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An integrated DEA-based approach for evaluating and sizing health care supply chains

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Abstract

Purpose – Evaluating the performance of supply chains is a convoluted task because of the complexity that is inextricably linked to the structure of the aforesaid chains. Therefore, the purpose of this paper is to present an integrated approach for evaluating and sizing real-life health-care supply chains in the presence of interval data.

Design/methodology/approach – To achieve the objective, this paper illustrates an approach called Latin hypercube sampling by replacement (LHSR) to identify a set of precise data from the interval data; then the standard data envelopment analysis (DEA) models can be used to assess the relative efficiencies of the supply chains under evaluation. A certain level of data aggregation is suggested to improve the discriminatory power of the DEA models and an experimental design is conducted to size the supply chains under assessment.

Findings – The newly developed integrated methodology assists the decision-makers (DMs) in comparing their real-life supply chains against peers and sizing their resources to achieve a certain level of production.

Practical implications – The proposed integrated DEA-based approach has been successfully implemented to suggest an appropriate structure to the actual public pharmaceutical supply chain in Morocco.

Originality/value – The originality of the proposed approach comes from the development of an integrated methodology to evaluate and size real-life health-care supply chains while taking into account interval data. This developed integrated technique certainly adds value to the health-care DMs for modelling their supply chains in today's world.

Keywords Performance management, Logistics, Healthcare, DEA, Modelling, Decision analysis

Paper type Research paper

1. Introduction

Today's competitive environment requires organizations to enhance their performances to survive. To improve health-care organizations' performance, many studies were undertaken by many practitioners using the data envelopment analysis (DEA), which is a widely used mathematical programming approach for benchmarking a set of homogenous decision-making units (DMUs) that convert multiple inputs into multiple outputs. Basic DEA models assume that all input and output data are exactly known. Nonetheless, this assumption may

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not always be true in real-life situations. Some DMUs may sometimes contain interval data because of uncertain circumstances. Therefore, the purpose of this paper is to present an integrated approach for evaluating and sizing real-life health-care supply chains in the presence of interval data.

Health-care supply chains are under an increasing pressure for delivering health-care products and services effectively and efficiently. In today's supply chain management, it is widely accepted that the supply chain design determines the structure of a chain and affects both its efficiency and effectiveness. Indeed, Mentzer and Konrad (1991) defined effectiveness as "the extent to which goals are accomplished", while Beamon (1999) defined efficiency in supply chain as the measurement of how well the supply chain resources are used to meet the system's goals. The strategic dimension of supply chains makes mandatory the improvement of their structures to achieve sustainable competitive advantage.

In Morocco, the ministry of health is in charge of providing all the public health premises with pharmaceuticals. Many efforts have been deployed in terms of economy of scale and quality assurance, whereas the availability of pharmaceutical products at the level of health centers is worrisome and patients do not completely take advantage of these efforts. Hence, conceptualizing a suitable pharmaceutical supply chain is a major concern to the Moroccan health-care decision-makers (DMs) over the past decade. DMs are struggling to select between a centralized and a decentralized supply chain, as each one has its own advantages and disadvantages. According to the head of the supply chain department of the Ministry of Health in Morocco, opting for a centralized supply chain increases local control of processes as centralized leadership is in charge of all major decisions and retains more control over the organization's operations, while opting for a decentralized supply chain is a serious attempt to improve reactivity by taking advantage of subcontractors' experiences. To clearly address this issue, managers need to first identify all alternative supply chain scenarios that may suit their supply chain strategy. Second, select a trade-off scenario to achieve strategic fit and, finally, map its future profile by sizing its resources to attain the desired performance level.

More importantly, the main objective of the current research is to extend the formulation of the DEA-based framework proposed by Chorfi *et al.* (2017) for evaluating and sizing health-care supply chains to real-world situations with mixtures of precise and interval data and then apply it to a real case study of public pharmaceutical supply chain in Morocco.

The remainder of the paper is organized as follows. Section 2 provides the relevant literature review on the application of DEA to health care and its application for evaluating supply chain performance; it also provides an overview of the most known approaches that deal with interval data in DEA and reviews some of the most relevant sampling methods for designing computer experiments. Section 3, first, presents the fundamentals of DEA, followed by a brief description of the used aggregation technique and an overview of the proposed Latin hypercube sampling by replacement (LHSR) to lay foundation for Section 4, in which a proposed DEA-based algorithm for evaluating and sizing health-care supply chains in the presence of interval data is proposed. Section 5 applies the proposed algorithm to the setting discussed in Section 1. Finally, Section 6 discusses some potential extensions of the research and, at the same time, summarizes some major concluding remarks.

2 Literature review

2.1 Data envelopment analysis in health care

In the literature, there are many studies in which DEA has been applied for evaluating performance in the health-care industry. Although there are several alternative methods to carry out efficiency analysis in health care, a predominant use of DEA has been noticed

(Pelone *et al.*, 2015). Health care is found to be one of the most popular application areas of DEA (Emrouznejad and Yang, 2017).

According to Ozcan (2008), DEA can help health-care managers assess their organization's relative performance and identify ways to stir their health-care organizations into becoming one of the best performers. The first application of DEA in health care dates to 1983, in the work of Nunamaker and Lewin (1983) for measuring the routine nursing service efficiency (Ozcan, 2008). Since then, DEA has been widely used in health-care studies all over the world (Ozcan, 2008).

Hu *et al.* (2012) evaluated the impact of the health insurance reform on the regional hospital efficiency in China from 2002 to 2008 by using the DEA model; they evaluate the technical efficiency of several hospitals dealing with multiple outputs and undesirable outputs. Marcelino *et al.* (2013) applied DEA models with variable returns to assess the performance of eight health programs and to investigate whether there are any scale inefficiencies in these programs in the aim of organizational positioning and improvement. Gautam *et al.* (2013) measured the relative efficiency of critical rural hospitals in Missouri using an input-oriented DEA with a variable return to scale assumption and compared their performances with other rural hospitals in the state. Torres-Jiménez *et al.* (2014) proposed a Monte Carlo DEA to evaluate the relative technical efficiency of complex health-care systems under uncertainty. Otay *et al.* (2017) proposed an integrated intuitionistic fuzzy AHP and DEA methodology for evaluating the performance of health-care institutions. Stefko *et al.* (2018) used DEA to evaluate the efficiency of health-care facilities in various regions of Slovakia from 2008 to 2015 to detect significant disparities.

At the best of our knowledge, the use of DEA for assessing and sizing health-care supply chains in the presence of both precise and interval data does not exist in the literature yet. Thus, the proposed decision-making framework is likely to make an innovative contribution to health-care performance evaluation and will be of great interest to health-care industry by offering to the health-care DMs a comprehensive way for modelling their supply chains in today's world.

2.2 Data envelopment analysis for supply chain performance evaluation

Supply chain performance evaluation is intrinsically a complex problem involving multiple activities and entities. Wong and Wong (2007) proposed two DEA models – the technical efficiency model and the cost efficiency model – for assessing supply chain performance. Their models were improved with scenario analysis to derive more meaningful business insights for managers in making resources planning decisions. Wong *et al.* (2008) developed a simple tool to measure supply chain performance in real environments. They first introduced a DEA supply chain model to measure the supply chain performance and then enhanced the model with Monte Carlo methodology to cater for efficiency evaluation in stochastic environment. Tavana *et al.* (2013) proposed a new network epsilon-based DEA model for supply chain performance evaluation. The proposed model considers radial and non-radial inputs and outputs simultaneously. Tajbakhsh and Hassini (2015) proposed a multi-stage DEA model that simultaneously assesses the overall efficiency score of a supply chain and the individual efficiency score of its partners. Tavana *et al.* (2015) presented a two-stage DEA method to evaluate the performance of a three-level supply chain including suppliers, manufacturers and distributors. The suggested model can be used for both constant returns to scale and variable returns to scale assumptions. Omrani *et al.* (2017) proposed a robust optimization DEA approach for measuring the efficiency of the producers and distributors to design an efficient supply chain network with uncertain data. Huang

(2018) established a hybrid network DEA model for measuring integrated and divisional performance for tourism supply chains.

This review is far from being complete; its purpose is to give an insight on some applications of DEA to evaluate the performance of supply chains and its ability to merge with other techniques.

2.3 An overview of data envelopment analysis with interval data

As a preliminary step in positioning our work and highlighting its importance, this chapter reviews some of the most known approaches that deal with interval data in DEA, provides a brief description and draws special attention to some advantages and disadvantages of each approach. Keywords searches are used to identify articles published between 1985 and 2019 in Science Direct database. We used keywords such as "DEA with interval data", "interval DEA", "DEA with imprecise data", "imprecise DEA" and "DEA with uncertain data". Several articles were identified and some of the most relevant ones were selected. Summary of the research results is shown in Table I.

