomous decision making entities. Although there is a lack of universally accepted definition (Otto and Kotzab, 1999), a well-used and typical definition of a supply chain is ‘a network of organizations that are involved, through upstream and downstream linkages in the different processes and activities that produce value in the form of products and services in the hand of the ultimate consumer.’ A wide range of metrics for supply chain performance have been proposed (cf. Neely et al., 1995) using an equally diverse portfolio of methodologies (cf. Estampe et al., 2011). Whereas most SCM literature has been devoted to the elaboration and evaluation of absolute metrics, usually linked to the dimensions cost (profit), time (rates) and flexibility (change of rate), there has also been a growing awareness of the need to perform external benchmarking (Beamon, 1999), the lack of integration of metrics, the lack of system’s view (Holmberg, 2000) and the lack of non-cost indicators. In response to this critique, several applications of non-parametric frontier analysis, such as Data Envelopment Analysis (DEA), have been proposed for supply chain management. The production-economic foundations and the capacity to derive a consistent set of informative performance metrics for a multi-input and multi-output setting qualify frontier analysis as a useful tool for operation management assessments. This paper summarizes the state-of-the-art in frontier analysis models for supply chain management and their applications, along with identification of future research directions. Special emphasis is put on the special case of multi-level DEA that is called the two-stage process.

2. Data envelopment analysis

The data envelopment analysis (DEA) approach to efficiency measurement is a deterministic method which does not require the definition of a functional relationship between inputs and outputs. The basic DEA model by Charnes et al. (1978) is a data-driven method for evaluating the relative efficiency of a set of entities with multi-inputs and multi-outputs. DEA has rapid and continuous growth in different areas since 1978. Emrouznejad et al. (2008) reported more than 4000 DEA
research studies published in journals or book chapters. Assume that there are \( n \) DMUs to be evaluated where every DMU produces \( s \) outputs, \( Y \in R^s_+ \), using \( m \) inputs, \( X \in R^m_+ \). The efficiency of a specific DMU\(^0\) is denoted by \( \theta^o(X,Y,\gamma) \) in input-oriented where \( \gamma \) represents the returns to scale. Therefore, \( \theta^o(X,Y,\gamma) \) is calculated by using the following mathematical DEA model

\[
\theta^o(X,Y,\gamma) = \min \{\lambda | X \lambda \leq \theta^o X^o, Y \lambda \geq Y^o, \lambda \in \Omega(\gamma) \}
\]

where \( \gamma = \"crs\", \ "drs\," \) or \( \"vrs\" \) and \( \Omega(\gamma) = R^+_\gamma \), \( \Omega(drs) = \{\lambda \in R^+_\gamma | 1 \leq \lambda \} \), \( \Omega(vrs) = \{\lambda \in R^+_\gamma | 1 \leq \lambda \} \).

3. **Performance evaluation in supply chain management**

Supply chain management (SCM) takes an integrated system’s view on the design, monitoring and control of the chain. This approach serves to arbitrate the potential conflicts of individual agents in the chain in order to coordinate the flow of products and services to best serve the ultimate customer. We refer to this framework as “centralized”, in that it represents the objective of a hypothetical benevolent supply chain coordinator with authority to implement any necessary decision throughout the chain. Performance management has both a predictive and normative use in SCM. Predictive in the sense that performance management provides data and estimates necessary for the management of material and information flows in order to meet stochastic demand, product and process changes or changes in the price/cost structure for inputs and outputs. Normative in the sense that the supply chain management interfaces with both operations and sourcing, providing targets for improvement as well as potentially credible threats of substitution or volume reductions in case of poor [relative] performance. Conventionally, the operations management literature limited the attention to performance measurement to the mere definition of absolute (e.g. cost per unit) and partial productivity (e.g. labor hours per unit produced) metrics without paying attention to their systemic or economic integration, or even to their value as predictors of future profitability or survival in the market place. However, naïve ratio-analysis may induce error in the assessment of performance, lacking any link to economic criteria and lead to infeasible targets, if applied for multiple dimensions.