According to the papers listed in Table I, several approaches that deal with interval data in DEA were discussed. Each of these methods has its own characteristics and applications. Some of them may lead to a rapid increase in computational burden and are then difficult to implement in real-world problems [e.g. the models by Cooper *et al.* (1999), Shokouhi *et al.* (2010)]. Others are argued to have some structural drawbacks which may affect their reliability [e.g. the models by Entani *et al.* (2002), Despotis and Smirlis (2002) and Zhu (2003)]. The present research suggests another way for dealing with interval data in DEA. The proposed approach is based on the Latin hypercube sampling technique to transform the original interval data into precise data and then uses the standard linear DEA models. This simple trick increases the number of DMUs under evaluation and improves the discriminatory power of DEA. We cannot claim that our approach is the best; it is simply better suited to the context of health-care supply chains with several inputs and outputs in the presence of interval data. We will refer to our data generating approach as Latin hypercube sampling by replacement (LHSR). For more details about the proposed approach, you can refer to Section 3.3. At the best of our knowledge, the use of a sampling technique to deal with interval data in DEA has not been considered in the literature yet.

2.4 Space filling designs for computer experiments

A computer experiment is an experiment used to emulate a deterministic process by constructing a surrogate model for saving time and resources. Space-filling designs are often thought to be particularly an appropriate class of sampling methods for deterministic computer experiments because in general they spread the design points out uniformly throughout the region of experimentation (Douglas, 2012). Space filling designs have been attracting a great deal of attention during the past two centuries and have resulted in a dedicated area of research known as design of experiments (DOE). DOE refers to the process of planning the experiment so that appropriate data will be collected and analyzed by statistical methods, resulting in valid and objective conclusions (Douglas, 2012).

In recent years, various types of space-filling designs have been suggested for computer experiments; some of the most known ones are reviewed hereafter:

The Monte Carlo Sampling (MCS) first introduced by Metropolis and Ulam (1949) in 1949 refers to the traditional technique for using randomness to sample from a multidimensional distribution. The MCS was the first formal method for the design of experiments and have particularly a wide range of applications in designing computer experiments (Sushant *et al.*,

Table I. Summary of published research related to interval data in DEA

Author (s)	Article title	Brief description	Advantages	Disadvantages
Cooper *et al.* (1999)	IDEA and AR-IDEA: models for dealing with imprecise data in DEA	The authors studied how to deal with imprecise data such as bounded data, ordinal data and ratio bounded data in DEA; their model transformed a non-linear programming problem into an equivalent linear programming problem	The paper provides a u nified approach to dealing with precise, ordinal as well as interval data simultaneously	Their models was argued by Zhu (2003) and Fan *et al.* (2015) for being complicated because of the great numbers of calculations required
Entani *et al.* (2002)	Dual models of interval DEA and its extension to interval data	The authors measured interval efficiencies based on DEA from optimistic and pessimistic viewpoints; their models were first developed for crisp data and then extended to interval data and fuzzy data		According to Wang and Luo (2006) and Entani's *et al.* (2002) models, the calculation of the worst possible relative efficiency has a serious disadvantage, as it lost some information on inputs and outputs because only one input and one output data of the DMU being evaluated were effectively utilized, while the other data were not used
Despotis and Smirlis (2002)	DEA with imprecise data	This paper developed an approach for dealing with interval data in DEA, which consists of transforming a non-linear DEA model to an equivalent linear programming model based on the original data set by applying transformations on the variables; upper and lower bounds for the efficiency scores are then derived from the proposed models	Because of their transformations, they show that a DEA model with interval data can be treated as a particular DEA model with exact data, which made their model easy to implement even if data change	According to Fan *et al.* (2015) and Hatami-Marbini *et al.* (2017), this approach fails to measure efficiency in a unified production frontier

(*continued*)

Table I.

Author (s)	Article title	Brief description	Advantages	Disadvantages
Zhu, J. (2003)	Imprecise data envelopment analysis (IDEA) a review and improvement with an application	The current paper develops an approach to reduce the computational burden of the IDEA approach introduced by Cooper *et al.* (1999) by using straightforward variables transformations	According to the author, this approach makes it easy to calculate efficiency scores and provides correct and valid efficiency results	According to Wang *et al.* (2005), the means Zhu (2003) uses to process ordinal preference information does not seem reasonable, as he used different numerical values for the evaluation of different DMUs
Wang *et al.* (2005)	Interval efficiency assessment using DEA	This paper developed a pair of interval DEA models to deal with imprecise data; their models are constructed on the basis of interval arithmetic and uses a unified production possibility set (PPS) for all the DMUs under assessment	According to the authors, there exists no scale transformations and variable alternations, which makes these models more concise and easier to use	
Kao (2006)	Interval efficiency measures in DEA with imprecise data	This paper constructs a pair of bi-level mathematical programming models, whose objective values represent the lower bound and upper bound for the imprecise efficiency for each DMU		
Shokouhi *et al.* (2010)	A robust optimization approach for imprecise DEA	The authors proposed an approach based on a robust optimization model for dealing with data uncertainties covering interval data based on the worst case solution with respect to the uncertainty set		This approach is difficult to implement in real-world problems because of the huge amount of calculations required

(*continued*)

Author (s)	Article title	Brief description	Advantages	Disadvantages
Jahanshahloo *et al.* (2011)	Ranking DMUs by ideal points with interval data in DEA	The interval DEA model proposed in this paper has been formulated to obtain an efficiency interval consisting of evaluations from both the optimistic and the pessimistic viewpoints	According to the authors, the advantage of this method is its ability to rank extreme and non-extreme DMUs	
Esmaeili (2012)	An enhanced Russell measure in DEA with interval data	This paper develops an approach based on the enhanced Russell measure (ERM) for dealing with interval data in DEA; the author finds upper and lower bounds for the possible ERM-efficiency scores that a unit might attain in an interval data setting		
Hatami-Marbini *et al.* (2014)	Interval data without sign restrictions in DEA	The research proposes a DEA model for measuring the relative efficiencies of a set of DMUs with both negative and interval data; the proposed method determines upper and lower bounds for the efficiency scores and classified accordingly these DMUs into three classes	The main advantage of this paper is to introduce negative and interval data simultaneously to DEA by using the (SORM) model	
Fan *et al.* (2015)	Dealing with interval DEA based on error propagation and entropy: A case study of energy efficiency of regions in China considering environmental factors	This paper tackles interval data by using error propagation and entropy along with traditional DEA models, uses idea of the modified cross efficiency to classify the DMUs		

Table I.

2017). However, a problem of clustering arises when a small number of iterations are performed (Sushant *et al.*, 2017).

The Latin hypercube sampling (LHS) first introduced by McKay *et al.* (1979) is a statistical method for producing stratified random samples from a multidimensional distribution. It is a widely used method for developing space-filling designs (Levy and Steinberg, 2010; Kang *et al.*, 2015). In the simplest version of the LHS:

> The continuous range of each input variable is partitioned into *n* intervals, and every interval of each variable is sampled exactly once, and the univariate sample values are randomly matched across all the variables to form the *n* sample points (McKay *et al.*, 1979; Chen et al., 2006).

The main advantage of LHS lies in the fact that even if a small number of experimental runs are performed, a significant amount of information can be obtained to explore the relationship between the response and the contributing factors. Because of this property, LHS is the most commonly used stratified sampling technique in many areas of computer-based experiments (Ingrida *et al.*, 2016). It has been proven that the LHS makes simulations achieve faster convergence than Monte Carlo sampling by using stratification to obtain a more uniform selection of samples (Dalbey and Karystinos, 2010).

The maximin sampling, also named the sphere packing sampling, was proposed by Johnson *et al.* (1990). It belongs to the class of distance-based sampling methods. The aim of maximin sampling is to scatter points in the region of experimentation such that the minimal pairwise distance between points is maximized. It is among the best methods to obtain an even coverage of the design space. However, it tends to prioritize decision vectors that are located near the boundary of the decision space (Ingrida *et al.*, 2016) and is cost demanding in high dimensions.

The uniform sampling was first proposed by Fang (1980). These designs attempt to place the design points so that they are uniformly scattered through the regions as would a sample from a uniform distribution. There are a number of algorithms for creating these designs and several measures of uniformity (Douglas, 2012). If the experimental domain is finite, then uniform designs are very similar to Latin hypercubes. When the experimental domain is continuous, the fundamental difference between these two designs is that in Latin hypercubes, points are selected at random from cells, whereas in a uniform design, points are selected from the center of cells (Simpson *et al.*, 2001).

Among all existing space filling designs coined for computer experiments, Latin hypercube designs have become particularly popular for their ease of use and their flexibility to provide data for modeling techniques based on very different statistical assumptions. They are also capable of covering small and large design spaces. Thus, LHS will be used in this research for generating a space filling design. For more details about the proposed approach, you can refer to Section 3.3.

3. Background

This section provides a brief background on the fundamentals of DEA, followed by a brief description of the used aggregation technique and an overview of the proposed LHSR to lay the foundations for the next section in which a DEA-based approach for evaluating and sizing real-life supply chains in the presence of interval data is provided.

3.1 Data envelopment analysis

DEA is a relatively new operations research tool based on linear programming for evaluating the relative efficiencies of a set of DMUs involving multiple inputs and outputs (Cooper *et al.*, 2011). Dyson *et al.* (2001) indicate that the number of DMUs should not be less than twice the product of the number of outputs and the number of inputs to boost the discriminatory power of DEA. Accordingly, only the most significant inputs and outputs should be used. Chorfi *et al.* (2017) pointed out that aggregation can be used to aggregate a set of inputs and/or outputs that best characterize the DMUs under evaluation into composite criteria. Within this framework, either a constant returns to scale (CRS) or a variable returns to scale (VRS) approach can be chosen. The CRS hypothesis suggests that DMUs are able to adapt their sizes to become fully efficient (Sadjadi and Omrani, 2008). According to Charnes *et al.* (1978), the CRS approach provides good results in terms of evaluating the global or overall efficiency of DMUs. However, the VRS approach assesses the productivity of DMUs within similar scale size and yields their pure technical efficiencies. This approach is adapted if the DMUs are not flexible to adjust their size (Sadjadi and Omrani, 2008). In addition, an input-oriented approach allows adjusting the output by changing the input parameters so as to maximize the efficiency. An input-oriented specification seems more appropriate for the health-care sector, as demand for their services is beyond the control of utilities and needs to be met to maintain a healthy community.

We are interested in determining the global efficiency θ^*_{CCR}, the pure technical efficiency θ^*_{BCC} and the scale efficiency of a decision-making unit k ($\mathrm{DMU_k}$).

The following notations are introduced:

- n: total number of DMUs;
- m: total number of inputs;
- s: total number of outputs;
- x_{ij}: input i consumed by $\mathrm{DMU_j}$ ($1 \le i \le m$; $1 \le j \le n$); and
- y_{rj}: output r produced by $\mathrm{DMU_j}$ ($1 \le r \le s$; $1 \le j \le n$).

Charnes *et al.* (1978) introduced the following linear program ($\mathrm{LP_1}$) named CCR model for evaluating the global efficiency θ^*_{CCR} of $\mathrm{DMU_k}$:

$$\left.\begin{array}{l} \min \theta \\ \text{s.t.} \sum_{j=1}^{n} \lambda_j x_{ij} - \theta \ x_{ik} \le 0, \quad i = 1, 2, \ldots m \\ \sum_{j=1}^{n} \lambda_j y_{rj} \ \ge y_{rk}, \quad r = 1, 2, \ldots s \\ \lambda_j \ge 0, \quad j = 1, 2, \ldots n \end{array}\right\} \qquad (\mathrm{LP_1})$$

Let $\lambda_j{}^*$ be the optimal weights of ($\mathrm{LP_1}$) and θ^*_{CCR} its optimal objective value.

It should be noted that solving the preceding model ($\mathrm{LP_1}$) amounts to solving the following two-stage problem ($\mathrm{LP_2}$) (Cooper *et al.*, 2011):

$$\left.\begin{array}{l} \min \theta - \epsilon \left(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+ \right) \\ \text{s.t.} \sum_{j=1}^{n} \lambda_j x_{ij} - \theta \ x_{ik} + s_i^- = 0, \ \ i = 1, 2, \ldots m \\ \sum_{j=1}^{n} \lambda_j y_{rj} - y_{rk} - s_i^+ = 0, \ \ r = 1, 2, \ldots s \\ \lambda_j, \ \ s_i^-, s_r^+ \ge 0, \ \ = 1, 2, \ldots n, \ \ i = 1, 2, \ldots m, \ \ r = 1, 2, \ldots s \end{array}\right\} \qquad (\mathrm{LP_2})$$

where the s_i^- and s_r^+ are slack variables used to convert the inequalities in (LP_1) to equivalent equations. ϵ is a so-called non-Archimedean element defined to be smaller than any positive real number. Problem (LP_2) first minimizes θ and then maximizes the slacks without altering the previously determined value of θ.

Banker *et al.* (1984) suggested an extension of the CCR model named BCC model to account for the variable returns to scale. The BCC model is simply obtained by adding a convexity constraint $\sum_{j=1}^{n} \lambda_j = 1$ to the CCR model. It should be noted that the pure technical efficiency θ^*_{BCC} of DMU_k can be expressed by solving the corresponding BCC model.

Scale efficiency (SE) can be calculated as follows:

$$SE = \theta^*_{CCR}/\theta^*_{BCC}$$

The CCR model yields the global efficiency θ^*CCR of a DMU which measures inefficiencies because of the input/output configuration as well as the size of operations, where scale efficiency SE is the component of global efficiency that can be attributed to the size of operations (long term) and pure technical efficiency θ^*BCC or managerial efficiency the component that measures inefficiencies because of only managerial underperformance (short term) (Cooper *et al.*, 2011).

3.2 Aggregation technique

Many methods have been used to aggregate criteria as discussed in Nardo *et al.* (2005) and Olsthoorn *et al.* (2001). The existing aggregation tools can be divided into two categories:

(1) the indirect approach which frequently involves the normalization of the underlying criteria and the weighting and aggregation of the normalized criteria by using multi-criteria decision analysis (MCDA); and

(2) the direct approach, in which an aggregated criterion is directly obtained from the underlying criteria using DEA.

The advantage of the direct approach is that it does not require the determination of weights for the original criteria. In recent years, many studies for constructing aggregated criteria have been undertaken using DEA (Mahlberg and Obersteiner, 2001; Cherchye, 2001; Despotis, 2005; Zhou *et al.*, 2007). We propose to use the Zhou *et al.*'s (2007) aggregation methodology for its clarity and ease of use. We present hereinafter a brief overview of the main guidelines of this methodology: Consider the case where there are m entities (e.g. supply chains) under assessment. These entities are characterized by a set of inputs and outputs called criteria; we assume further that these criteria were classified into several categories and our aim is to aggregate each category into one aggregated criterion to evaluate the performance of entity i with respect to a given category.

The problem is to aggregate a set of criterion values I_{ij} ($j = 1, 2 \ldots n$) for a given category into a single aggregated criterion I_i (α). We first need to solve the following linear program (LP_3) for each entity i once:

$$\left.\begin{array}{l} \max gI_i = \sum_{j=1}^{n} w_{ij}^{g} I_{ij} \\ \text{s.t.} \ \sum_{j=1}^{n} w_{ij}^{g} I_{kj} \leq 1, \ k = 1, 2, \ldots m \\ w_{ij}^{g} \geq 0, \ j = 1, 2, \ldots n \end{array}\right\} \qquad (LP_3)$$

Model (LP_3) determines the "best" vector of weights w_{ij}^{g} for the different criterion values I_{ij} (j = 1, 2... n) of each entity i. Let gI_i^* be the optimal solution of (LP_3) in favor of entity i. It should be noted that m resolutions for (LP_3) are required. We will obtain a set of performance scores gI_1^*, gI_2^*... gI_m^* for these entities.

We then need to solve the following linear program (LP_4) for each entity i once:

$$\left.\begin{aligned} &\min bI_i = \sum_{j=1}^{n} w_{ij}^{b} I_{ij} \\ &\text{s.t.} \sum_{j=1}^{n} w_{ij}^{b} I_{kj} \geq 1, \quad k = 1, 2, \ldots m \\ &w_{ij}^{b} \geq 0, \quad j = 1, 2, \ldots n \end{aligned}\right\} \qquad (LP_4)$$

Contrary to Model (LP_3), Model (LP_4) determines the "worst" vector of weights w_{ij}^{b} for the different criterion values I_{ij} (j = 1, 2... n) of each entity i. Let bI_i^* be the optimal solution of (LP_4) against entity i. It should be noted that m resolutions for (LP_4) are required. We will obtain a set of performance scores bI_1^*, bI_2^*,..., bI_m^* for these entities.

The two performance scores provided by (LP_3) and (LP_4) for entity i can be combined into an aggregated criterion $I_i(\alpha)$ by the following way:

$$I_i(\alpha) = \alpha . \frac{gIi^* - gI^-}{gI^+ - gI^-} + (1 - \alpha) . \frac{bIi^* - bI^-}{bI^+ - bI^-}$$

where:

$gI^+ = \max \{gI_i^*, i = 1, 2 \ldots m\}$;
$gI^- = \min \{gI_i^*, i = 1, 2 \ldots m\}$;
$bI^+ = \max \{bI_i^*, i = 1, 2 \ldots m\}$; and
$bI^- = \min \{bI_i^*, i = 1, 2 \ldots m\}$.

$0 \leq \alpha \leq 1$ is an adjusting parameter which reflects the DM's preferences. If the DM does not have any particular preference, then $\alpha = 0.5$ is generally used. If $\alpha = 1$, then $I_i(\alpha)$ will become a normalized version of gI_i^*. If $\alpha = 0$, then $I_i(\alpha)$ will become a normalized version of bI_i^*. For other cases, $I_i(\alpha)$ makes a compromise between the two performances scores gI_i^* and bI_i^*.