4. **A generic DEA-SCM case**

Given the multi-stage structure of a supply chain, a relevant frontier model must be capable of decomposing both centralized and decentralized metrics from a coherent model. Figure 1 shows a generic model of a two-stage process with the shared resource, where each DMU is composed of two sub-DMUs in series, and intermediate products by the sub-DMU in stage 1 is consumed by the sub-DMU in stage 2.

![Insert Figure 1 here.....](image)

Suppose that stage 1 of each DMU has \( m \) direct inputs \( X_1 \) and two sets of direct outputs: \( p \) outputs \( Y_1 \) and \( q \) outputs \( Z \), while stage 2 of each DMU consists of \( s \) direct outputs \( Y_2 \) and two sets of direct inputs: \( t \) inputs \( X_2 \) and \( q \) inputs \( Z \). We also assume \( k \) shared inputs \( X_3 \) which are allocated among two stages. Note that \( Z \) is the intermediate measure e.g. the outputs of first stage become inputs to the subsequent stage. In this study, we denote the efficiencies of stage 1 and stage 2 by \( E_k(X_1,Y_1,Z,\gamma) \), \( k=1,2 \) and the overall efficiency is denoted by \( E^o(X_1,Y_1,Z,\gamma) \) in the input oriented case.

5. **Literature Review**

In conventional DEA, DMUs are treated as a black-box in the sense that internal structures are generally ignored, and the performance of a DMU is assumed to be a function of the chosen inputs and outputs. Färe and Primont (1984) constructed multi-plant efficiency measures and illustrated their models by analyzing utility firms each of whom operated several electric generation plants, extended in (Färe, 1991; Färe and Whittaker, 1995; Färe and Grosskopf, 1996a). The studies of Färe and Grosskopf (1996b, 2000) as the multi-stage model with intermediate inputs-outputs is commonly called network DEA. A two-stage process, a special case of Färe and Grosskopf’s multi-stage
framework, is found in a large number of real evaluation problems. In this section, we present a literature review on models relevant to supply chain management.

5.1. Two-stage DEA

Wang et al. (1997) were the first to apply a two-stage structure for frontier models. Their model was composed of $X_1$, $Z$ and $Y_2$ which are the input vector of stage 1, the intermediate vector and the output vector of stage 2, respectively (see Figure 1). Wang et al. (1997) ignored the intermediate measures and obtained an overall efficiency with the inputs of the first stage and the outputs of the second stage (see model (2)). Similarly, Seiford and Zhu (1999) proposed a two-stage method to obtain the profitability and marketability of the top 55 U.S. commercial banks, consisting of $X_1$, $Z$ and $Y_2$ presented in Figure 1. Seiford and Zhu (1999) used independent CRS models (2), (3) and (4) to measure the overall efficiency and the efficiencies of stage 1 and stage 2, respectively:

$$E^e(X_1, Y_2, Z, crs) = \max \left\{ w^o Z^o \left| \nu X_1^o = 1, w^o Y_2 - v X_1 \leq 0, u, v \geq 0 \right. \right\} \quad (2)$$

Stage 1: $$E^e(X_1, Y_2, Z, crs) = \max \left\{ w^o Z^o \left| \nu X_1^o = 1, w^o Z - v X_1^o \leq 0, w^o Y_2 - v Z \leq 0, u, w \geq 0 \right. \right\} \quad (3)$$

Stage 2: $$E^e(X_1, Y_2, Z, crs) = \max \left\{ w^o Z^o \left| w^o Y_2 = 1, w^o Y_2 - v Z \leq 0, u, w \geq 0 \right. \right\} \quad (4)$$

The intermediate measures can detect the potential conflicts between two stages. For example, the second stage may reduce its inputs (intermediate measures) to achieve an efficient status. Such an action would, however, imply a reduction in the first stage outputs, thereby reducing the efficiency of the first stage. Zhu (2000) applied a method similar to that of Seiford and Zhu (1999) to the Fortune Global 500 companies. When the model consists of $X_1$, $Z$ and $Y_2$, another conventional CRS model is to use the intermediate measure as an output ($Z + Y_2$) for measuring the overall efficiency. Chen and Zhu (2004) demonstrated that such a DEA model fails to correctly characterize the two-stage process, distorting the decentralized frontier assessment, i.e., the performance improvement of one stage affects the efficiency status of the other, because of the presence of intermediate measures. Ignoring the intermediate measures $Z$ associated with two stages, the production space characterization is here incomplete, as highlighted by Chen and Zhu (2004). Alternatively, one can consider the following DEA model that is the average efficiency of two stages:

$$E^e(X_1, Y_2, Z, crs) = \max \left\{ \frac{1}{2} \left( \frac{w^o Z^o}{\nu X_1^o} + \frac{u^o Y_2}{w^o Z^o} \right) \left| \nu Z - v X_1 \leq 0, u Y_2 - w Z \leq 0, u, w \geq 0 \right. \right\} \quad (5)$$

Although model (5) includes intermediate measures $Z$, it does not consider the relationship between the first and second stages (Liang et al., 2006). Chen and Zhu (2004) suggested the following linear model for the two-stage process based upon VRS consisting of $X_1$, $Z$ and $Y_2$ presented in Figure 1:

$$E^e(X_1, Y_2, Z, vrs) = \min \left\{ \gamma_1 \alpha - \gamma_2 \beta \left| X_1 \lambda \leq \alpha X_1^o, Z \lambda \leq \frac{1}{\gamma_2 Z^o}, \gamma_2 Z^o \leq 1, \mu = Z^o, Z \mu \leq 1, \mu = 1, \mu = 0 \right. \right\} \quad (6)$$

where $\gamma_1$ and $\gamma_2$ are the predetermined weights reflecting the preference over the two stages’ performance and $Z$ which is unknown decision variables represents an intermediate measure for a specific DMU. According to model (6), if each stage is efficient, (that is $\alpha^0 = \beta^0 = 1$) then the two-stage process also is efficient. Note that model (6) not only measures the overall efficiency, but also obtains optimized values on the intermediate measures for a DMU under evaluation. Chen et al. (2006) applied a DEA model to assess the IT impact on firm performance by considering both stages of the scenario studied in Wang et al. (1997) and Chen and Zhu (2004). They decomposed some inputs in the first stage into the second stage. Chen et al. (2006) developed a shared two-stage DEA with respect to $X_1$, $Z$ and $Y_2$. Assume, therefore, that $X_1$ is split into two parts $\alpha X_1^o$ and $(1-\alpha)X_1^o$. The average CRS ratios of stages 1 and 2 in the program (7) is used to measure the overall efficiency with common input and output weights for the two stages.
Due to the \( k u Y \) term, model (7) is a nonlinear program. For a given \( k (\geq w^* Z^o) \), however, the model can be treated as a linear parametric program. The efficiencies of the first and second stages can be then attained, respectively, via \( w^* Z^o \) and \( u^* Y^o \) where \( w^* \) and \( u^* \) are optimal measures obtained from (7). The overall efficiency is the average efficiency of the two-stage process \( 1/2(w^* Z^o + u^* Y^o) \). Furthermore, \( \alpha = v^*_1 / v^*_2 \) demonstrates how to allocate the resource \( (X_1) \) to two stages so as to maximize the average efficiency of whole process.

Contrary to previous studies (e.g. Seiford and Zhu (1999)), which treated the whole process and the two sub-processes as independent, Kao and Hwang (2008) considered a series of relationship between the whole process and the two sub-processes in measuring the efficiencies when a production process is composed of \( X_1, Z \) and \( Y_2 \) as depicted in Figure 1. The overall efficiency is decomposed into the product of the two individual efficiencies, namely

\[
E^o = E_1^o \times E_2^o = \frac{wZ^o}{vX_1^o} \times \frac{uY_1^o}{wZ^o} = \frac{uY_1^o}{wZ^o} \times \frac{wZ^o}{vX_1^o} \quad (8)
\]

Consequently, the overall efficiency \( E_o \) under the CRS assumption is determined as:

\[
E^o(X_1, Y_2, Z, CRS)^{ok} = \max \left\{ uY_2^o | vX_1^o = 1, uY_2^o - vX_1^o \leq 0, wZ - vX_1^o \leq 0, uY_2^o - wZ \leq 0, u, v, w \geq 0 \right\} \quad (9)
\]