3.3 Proposed Latin hypercube sampling by replacement

In real-life supply chain problems, the DMs often fail to provide precise data, as they are dealing with uncertain situations. They are sometimes only able to provide interval data characterized by lower and upper bounds. To overcome this issue, we suggest replacing the original interval data with precise data by using the LHS previously introduced in Section 2.4 to use the conventional aggregation technique used in Step 2 of the proposed DEA-based algorithm (refer to Section 4). According to the aforementioned definition of the LHS and for a given supply chain scenario, the bounded range of each data variable can be partitioned into n intervals; every interval of each variable is sampled exactly once; the univariate sample values are randomly matched across all the variables to form the n sample points for a given scenario. This simple trick allows increasing the number of supply chains under evaluation, as each supply chain scenario generates a number of samples equal to the number of the generated intervals in the stratified random sampling. More importantly, this approach improves the discriminatory power of DEA, as it increases the number of the DMUs while keeping the number of the inputs and outputs variables constant. The choice of the LHS comes from the need to conduct an experimental study based on computer experiment on Step 5 of the proposed DEA-based algorithm (refer to Section 4). The generated design space can be used to implement the proposed computer experiment methodology in Step 5 of the proposed DEA-based algorithm (refer to Section 4). We will call our data generating approach LHSR. According to Manache and Melching (2007), no firm rules are available for choosing the sample size *n*; we will then choose the sample size that provides good results in term of accuracy in the final results.

4. Proposed data envelopement analysis-based algorithm for assessing and sizing health-care supply chains in the presence of interval data

In this paper, we generalize the framework introduced by Chorfi *et al.* (2017). We introduce the following algorithm illustrated in Figure 1 for assessing and sizing health-care supply chains in the presence of interval data. The proposed approach can help the DMs

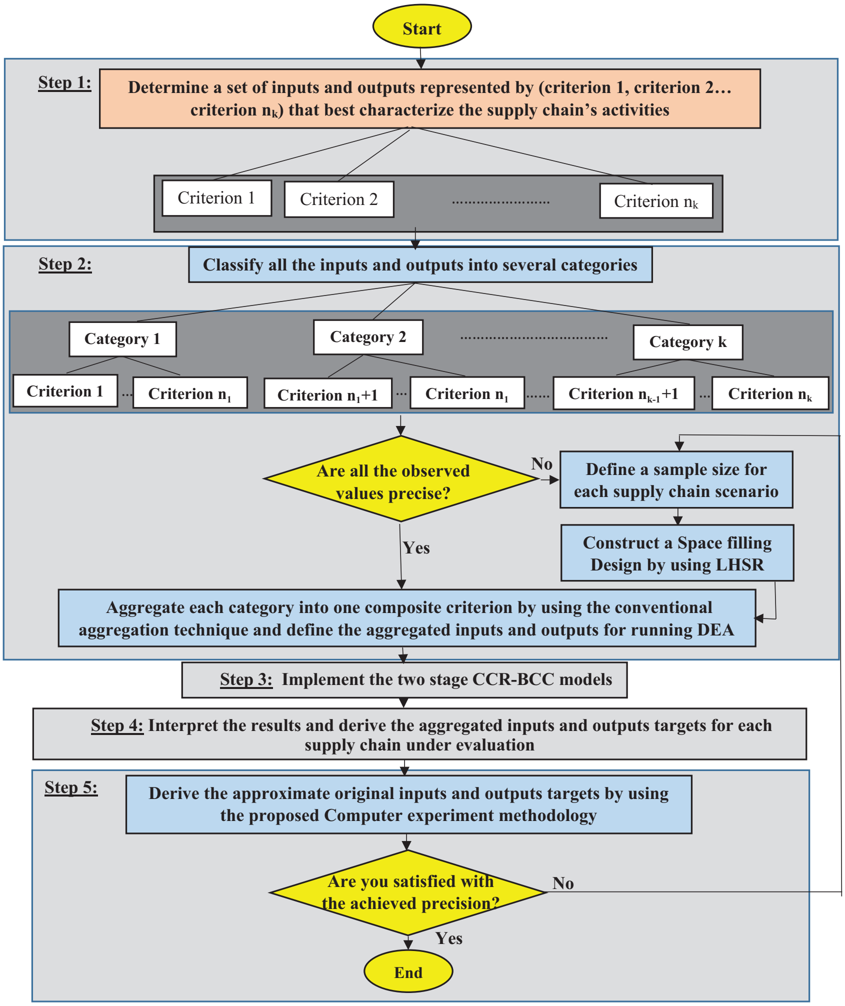

Figure 1.
Proposed algorithm for evaluating and sizing health-care supply chains in the presence of interval data

conceptualize suitable supply chains aligned with their organization's strategies. The details of the algorithm are as follows:

- *Step 1:* Determine a set of inputs and outputs that best describe the supply chain's operations.
- *Step 2:* Classify all the inputs and outputs into several categories for each supply chain and then aggregate each category's criteria into a single aggregated criterion. Please notice that the aforementioned conventional aggregation technique assume that all the data are exactly known. However, in real-life problems, some or all observed values are sometimes only known to lie within bounded intervals (interval data). To overcome this issue, we propose to construct a space filling design for each supply chain scenario with interval data to characterize the original data by using the suggested LHSR. The adopted sample size must provide good results in terms of accuracy in the final results. Then, each sample's criteria for a given category can be aggregated into one aggregated criterion by using the aforesaid aggregation technique. The resulted aggregated criteria can be used as inputs and outputs for executing the conventional DEA models in Step 3.
- *Step 3:* Implement the conventional CCR-BCC DEA models to determine the relative efficiencies of each supply chain with regard to other supply chains.
- *Step 4:* Interpret the results; short-term actions can be suggested to eliminate the managerial underperformance according to the BCC model and long-term actions to eliminate the scale inefficiency by using the CCR model. When both CCR and BCC scores are equal to one, the most productive scale size (MPSS) is achieved (Cooper *et al.*, 2011). Consequently, the aggregated inputs and outputs targets for each supply chain sample can be obtained according to the CCR model.
- *Step 5:* Derive the original inputs and outputs targets by disaggregating the composite criteria according to the computer experiment methodology proposed by Chorfi *et al.* (2017) (See also Chorfi *et al.*, 2016b). It must be noted that the space filling design generated in Step 2 can be used in the proposed computer experiment methodology.

If the researcher finds that the accuracy of prediction is unsatisfactory, then he has to choose a larger sample size in Step 2 and reconduct the study.

5. Application

5.1 Description of potential public pharmaceutical supply chains in Morocco

According to the head of the supply chain department of the Moroccan Ministry of Health, three main alternative scenarios for the public pharmaceutical supply chain in Morocco exist:

5.1.1 Centralized scenario. A centralized supply chain (Scenario 1) is a setup in which all decision-making responsibilities and supply chain activities (procurement, warehousing and distribution) are managed internally. This scenario allows the DM to retain more control over all chain operations, but this can result in low responsiveness because operations may take a long time to be completed than with decentralization. This structure represents the actual configuration for the Moroccan pharmaceutical supply chain as elucidated in Figure 2.

5.1.2 Decentralized scenario. A decentralized supply chain (Scenario 2) is a setup in which distribution and warehousing activities including the inbound and outbound logistics are delegated by top management to subcontractors, allowing top management to focus

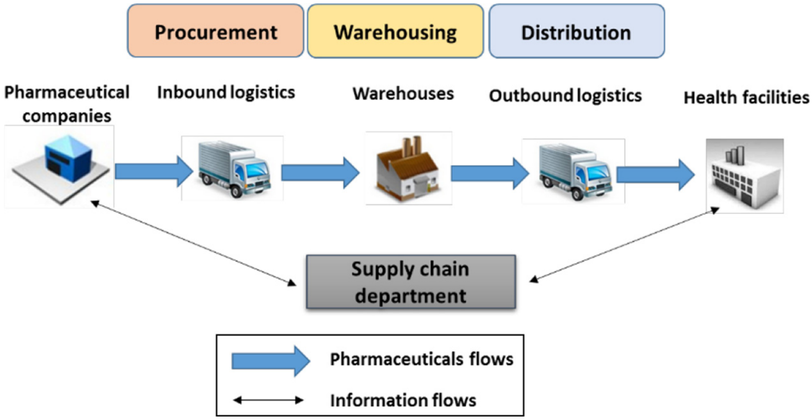

Figure 2.
Centralized pharmaceutical supply chain

more on major decisions and procurement activities. Outsourcing warehousing and distribution activities is an attempt to improve responsiveness by learning from the subcontractrors' experiences. It may improve the availability of pharmaceutical products within health premises and minimize losses while taking advantages of potential economies of scale during the procurement phase. However, it may create a kind of dependency on subcontractors, as a failure occurring within subcontractors activities can lead to serious damages, especially in the case of essential pharmaceutical products.

5.1.3 Combined scenario. The combined scenario (Scenario 3) is a hybrid structure that takes advantages of both centralized and decentralized scenarios, as the warehousing and the distribution of some pharmaceutical products can be outsourced while that of essential pharmaceutical products can be managed in house.