The constraint set of (9) is the envelope of those of models (2), (3) and (4). Note that the dual weights associated with \( Z \) in the constraints are assumed to be common. It means that it does not matter whether the intermediate measures play the role of output or input. This assumption, linking the two stages, permits the conversion of their original non-linear program into a linear programming problem. Note also that the constraint \( uY_2^o - vX_1^o \leq 0 \) is redundant in model (9) because of existing two constraints \( wZ - vX_1^o \leq 0 \) and \( uY_2^o - wZ \leq 0 \). If \( u^*, v^* \) and \( w^* \) be the optimal multipliers of (9), the overall efficiency, the efficiencies of stages 1 and 2 are calculated by

\[
E_1^o = u^* Y_2^o, \quad E_2^o = w^* Z^o / v^* X_1^o, \quad E^o = u^* Y_2^o / w^* Z^o \quad (10)
\]

The decomposition of \( E^o = E_1^o \times E_2^o \) would not be unique. Kao and Hwang (2008) proposed the following model so as to find the set of multipliers producing the largest \( E_1^o \) while maintaining the overall efficiency score at \( E^o \) calculated from (9):

\[
E^o(X_1, Y_2, Z, CRS)^{ok} = \max \left\{ wZ^o | vX_1^o = 1, uY_2^o - E^o(vX_1^o) = 0, wZ - vX_1^o \leq 0, uY_2^o - wZ \leq 0, u, v, w \geq 0 \right\} \quad (11)
\]

The relationship \( E^o = E_1^o \times E_2^o \) enables us to obtain the efficiency of the second stage.

Chen et al. (2009a) investigated the relationship between the approaches of Chen and Zhu (2004) and Kao and Hwang (2008) for evaluation performance of two-stage processes. Note that the Kao and Hwang (2008)’s model is developed under CRS in the multiplier DEA model (see model (9)), while the Chen and Zhu (2004)’s model is developed under VRS in the envelopment DEA model (see model (6)).

According to Kao and Hwang (2008) approach, Chen et al. (2009b) used the additive efficiency decomposition approach to calculate the overall efficiency which have expressed as a weighted sum of the efficiencies of the individual stages. In fact, Chen et al. (2009b) claimed that the two-stage DEA model of Kao and Hwang (2008) cannot be extended to VRS assumption because \( E^o = ((wZ^o + u^*) / vX_1^o) \times ((u^* Y_2^o + u^*) / wZ^o) \) could not be transformed into a linear program even if assuming the same weights on the intermediate measures for the two stages. However, Chen et al. (2009b) approach can be applied under both CRS and VRS assumptions while the method proposed by Kao and Hwang (2008) restricted to the CRS assumption. Chen et al. (2009b) used a weighted additive (arithmetic mean) approach to calculate the overall efficiency of the process under the VRS assumption by solving the following problem instead of combining the stages in a multiplicative (geometric) way proposed in Kao and Hwang (2008):

\[
E^o(X_1, Y_2, Z, CRS)^{ok} = \max \left\{ wZ^o | vX_1^o = 1, uY_2^o - E^o(vX_1^o) = 0, wZ - vX_1^o \leq 0, uY_2^o - wZ \leq 0, u, v, w \geq 0 \right\} \quad (11)
\]
where $\lambda_1 = \frac{vX_1^0}{vX_1^0 + wZ^0}$, $\lambda_2 = \frac{wZ^0}{vX_1^0 + wZ^0}$ are the relative importance of stages 1 and 2, respectively, by means of the ‘relative sizes’ of two stages for measuring the overall performance of the process. Analogous to Kao and Hwang (2008), the weights (or multipliers) for the intermediate measures are the same for the two stages. Once an optimal solution to (11) is obtained, the efficiency scores for the two individual stages can be calculated as in Kao and Hwang (2008) (see model (10)). In other words, Chen et al. (2009b) used Kao and Hwang’s (2008) approach to find a set of multipliers that produces the largest first (or second) stage efficiency score whilst maintaining the overall efficiency score computed from model (11).