5.2 Illustrative application to Moroccan public pharmaceutical products supply chains

As a numerical illustration, we apply the proposed algorithm for evaluating and sizing health-care supply chains in the presence of interval data to the Moroccan public pharmaceutical products supply chain by using empirical data collected through several interviews carried out with the head of the supply chain department of the Ministry of Health in Morocco.

The list of inputs and outputs that best characterize the Moroccan pharmaceutical products supply chains activities is confidential data. We are under obligation to represent them by variables as follows: C_1, C_2, C_3, C_4, R_1, D_1, D_2, D_3, E_1, E_2, E_3 and E_4.

Please notice that C_1, C_2, C_3 and C_4 are cost-related indicators, R_1 is a responsiveness-related indicator, D_1, D_2 and D_3 are design-related indicators and E_1, E_2, E_3 and E_4 are effectiveness-related indicators. All these variables are exactly known (precise data) or are only known to lie within bounded intervals (interval data).

Input orientation in DEA means that when trying to improve efficiency, inputs are reduced, while outputs remain constant. Thus, if an input variable is to be maximized, then we must transform it into an input variable to be minimized. To transform a variable I_i to maximize into a variable I_i' to minimize, we use a simple trick. We replace I_i by I_i' such as $I_i' = 1/I_i$. The inputs and the outputs values of this example are illustrated in Tables AI and AII2.

After that, we propose to classify the inputs and the outputs according to the following categories: The supply chain cost-based indicators category including C_1, C_2, C_3 and C_4, the supply chain responsiveness indicators category including R_1, the design-based indicators category including D_1, D_2 and D_3 and the supply chain effectiveness indicators category including E_1, E_2, E_3 and E_4.

Some observed values of the Moroccan public pharmaceutical products supply chains are interval data (refer to Tables AI and AII in Appendix). We propose to construct a space filling design for each scenario to transform the interval data into precise data by using the suggested LHSR. If the data of a specific scenario is precise, then there is no need for sampling; DMU_i corresponds to scenario i. In this study, we have first used five samples in the LHS for each scenario, then ten, but we decided finally to study 15 samples to obtain a satisfactory accuracy of prediction in the final result. In so doing, let us note DMUi_j the jth Latin hypercube sample for the supply chain scenario i. The generated Latin hypercube samples assume the form of specific numerical values and can be used as new DMUs with precise data for the different scenarios. The generated Latin hypercube samples are represented in Tables AIII-AVI.

By using the aforementioned aggregation technique, the indicators of a given category were aggregated into one composite indicator to define the aggregated inputs and aggregated outputs for running DEA. In other words, the supply chain cost-based indicators C_1, C_2, C_3 and $C_4{}^{'}$ were aggregated into one composite indicator named the aggregated cost-based metric (Table AIII in Appendix); the design-based indicators D_1, D_2 and D_3 were aggregated into one composite indicator named the aggregated design-based metric (Table IV in Appendix); the supply chain effectiveness indicators E_1, E_2, E_3 and E_4 were aggregated into one composite indicator named the aggregated effectiveness-based metric (Table VI in Appendix); there is only one indicator R_1 in the supply chain responsiveness indicators category, so there is no need for aggregation (Table AV in Appendix). By way of example, the indicators values $C_1 = 433.00$; $C_2 = 86.00$; $C_3 = 0.00070$ and $C_4{}^{'} = 1.540$ of DMU_1 in Table AIII (Appendix) represent the I_{ij} *(j = 1.4)* to be used in the aggregation method. The corresponding aggregated cost-based metric is the I_i (0.5) calculated by using equation (2).

The final aggregated inputs and outputs used for the calculations of the efficiency scores by implementing the conventional CCR-BCC DEA models are: the aggregated cost-based metric (Input 1), the aggregated design-based metric (Input 2) and the responsiveness indicator R_1 (Input 3). The aggregated effectiveness-based metric is the only aggregated output metric considered (Output 1). The generated data are listed by categories and are set out in Tables AIII-AVI (Appendix).

5.3 Results and discussions

The global results obtained by applying the input-oriented CCR-BCC models are summarized in Table II.

Four supply chains ($DMU_{2,1}$, $DMU_{2,3}$, $DMU_{2,5}$ and $DMU_{2,12}$) resulting from the second scenario (decentralized scenario) are performants with an overall technical efficiency score (CCR efficiency) equal to one. However, only one supply chain ($DMU_{3,1}$) resulting from the third scenario (combined scenario) is a performant. Hence, the decentralized scenario may be considered as the supply chain network that may best suit the Moroccan pharmaceutical products supply chain strategy with respect to efficiency and effectiveness. However, according to the head of the supply chain department of the Ministry of Health in Morocco, to avoid supply chain breakdown, it is important to proactively managing supply chain risks by moving slowly toward the decentralized scenario. The combined scenario can be considered as a trade-off network to make a first move toward the decentralized scenario to avoid any shortage of supply of essential

Supply chains	CCR efficiency: (CCR model)	BCC efficiency: (BCC model)	SE: [equation (1)]	Return to scale
Scenario 1				
DMU_1	0.000	0.888	0.000	IRS
Scenario 2				
$DMU_{2,1}$	1.000	1.000	1.000	–
$DMU_{2,2}$	0.686	1.000	0.686	IRS
$DMU_{2,3}$	1.000	1.000	1.000	–
$DMU_{2,4}$	0.799	1.000	0.799	IRS
$DMU_{2,5}$	1.000	1.000	1.000	–
$DMU_{2,6}$	0.610	1.000	0.610	IRS
$DMU_{2,7}$	0.790	1.000	0.790	IRS
$DMU_{2,8}$	0.807	1.000	0.807	IRS
$DMU_{2,9}$	0.684	1.000	0.684	IRS
$DMU_{2,10}$	0.687	1.000	0.687	IRS
$DMU_{2,11}$	0.793	1.000	0.793	IRS
$DMU_{2,12}$	1.000	1.000	1.000	–
$DMU_{2,13}$	0.661	1.000	0.661	IRS
$DMU_{2,14}$	0.840	1.000	0.840	IRS
$DMU_{2,15}$	0.975	1.000	0.975	IRS
Scenario 3				
$DMU_{3,1}$	1.000	1.000	1.000	–
$DMU_{3,2}$	0.747	0.979	0.762	IRS
$DMU_{3,3}$	0.720	0.979	0.735	IRS
$DMU_{3,4}$	0.680	0.977	0.696	IRS
$DMU_{3,5}$	0.860	0.990	0.869	IRS
$DMU_{3,6}$	0.720	0.979	0.735	IRS
$DMU_{3,7}$	0.926	0.991	0.934	IRS
$DMU_{3,8}$	0.820	0.987	0.831	IRS
$DMU_{3,9}$	0.690	0.977	0.706	IRS
$DMU_{3,10}$	0.670	0.977	0.686	IRS
$DMU_{3,11}$	0.788	0.979	0.805	IRS
$DMU_{3,12}$	0.600	0.977	0.614	IRS
$DMU_{3,13}$	0.800	0.985	0.812	IRS
$DMU_{3,14}$	0.890	0.992	0.897	IRS
$DMU_{3,15}$	0.810	0.986	0.822	IRS

Table II.
The efficiency summary of the Moroccan public pharmaceutical supply chains

pharmaceuticals (as they are managed in house). Therefore, we suggest to size our supply chain according to the combined scenario.

For the combined scenario, the efficiency scores obtained through the BCC model are higher than that of the CCR model for all DMUs which means that the management performance of the different pharmaceutical supply chains is relatively performant with regards to the size of operations. However, the totality of DMUs are operating under IRS; then these DMUs will need to plan for expansion (Cooper *et al.*, 2011). One supply chain ($DMU_{3,1}$) had a scale efficiency of 100 per cent meaning that it was operating at its most productive scale size (MPSS). The remaining supply chains ($DMU_{3,2}$; $DMU_{3,3;}$ . . .. $DMU_{3,15}$) had scale efficiency scores of less than 100 per cent and were thus deemed scale inefficient under an increasing return to scale (IRS). Thus, these DMUs may need to increase their size to achieve optimal scale size. The long-term aggregated inputs targets for individual supply chains (after removing the scale and managerial inefficiencies) are obtained by applying the CCR model and are displayed in Table AVII (Appendix).

5.4 Sizing the Moroccan public pharmaceutical supply chain

As illustrated before, the combined scenario can be considered as a trade-off network to make the first move toward a decentralized supply chain to avoid the supply chain breakdown.

According to our research, there are as many possible sizing for the Moroccan pharmaceutical supply chain as the number of DMUs under evaluation in the combined scenario. We have already proven that $DMU_{3,1}$ was operating at its MPSS; then one direct sizing for the Moroccan pharmaceutical supply chain is obvious and corresponds to the original inputs (C_1, C_2, C_3, C_4, D_1, D_2, D_3 and R_1) of the $DMU_{3,1}$ as illustrated in Tables III-AV (Appendix).

The aim of this section is, therefore, to derive the approximate original inputs (D_1, D_2, D_3) for $DMU_{3,13}$ with regard to the targeted value of the aggregated design metric 0.536 as illustrated in Table VII (Appendix) by using Step 5 of the proposed algorithm.

5.4.1 Problem modelling. Suppose we have 31 supply chains under assessment named DMUs and each DMU has three underlying sub-indicators aggregated into one aggregated design indicator by using the aforementioned aggregation technique.

As illustrated before, the inputs for our computer experiment design are varying in the following ranges:

$$I_{32,1} = D_1 = [4, 64]\; I_{32,2} = D_2 = [25000, 400000]\; I_{32,3} = D_3 = [560000, 700000]$$

We aim to find one combination of sub-indicators $I_{32,\,j}$ (j = 1.3) for a fictional supply chain 32 called $DMU'_{3,13}$ such as the composite index $I_{32}(0.5) = \mathit{0.536}$.

The response for the problem is considered to be $I_{32}(0.5)$. Let us put $R_1 = E\,(I_{32}(0.5))$ the approximate function of $I_{32}(0.5)$. The response function can be expressed as $I_{32}(0.5) = f\,(I_{32,1}, I_{32,2}, I_{32,3})$ where function f is known but has no analytic expression. For this example, the inputs values are taken to be ($I_{32,1}$, $I_{32,2}$, $I_{32,3}$). The input and the output values for running computer experiment are illustrated in Table III.

In this example, we want to predict the relationships between the inputs variables ($I_{32,1}$, $I_{32,2}$, $I_{32,3}$) and the response $I_{32}(0.5)$ and to find one inputs-combination ($I_{32,1}$, $I_{32,2}$, $I_{32,3}$) minimizing the error observed in the response. The response target is $I_{32}(0.5) = 0.536$.

As illustrated in Step 2, we have decided to study 15 samples for each scenario in the LHS.

5.4.2 Response surface modeling. After constructing a space filling design by using LHS, the resulting data are used to construct surrogate models using regression analysis. The results from a statistical software for fitting the response $I_{32}(0.5)$ according to the inputs variables ($I_{32,1}$, $I_{32,2}$, $I_{32,3}$) are addressed in Tables IV and V.

The Quadratic model is suggested to emulate our response R_1. On the basis of the above analysis, Table V shows that there are many significant terms characterized by a p-value inferior or equal to the level of significance $\alpha = 0.05$. Accordingly, the model terms C, AC and B^2 are significant. The parameter estimates for the reduced model excluding insignificant terms are shown in Table VI.

The software provides a satisfactory accuracy of prediction, as the difference between the predicted $R^2 = 0.9393$ and the adjusted $R^2 = 0.9776$ for the reduced model is

Table III. The original and the aggregated design-based indicators for supply chains

DMUs	D_1 ($I_{i,1}$)	D_2 ($I_{i,2}$)	D_3 ($I_{i,3}$)	$I_i(0.5)$
Scenario 1				
i = 1: DMU_1	4	40,000.00	700,000.00	0.50
Scenario 2				
i = 2: $DMU_{2,1}$	60	28,000.00	565,000.00	0.00
i = 3: $DMU_{2,2}$	60	29,500.00	595,000.00	0.18
i = 4: $DMU_{2,3}$	60	25,000.00	575,000.00	0.01
i = 5: $DMU_{2,4}$	60	32,000.00	570,000.00	0.16
i = 6 : $DMU_{2,5}$	60	31,500.00	560,000.00	0.01
i = 7: $DMU_{2,6}$	60	30,000.00	615,000.00	0.41
i = 8: $DMU_{2,7}$	60	26,000.00	630,000.00	0.40
i = 9: $DMU_{2,8}$	60	25,500.00	625,000.00	0.30
i = 10: $DMU_{2,9}$	60	26,500.00	620,000.00	0.34
i = 11: $DMU_{2,10}$	60	30,500.00	610,000.00	0.36
i = 12: $DMU_{2,11}$	60	27,500.00	580,000.00	0.08
i = 13: $DMU_{2,12}$	60	29,000.00	600,000.00	0.19
i = 14: $DMU_{2,13}$	60	28,500.00	605,000.00	0.22
i = 15: $DMU_{2,14}$	60	27,000.00	585,000.00	0.09
i = 16: $DMU_{2,15}$	60	31,000.00	590,000.00	0.20
Scenario 3				
i = 17: $DMU_{3,1}$	64	28,071.43	592,000.00	0.67
i = 18: $DMU_{3,2}$	64	25,614.29	612,000.00	0.60
i = 19: $DMU_{3,3}$	64	31,757.14	596,000.00	0.75
i = 20: $DMU_{3,4}$	64	28,685.71	608,000.00	0.78
i = 21: $DMU_{3,5}$	64	29,300.00	632,000.00	0.91
i = 22: $DMU_{3,6}$	64	32,985.71	588,000.00	0.70
i = 23: $DMU_{3,7}$	64	30,528.57	624,000.00	0.89
i = 24: $DMU_{3,8}$	64	29,914.29	616,000.00	0.84
i = 25: $DMU_{3,9}$	64	26,228.57	600,000.00	0.68
i = 26: $DMU_{3,10}$	64	27,457.14	628,000.00	0.85
i = 27: $DMU_{3,11}$	64	25,000.00	620,000.00	0.50
i = 28: $DMU_{3,12}$	64	33,600.00	604,000.00	0.81
i = 29: $DMU_{3,13}$	64	32,371.43	640,000.00	0.99
i = 30: $DMU_{3,14}$	64	26,842.86	636,000.00	0.79
i = 31: $DMU_{3,15}$	64	31,142.86	644,000.00	1.00
i = 32: $DMU'_{3,13}$	?	?	?	0.536

Table IV. Summary statistics for the response R_1

			Model summary statistics			
Source	SD	R^2	Adjusted R^2	Predicted R^2	PRESS	
Linear	0.16	0.7854	0.7616	−8.6035	30.14	
2FI	0.054	0.9778	0.9723	−2.1196	9.79	
Quadratic	0.046	0.9859	0.9798			± Suggested
Cubic	0.021	0.9980	0.9957			+ Aliased

less than 0.2 which means that the reduced model can be used to navigate the design space. The software also provides a surrogate model to emulate the response $I_{32}(0.5)$ called R_1 over the experimental region by using the reduced model terms; the prediction equation is:

ANOVA for response surface quadratic model Analysis of variance table [Partial sum of squares - Type III]						
Source	Sum of squares	df	Mean square	*F*-value	*p*-value Prob > F	
Model	3.09	9	0.34	162.79	<0.0001	Significant
A-D1	*6.045E-003*	*1*	*6.045E-003*	*2.86*	*0.1054*	
B-D2	*7.847E-004*	*1*	*7.847E-004*	*0.37*	*0.5487*	
C-D3	*0.018*	*1*	*0.018*	*8.56*	*0.0081*	
AB	*1.053E-003*	*1*	*1.053E-003*	*0.50*	*0.4879*	
AC	*0.014*	*1*	*0.014*	*6.60*	*0.0179*	
BC	*3.294E-003*	*1*	*3.294E-003*	*1.56*	*0.2254*	
A^2	*3.944E-005*	*1*	*3.944E-005*	*0.019*	*0.8926*	
B^2	*0.016*	*1*	*0.016*	*7.40*	*0.0128*	
C^2	*7.509E-003*	*1*	*7.509E-003*	*3.56*	*0.0733*	
Residual	0.044	21	2.112E-003			
Cor total	3.14	30				

Table V. Parameter estimates for the response R_1

ANOVA for response surface reduced quadratic model Analysis of variance table [Partial sum of squares - Type III]						
Source	Sum of squares	df	Mean square	*F*-value	*p*-value Prob > F	
Model	3.08	6	0.51	219.09	<0.0001	Significant
A-D1	*1.13*	*1*	*1.13*	*483.68*	*<0.0001*	
B-D2	*1.352E-004*	*1*	*1.352E-004*	*0.058*	*0.8122*	
C-D3	*0.76*	*1*	*0.76*	*322.06*	*<0.0001*	
AC	*0.44*	*1*	*0.44*	*189.27*	*<0.0001*	
B^2	*0.017*	*1*	*0.017*	*7.14*	*0.0133*	
C^2	*0.023*	*1*	*0.023*	*9.76*	*0.0046*	
Residual	0.056	24	2.345E-003			
Cor total	3.14	30				

Table VI. Parameter estimates for the reduced model of the response R_1

$$R_1 = -36.21107 + 0.76739\,A + 2.82162*10^{-4}B + 1.02951*10^{-5}C - 1.07666*10^{-6}AC - 4.38656*10^{-9}B^2$$

We have used an experimental design and optimization software to find the inputs combinations that provide a given response value. The software yields several combinations of the inputs values ($I_{32,1}$, $I_{32,2}$, $I_{32,3}$) such that the predicted response of I_{32} (0.5) is equal to 0.5762. We choose the one with the closest real response to the predicted response.