Wang and Chin (2010) demonstrated that a two-stage DEA model with a weighted harmonic mean of the efficiencies of two individual stages is equivalent to Chen et al. (2009b)’s model. The weighted harmonic mean of the efficiencies of the two individual stages is here calculated by the program:

$$E^w(X_2, Y_2, Z)_{crs} = \max \left\{ \frac{1}{\lambda_1 \cdot (vX_1^0/wZ^0) + \lambda_2 \cdot (wZ^0/uY_2^0 + u_2)} \left| \frac{wZ + u}{vX_1} \leq 1, \frac{uY_2^0 + u_2}{wZ^0} \leq 1, u, v, w \geq 0 \right. \right\}$$

(12)

where $\lambda_1 = \frac{vX_1^0}{vX_1^0 + wZ^0}$ and $\lambda_2 = \frac{wZ^0}{vX_1^0 + wZ^0}$ are the relative importance of performances of stages 1 and 2, respectively. These weights, similar to those of Chen et al. (2009b), are the relative sizes of the two stages. By substituting $\lambda_1$ and $\lambda_2$ into the objective function of (12), we achieve exactly the same model proposed by Chen et al. (2009b) in order to get the overall efficiency of the two-stage process under the CRS assumption. Likewise, the overall efficiency of two-stage process under the VRS condition can be modeled as follows:

$$E^w(X_2, Y_2, Z)_{crs} = \max \left\{ \frac{1}{\lambda_1 \cdot (vX_1^0/wZ^0 + u) + \lambda_2 \cdot (wZ^0/uY_2^0 + u_2)} \left| \frac{wZ + u}{vX_1} \leq 1, \frac{uY_2^0 + u_2}{wZ^0} \leq 1, u, v, w \geq 0 \right. \right\}$$

(13)

Similarly, $\lambda_1$ and $\lambda_2$ which are the weights assigned to stages 1 and 2 can be defined as $\left(\frac{wZ^0 + u_1}{wZ^0 + u + uY_2^0 + u_2}\right)$ and $\left(\frac{uY_2^0 + u_2}{wZ^0 + u + uY_2^0 + u_2}\right)$, respectively. By setting these weights into the objective function of (13), the same model defined by Chen et al. (2009b) can be obtained for evaluation of the overall efficiency for VRS. Once $E^w_1$ or $E^w_2$ is obtained, using Chen et al. (2009b), the another one can be determined by $E_2^w = \lambda_2^* / (1/E^w) - (\lambda_2^* / E_1^w)$ or $E_1^w = \lambda_1^* / (1/E^w) - (\lambda_1^* / E_2^w)$, where $\lambda_1$ and $\lambda_2$ are harmonic mean weights.

Wang and Chin (2010) additionally extended the Kao and Hwang (2008)’s model under the CRS assumption to the VRS assumption. Furthermore, Wang and Chin (2010) generalized Chen et al. (2009b)’s models to taking into consideration the relative importance weights of two individual stages. To do, a two-stage process is transformed to a single process in which the two stages are treated equally. In other words, the single process considers stage 1’s input ($X_2$) and an intermediate measure ($Z$) as inputs, and stage 2’s output ($Y_2$) and an intermediate measure ($Z$) as outputs. The generalized overall efficiency of Chen et al. (2009b)’s model under the VRS assumption is given by

$$E^w(X_1, Y_2, Z, vrs)_{crs} = \max \left\{ \frac{\lambda_1 \cdot (wZ^0 + u_1) + \lambda_2 \cdot (uY_2^0 + u_2)}{\lambda_1 \cdot vX_1^0 + \lambda_2 \cdot wZ^0} \left| \frac{wZ + u}{vX_1} \leq 1, \frac{uY_2^0 + u_2}{wZ^0} \leq 1, u, v, w \geq 0 \right. \right\}$$

(15)

Chen et al. (2010) proposed an approach to specify the frontier points for inefficient DMUs based upon the Kao and Hwang (2008)’s model. The dual of model (9) proposed by Kao and Hwang (2008) can be expressed as

$$DE^w(X_1, Y_2, Z, vrs)_{crs} = \min \left\{ \theta | X_1, \lambda \leq \theta X_1, Y \mu \geq Y_2, Z(\lambda - \mu) \geq 0, \lambda, \mu \geq 0 \theta \leq 1 \right\}$$