We find that the input combination $I_{32,1} = 64$; $I_{32,2} = 25{,}090.85$ and $I_{32,3} = 593{,}414.12$ gives a real response I_{32} (0.5) of 0.5333, while the expected response is equal to 0.5360 which yields an error of 0.0027.

If the accuracy of prediction is judged unsatisfactory, then we can improve the results by increasing the Latin hypercube sample size in Step 2 and reconduct the study.

6. Conclusion

The overarching objective of the current research is to propose an integrated DEA-based approach for evaluating and sizing real-life health-care supply chains with interval data. To deal with interval data, a LHSR approach was used to generate a space filling design for each scenario with interval data. The findings of this study will assist the DMs in comparing their supply chains against peers and sizing their resources to achieve a certain level of production.

An aggregation technique is first used to aggregate a set of inputs or outputs into one composite metric, and then DEA models are used to measure the relative efficiencies of the supply chains under evaluation. In fact, decomposing technical efficiency scores into pure technical efficiency and scale efficiency provides guidance on what can be achieved in the short and the long term. Finally, the proposed approach provides the most appropriate scenario for the Moroccan pharmaceutical products supply chain and allows the determination of the original inputs and outputs targets of the different DMUs under evaluation by using computer experiment.

Some of the advantages of the proposed methodology for evaluating and sizing real-life health-care supply chains in the presence of interval data are the improvement of the discriminatory power of DEA by limiting the number of the considered inputs and outputs while increasing the number of the DMUs under evaluation. The findings of this research establish a foundation for promising future work. First, the proposed algorithm for evaluating and sizing health-care supply chains is valid for crisp and interval data only. It would be worthwhile to extend its formulation to take into account other types of data such as categorical data, missing data and negative data. Second, the proposed computer experiment methodology used in Step 5 of the proposed algorithm yields only an approximate sizing of the supply chains operations, several research paths are conceivable to provide an exact sizing of the supply chains operations. One eventual track of research is to use multi-objective optimization to provide an exact sizing of the health-care supply chains operations.

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Appendix

Scenarios	Cost based indicators				Design indicators			Responsiveness indicator
	C_1	C_2	C_3	C_4'	D_1	D_2	D_3	R_1'
Scenario 1	433	86	0.0007	1.54	4	40000	700000	1.250
Scenario 2	[346.4,389.7]	[69.28,77.94]	[0.00056,0.00063]	[1.23,1.39]	60	[25000,32000]	[560000,630000]	1.110
Scenario 3	[363.72,398.36]	[72.62,79.55]	[0.00058,0.00064]	[1.29,1.42]	64	[25000,33600]	[588000,644000]	1.136

Table AI.
The inputs values of the Moroccan public pharmaceutical supply chains

Table AII.
The outputs values of the Morccan public pharmaceutical supply chains

Scenarios	Effectiveness indicators E_1	E_2	E_3	E_4
Scenario 1	0.8	0.75	0.9	0.7
Scenario 2	0.92	[0.8,0.85]	[0.9,0.92	[0.78,0.84]
Scenario 3	0.90	[0.85,0.9]	[0.92,0.94]	[0.80,0.90]

Table AIII.
The generated data for the Moroccan public pharmaceutical supply chains operations: cost based indicators

DMUs	The generated latin hypercube samples for the cost based indicators C_1	C_2	C_3	C_4’	Aggregated cost based metric (input 1) (α =0.5): (Eq. 2)
Scenario 1					
DMU_1	433.00	86.00	0.00070	1.540	1.000
Scenario 2					
$DMU_{2,1}$	383.51	77.94	0.00060	1.310	0.278
$DMU_{2,2}$	364.95	71.75	0.00057	1.378	0.165
$DMU_{2,3}$	377.33	72.37	0.00059	1.367	0.197
$DMU_{2,4}$	386.61	71.13	0.00062	1.241	0.159
$DMU_{2,5}$	361.86	74.22	0.00059	1.287	0.081
$DMU_{2,6}$	368.05	77.32	0.00058	1.264	0.178
$DMU_{2,7}$	389.70	73.61	0.00057	1.344	0.184
$DMU_{2,8}$	349.49	76.70	0.00061	1.252	0.156
$DMU_{2,9}$	371.14	69.28	0.00062	1.321	0.137
$DMU_{2,10}$	355.67	69.89	0.00061	1.332	0.089
$DMU_{2,11}$	374.23	72.99	0.00063	1.230	0.181
$DMU_{2,12}$	352.58	70.51	0.00058	1.298	0.000
$DMU_{2,13}$	358.77	76.08	0.00063	1.355	0.257
$DMU_{2,14}$	380.42	74.84	0.00056	1.390	0.191
$DMU_{2,15}$	346.40	75.46	0.00060	1.275	0.111
Scenario 3					
$DMU_{3,1}$	378.56	72.62	0.00058	1.336	0.124
$DMU_{3,2}$	381.04	77.07	0.00059	1.290	0.207
$DMU_{3,3}$	363.72	77.57	0.00064	1.373	0.339
$DMU_{3,4}$	368.66	76.08	0.00062	1.299	0.209
$DMU_{3,5}$	376.09	74.60	0.00063	1.345	0.306
$DMU_{3,6}$	383.51	73.11	0.00062	1.410	0.343
$DMU_{3,7}$	373.61	73.61	0.00059	1.308	0.105
$DMU_{3,8}$	385.98	75.09	0.00064	1.327	0.354
$DMU_{3,9}$	395.88	78.06	0.00060	1.364	0.337
$DMU_{3,10}$	366.19	79.05	0.00063	1.317	0.353
$DMU_{3,11}$	371.14	78.56	0.00061	1.420	0.382
$DMU_{3,12}$	390.93	74.10	0.00058	1.355	0.229
$DMU_{3,13}$	398.36	75.59	0.00061	1.392	0.392
$DMU_{3,14}$	393.41	79.55	0.00061	1.382	0.414
$DMU_{3,15}$	388.46	76.58	0.00060	1.401	0.341

DMUs	The generated latin hypercube samples for the design indicators D_1	D_2	D_3	Aggregated design based metric (input 2) (α =0.5): (Eq.2)
Scenario 1				
DMU_1	4	40,000.00	700,000	0.50
Scenario 2				
$DMU_{2,1}$	60	28,000.00	565,000	0.00
$DMU_{2,2}$	60	29,500.00	595,000	0.18
$DMU_{2,3}$	60	25,000.00	575,000	0.01
$DMU_{2,4}$	60	32,000.00	570,000	0.16
$DMU_{2,5}$	60	31,500.00	560,000	0.01
$DMU_{2,6}$	60	30,000.00	615,000	0.41
$DMU_{2,7}$	60	26,000.00	630,000	0.40
$DMU_{2,8}$	60	25,500.00	625,000	0.30
$DMU_{2,9}$	60	26,500.00	620,000	0.34
$DMU_{2,10}$	60	30,500.00	610,000	0.36
$DMU_{2,11}$	60	27,500.00	580,000	0.08
$DMU_{2,12}$	60	29,000.00	600,000	0.19
$DMU_{2,13}$	60	28,500.00	605,000	0.22
$DMU_{2,14}$	60	27,000.00	585,000	0.09
$DMU_{2,15}$	60	31,000.00	590,000	0.20
Scenario 3				
$DMU_{3,1}$	64	28,071.43	592,000	0.67
$DMU_{3,2}$	64	25,614.29	612,000	0.60
$DMU_{3,3}$	64	31,757.14	596,000	0.75
$DMU_{3,4}$	64	28,685.71	608,000	0.78
$DMU_{3,5}$	64	29,300.00	632,000	0.91
$DMU_{3,6}$	64	32,985.71	588,000	0.70
$DMU_{3,7}$	64	30,528.57	624,000	0.89
$DMU_{3,8}$	64	29,914.29	616,000	0.84
$DMU_{3,9}$	64	26228.57	600,000	0.68
$DMU_{3,10}$	64	27,457.14	628,000	0.85
$DMU_{3,11}$	64	25,000.00	620,000	0.50
$DMU_{3,12}$	64	33,600.00	604,000	0.81
$DMU_{3,13}$	64	32,371.43	640,000	0.99
$DMU_{3,14}$	64	26,842.86	636,000	0.79
$DMU_{3,15}$	64	31,142.86	644,000	1.00

Table AIV. The generated data for the moroccan public pharmaceutical supply chains operations: design indicators