(16)
Model (10) can just obtain an overall efficiency score under the assumption of CRS, but would not be able to identify how to project inefficient DMUs on to the DEA frontier. Chen et al. (2010), therefore, put forward the following model that is equivalent to the model (16):

\[
\begin{align*}
\min \{ \theta | X_i, \lambda \leq \theta X_i, Y_i, \mu \geq Y_i, Z \lambda \geq Z^\circ, Z \mu \leq Z^\circ, \lambda, \mu, Z^\circ \geq 0, \theta \leq 1 \}
\end{align*}
\]  

(17)

where the decision variable \( Z^\circ \) in the constraints \( Z \lambda \geq Z^\circ \) and \( Z \mu \leq Z^\circ \) treats as output and input, respectively, for the intermediate measure. According to model (17), the projection point for DMU \( o \) is given by \( (\theta X_i^o, Z^o, Y^o) \) which is efficient under models (16) and (17).

5.2. DEA using bilevel programming

Wu (2010) was first to explore a bi-level programming DEA approach by combining DEA cost efficiency into the bi-level programming framework in order to evaluate the a two-stage process performance in decentralized decisions. In their study, each DMU includes two decentralized subsystems: a leader (stage 1) and a follower (stage 2) as it is depicted in Figure 2.

The leader uses two types of inputs, i.e., the shared input \( X_3^1 \) and the direct input \( X_1 \), to produce two different types of outputs: the intermediate measure \( Z \) and the direct output \( Y_1 \). The follower uses three types of inputs, i.e., the shared input \( X_3^2 \) and the direct input \( X_2 \) and the intermediate measure \( Z \), to produce the output \( Y_2 \). Furthermore, assume that \( C_3^1, C_3^2, C_2 \) and \( C_2 \) are the input unit cost vectors associated with \( X_3^1, X_1, Z \) and \( X_2 \), respectively. The bi-level programming cost efficiency DEA model can be expressed as:

\[
\begin{align*}
E^* = \min \left\{ C_3^1 \tilde{X}_3^1 + C_3^2 \tilde{X}_3^2 + C_2 Z \tilde{X}_3^2, X_3^2, \tilde{X}_3^2, X_2, Z, Y_2, Y_1, \tilde{X}_3^1, \tilde{X}_3^2, \tilde{Z}, 0 \right\}
\end{align*}
\]  

(18)

The shared input \( \tilde{X}_3^1 \), the direct input \( \tilde{X}_3^2 \) and an optimal multiplier \( \lambda \) can be calculated by the first level of model (18) so as to minimize the total costs for the leader. As a result, \( \tilde{X}_3^2 \) is simply obtained for the follower using \( \tilde{X}_3^1 + \tilde{X}_3^2 = F \). Note that in the above bi-level programming cost efficiency DEA model intermediate measure is output for the leader in the upper level and also input for the follower in the lower level. In addition, Wu (2010) dealt with this problem when the total amount of the shared input has the fixed maximum value.

6. Discussion and future research directions

Supply chain management (SCM) is a particularly relevant application for frontier analysis, such as DEA, to provide performance targets and allocate resources. However, standard DEA does not provide adequate detail for management to specify the specific sources of inefficiency embedded in interactions among various divisions that comprise the organization. The development of multi-stage models, in particular for the two-stage setting, has been intensive in the last five years and now offer a consolidated set of metrics based on both centralized and decentralized perspectives. The models can be categorized into three common approaches: the two-stage process, bi-level programming and game theory. This paper presents the current methods of two first categories. However, the state of the art in the area still reveals a lack of frameworks for decomposition of efficiency metrics, as well as economically meaningful interpretations for the proposed centralized metrics. Further work in gametheoretical directions and with activity modeling may be useful here. Moreover, the literature on applications is scarce, in spite of the prevalence of supply chain problems solved using other methodologies, mainly resorting to numerical instances or stylized toy problems. Research into applications of supply chain performance management using frontier analysis would bring valuable input to the methodological development.

References

See supplementary material.

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Supplement document

Figures

Fig. 1 The generic activity model.

Fig. 2. A leader-follower supply chain structure
References


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