DMUs	Responsiveness indicator R_1 (input 3) R'_1
Scenario 1	
DMU_1	1.25
Scenario 2	
$DMU_{2,1}$	1.11
$DMU_{2,2}$	1.11
$DMU_{2,3}$	1.11
$DMU_{2,4}$	1.11
$DMU_{2,5}$	1.11
$DMU_{2,6}$	1.11
$DMU_{2,7}$	1.11
$DMU_{2,8}$	1.11
$DMU_{2,9}$	1.11
$DMU_{2,10}$	1.11
$DMU_{2,11}$	1.11
$DMU_{2,12}$	1.11
$DMU_{2,13}$	1.11
$DMU_{2,14}$	1.11
$DMU_{2,15}$	1.11
Scenario 3	
$DMU_{3,1}$	1.136
$DMU_{3,2}$	1.136
$DMU_{3,3}$	1.136
$DMU_{3,4}$	1.136
$DMU_{3,5}$	1.136
$DMU_{3,6}$	1.136
$DMU_{3,7}$	1.136
$DMU_{3,8}$	1.136
$DMU_{3,9}$	1.136
$DMU_{3,10}$	1.136
$DMU_{3,11}$	1.136
$DMU_{3,12}$	1.136
$DMU_{3,13}$	1.136
$DMU_{3,14}$	1.136
$DMU_{3,15}$	1.136

Table AV. The data for the Moroccan public pharmaceutical supply chains operations: responsiveness indicator

DMUs	The generated latin hypercube samples for the effectiveness indicators E_1	E_2	E_3	E_4	Aggregated effectiveness based metric (output 1) ($\alpha = 0.5$): (Eq. 2)
Scenario 1					
DMU_1	0.80	0.750	0.900	0.800	0.00
Scenario 2					
$DMU_{2,1}$	0.92	0.817	0.911	0.830	0.61
$DMU_{2,2}$	0.92	0.842	0.912	0.780	0.50
$DMU_{2,3}$	0.92	0.828	0.918	0.800	0.65
$DMU_{2,4}$	0.92	0.850	0.907	0.840	0.57
$DMU_{2,5}$	0.92	0.810	0.910	0.797	0.58
$DMU_{2,6}$	0.92	0.814	0.901	0.810	0.52
$DMU_{2,7}$	0.92	0.835	0.917	0.818	0.67
$DMU_{2,8}$	0.92	0.821	0.914	0.814	0.64
$DMU_{2,9}$	0.92	0.807	0.905	0.827	0.55
$DMU_{2,10}$	0.92	0.800	0.915	0.792	0.53
$DMU_{2,11}$	0.92	0.846	0.904	0.788	0.54
$DMU_{2,12}$	0.92	0.825	0.902	0.822	0.53
$DMU_{2,13}$	0.92	0.839	0.900	0.784	0.50
$DMU_{2,14}$	0.92	0.803	0.908	0.805	0.58
$DMU_{2,15}$	0.92	0.832	0.920	0.835	0.69
Scenario 3					
$DMU_{3,1}$	0.90	0.896	0.934	0.807	1.00
$DMU_{3,2}$	0.90	0.871	0.927	0.871	0.72
$DMU_{3,3}$	0.90	0.864	0.928	0.850	0.72
$DMU_{3,4}$	0.90	0.857	0.925	0.864	0.68
$DMU_{3,5}$	0.90	0.853	0.937	0.900	0.86
$DMU_{3,6}$	0.90	0.867	0.922	0.892	0.72
$DMU_{3,7}$	0.90	0.850	0.938	0.828	0.86
$DMU_{3,8}$	0.90	0.875	0.935	0.835	0.82
$DMU_{3,9}$	0.90	0.885	0.920	0.878	0.69
$DMU_{3,10}$	0.90	0.889	0.921	0.814	0.67
$DMU_{3,11}$	0.90	0.892	0.924	0.842	0.72
$DMU_{3,12}$	0.90	0.860	0.930	0.800	0.60
$DMU_{3,13}$	0.90	0.882	0.931	0.885	0.80
$DMU_{3,14}$	0.90	0.878	0.940	0.857	0.89
$DMU_{3,15}$	0.90	0.900	0.932	0.821	0.81

Table AVI.
The data for the Moroccan public pharmaceutical supply chains operations: effectiveness indicators

DMUs	Aggregated input	Actual value	Target value
Scenario 1			
DMU_1	Aggregated cost based metric	1.00	0.000
	Aggregated design metric	0.50	0.000
	Responsiveness metric	1.25	0.000
Scenario 2			
$DMU_{2,1}$	Aggregated cost based metric	0.28	
	Aggregated design metric	0.00	
	Responsiveness metric	1.11	
$DMU_{2,2}$	Aggregated cost based metric	0.17	0.113
	Aggregated design metric	0.18	0.123
	Responsiveness metric	1.11	0.761
$DMU_{2,3}$	Aggregated cost based metric	0.20	
	Aggregated design metric	0.01	
	Responsiveness metric	1.11	
$DMU_{2,4}$	Aggregated cost based metric	0.16	0.127
	Aggregated design metric	0.16	0.127
	Responsiveness metric	1.11	0.886
$DMU_{2,5}$	Aggregated cost based metric	0.08	
	Aggregated design metric	0.01	
	Responsiveness metric	1.11	
$DMU_{2,6}$	Aggregated cost based metric	0.18	0.091
	Aggregated design metric	0.41	0.250
	Responsiveness metric	1.11	0.676
$DMU_{2,7}$	Aggregated cost based metric	0.18	0.119
	Aggregated design metric	0.40	0.316
	Responsiveness metric	1.11	0.877
$DMU_{2,8}$	Aggregated cost based metric	0.16	0.126
	Aggregated design metric	0.30	0.242
	Responsiveness metric	1.11	0.896
$DMU_{2,9}$	Aggregated cost based metric	0.14	0.093
	Aggregated design metric	0.34	0.232
	Responsiveness metric	1.11	0.759
$DMU_{2,10}$	Aggregated cost based metric	0.09	0.061
	Aggregated design metric	0.36	0.247
	Responsiveness metric	1.11	0.762
$DMU_{2,11}$	Aggregated cost based metric	0.18	0.144
	Aggregated design metric	0.08	0.063
	Responsiveness metric	1.11	0.880
$DMU_{2,12}$	Aggregated cost based metric	0.00	
	Aggregated design metric	0.19	
	Responsiveness metric	1.11	
$DMU_{2,13}$	Aggregated cost based metric	0.26	0.114
	Aggregated design metric	0.22	0.145
	Responsiveness metric	1.11	0.733
$DMU_{2,14}$	Aggregated cost based metric	0.19	0.158
	Aggregated design metric	0.09	0.075
	Responsiveness metric	1.11	0.932
$DMU_{2,15}$	Aggregated cost based metric	0.11	0.108
	Aggregated design metric	0.20	0.194
	Responsiveness metric	1.11	1.081

(*continued*)

Table AVII. Aggregated inputs targets for the inefficient DMUs according to the input oriented CCR model (long term)

DMUs	Aggregated input	Actual value	Target value
Scenario 3			
$DMU_{3,1}$	Aggregated cost based metric	0.1243	
	Aggregated design metric	0.6700	
	Responsiveness metric	1.1360	
$DMU_{3,2}$	Aggregated cost based metric	0.21	0.099
	Aggregated design metric	0.60	0.447
	Responsiveness metric	1.13	0.848
$DMU_{3,3}$	Aggregated cost based metric	0.34	0.089
	Aggregated design metric	0.75	0.482
	Responsiveness metric	1.13	0.817
$DMU_{3,4}$	Aggregated cost based metric	0.21	0.084
	Aggregated design metric	0.78	0.455
	Responsiveness metric	1.13	0.772
$DMU_{3,5}$	Aggregated cost based metric	0.31	0.106
	Aggregated design metric	0.91	0.576
	Responsiveness metric	1.13	0.977
$DMU_{3,6}$	Aggregated cost based metric	0.34	0. 089
	Aggregated design metric	0.70	0.482
	Responsiveness metric	1.13	0.817
$DMU_{3,7}$	Aggregated cost based metric	0.10	0.097
	Aggregated design metric	0.89	0.551
	Responsiveness metric	1.13	1.052
$DMU_{3,8}$	Aggregated cost based metric	0.35	0.101
	Aggregated design metric	0.84	0.549
	Responsiveness metric	1.13	0.931
$DMU_{3,9}$	Aggregated cost based metric	0.34	0.085
	Aggregated design metric	0.68	0.462
	Responsiveness metric	1.13	0.783
$DMU_{3,10}$	Aggregated cost based metric	0.35	0.083
	Aggregated design metric	0.85	0.448
	Responsiveness metric	1.13	0.761
$DMU_{3,11}$	Aggregated cost based metric	0.38	0.113
	Aggregated design metric	0.50	0.394
	Responsiveness metric	1.13	0.895
$DMU_{3,12}$	Aggregated cost based metric	0.23	0.074
	Aggregated design metric	0.81	0.402
	Responsiveness metric	1.13	0.681
$DMU_{3,13}$	Aggregated cost based metric	0.40	0.099
	Aggregated design metric	0.99	0.536
	Responsiveness metric	1.13	0.908
$DMU_{3,14}$	Aggregated cost based metric	0.41	0.110
	Aggregated design metric	0.79	0.596
	Responsiveness metric	1.13	1.011
$DMU_{3,15}$	Aggregated cost based metric	0.34	0.100
	Aggregated design metric	1.00	0.542
	Responsiveness metric	1.13	0.920

Table AVII.

About the authors

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