Proposed Performance Evaluation Framework For Assessing and providing Approximate Dimensioning of Supply Chains: Case Study Of Public Pharmaceutical Products Supply Chains

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Abstract

Evaluating the performance of supply chains is a difficult task due to the complexity inherent to the size and the structure of the supply chain. This paper presents a framework for evaluating and providing approximate dimensioning for supply chains. The framework is based on Data Envelopment Analysis (DEA) as a dynamic tool for measuring the relative technical, pure technical and scale efficiencies of a supply chain. The objectives of this study were (a) to construct a set of aggregated indicators that best characterize the performance of supply chains (b) to estimate the relative technical, pure technical and scale efficiencies of supply chains and interpret the results, (c) to estimate the magnitudes of input adjustments that would have been required to make each supply chain efficient, and finally (d) to propose an experimental approach to provide an approximate dimensioning for the supply chains operations.

Keywords
Data Envelopment Analysis (DEA), Framework, technical efficiency, pure efficiency, scale efficiency, supply chain performance, experimental approach, approximate dimensioning for the supply chain operations.

1. Introduction

Supply chain performance evaluation is a very complex task the managers should undertake to take appropriate actions for continuous improvement. According to Mentzer et al. (2001), supply chain management is defined as the systemic, strategic coordination of the traditional business functions and the tactics across these business functions within a particular company and across businesses within the supply chain, for the purpose of improving the long-term performance of the individual companies and the supply chain as a whole**.** Thus an effective and efficient management of an organization's supply chain is an essential cornerstone for companies to achieve sustainable competitive advantage. Nelly et al. (1995) consider quality, time, cost and flexibility as the main measures of the performance in manufacturing. Beamon (1999) proposes a framework for measuring the performance of supply chains considering three vital components to supply chain success which are: resources measures (usually costs), outputs measures (usually customer responsiveness) and flexibility measures (system reaction to uncertainty) .In fact, the performance measurement literature tends to be various, this means that practitioners have focused on different measures to evaluate system's performance.

In this work, we investigate the supply chain performance measurement problem. Traditionally, a well-known method for measuring the efficiency was the ratio of single output to single input such as Return on sales and return on investment (Zhu 2014)**.** These measures may be used as indices to characterize the financial performance of the supply chain only and are not sufficient to evaluate overall supply chain efficiency.Another popular tools used to measure supply chain efficiency are the "spider" or "radar" diagram and the "Z" chart. These tools are very graphical in nature. However, it is inconvenient to measure the efficiency using these tools if multiple inputs and outputs have to be taken into account (Chaki et al. 2011)**.** Since, measuring supply chain efficiency is a complex task requiring more than a single criterion to be characterized. Therefore, an approach for measuring the efficiency of supply chains is extremely required.

This paper takes an opposite stance and presents a framework for evaluating and providing an approximate dimensioning for supply chains. Section 2 provides the relevant literature review and lays foundation for section 3, in which a framework for assessing the performance of several supply chains and dimensioning their resources is proposed. In section 4 an application of the proposed approach to an illustrative example of several public pharmaceutical products supply chains is provided. Finally, section 5 summarizes some concluding remarks and discusses some potential extensions of the research.

2. Data Envelopment Analysis

Data Envelopment Analysis (DEA) is a "data-oriented" approach for evaluating the efficiency of a set of peer entities called Decision-Making Units (DMUs), which convert multiple inputs into multiple outputs (Cooper et al. 2011). DEA relies on linear programming to construct a best practice frontier to which each inefficient DMUs is compared. The first model of DEA named after its developers Charnes, Cooper & Rhodes was proposed by Charnes et al. **(**1978**).** The CCR model measures the overall technical efficiency of a firm by considering that all DMUs are operating under constant return to scale. This, of course, is rather restrictive as constant return to scale doesn't always hold globally in many realistic cases. As a result, Banker, Charnes & Cooper generalized the original DEA model by suggesting the BCC model for firm's exhibiting variable return to scale (constant, increasing or decreasing return to scale) (Charnes et al. 1978)**..** Dyson et al. (2001) suggest that the sample size of DMUs should be at least twice the product of the number of inputs and the number of outputs in order to keep the discriminatory power of DEA**.** To overcome this limitation only inputs and outputs that provides the essential of the production process should be used. In order to keep the maximum information required in a minimum number of output and inputs, we suggest to use DEA to aggregate a set of indicators into one composite indicator. Section 2.4 provides more details about the proposed methodology.

2.1 Basic DEA model: CCR model

The CCR model is one of the most basic DEA models, and it has been proven that it produces good results in term of evaluating the overall efficiency of DMUs (Charnes et al. 1978)**.**
Suppose that we have n DMUs $\{DMU_j, j=1, 2,...,n\}$, which produce s outputs y_{rj} : $r=1,2,....s$, $j = 1, 2,...,n$ by consuming m inputs x_{ij} : $i = 1,2,....m$, $j = 1, 2,...,n$. Relative efficiency is defined as the ratio of total weighted outputs to the total weighted inputs. Let v_i and u_r be respectively the weights to be determined for input i and output r and v_i* and u_r* the optimal solutions for v_i and u_r. The overall technical efficiency θ_k of a selected unit k (DMU_k) is given by the following mathematical model (Cooper et al. 2011)**:**

$$\left.\begin{array}{lll} & \max \theta_k = \dfrac{\sum_{r=1}^{s} u_r y_{rk}}{\sum_{i=1}^{m} vi\, x_{ik}} & \\ \text{Subject to} & \dfrac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} vi\, x_{ij}} \le 1, \ (1 \le j \le n) & (1) \\ & u_r \ge 0 ; v_i \ge 0, \ (1 \le r \le s), (1 \le i \le m) & (2) \end{array}\right\} \quad 2.1$$

The mathematical programming problem (2.1) is equivalent to the following linear programming problem with the unique free decision variable θ:

$$\left.\begin{array}{lll} & \min \theta & \\ \text{Subject to} & \sum_{j=1}^{n} \lambda_j x_{ij} - \theta x_{ik} \le 0, \ (1 \le i \le m) & (3) \\ & \sum_{j=1}^{n} \lambda_j y_{rj} \ge y_{rk}, \ (1 \le r \le s) & (4) \\ & \lambda_j \ge 0, \ (1 \le j \le n) & (5) \end{array}\right\} \quad 2.2$$

θ^*_{CCR} is the optimal solution for the problem (2.2) and λ_j is the weight to be determined for DMU_j. A DMU is globally inefficient if the efficiency score given by the optimal value for the linear programming problems is less than one ($\theta^*_{CCR} < 1$ or $z^* < 1$). All the points with ($\theta^*_{CCR} = 1$ or $z^* = 1$) lie on the frontier. An inefficient DMU can be made more efficient by projection into the frontier.

2.2 Extension of DEA model : BCC model

The pure technical efficiency of a specific DMU_k under variable return to scale can be calculated by the following BCC model with the unique free decision variable θ (Cooper et al. 2011)**:**

$$\left.\begin{array}{lll} & \min \theta & \\ \text{Subject to} & \sum_{j=1}^{n} \lambda_j \, x_{ij} - \theta \, x_{ik} \leq 0 \;, \; (1 \leq i \leq m) & (6) \\ & \sum_{j=1}^{n} \lambda_j \, y_{rj} \geq y_{rk} \;, \; (1 \leq r \leq s) & (7) \\ & \sum_{j=1}^{n} \lambda_j = 1 \;, \; (1 \leq j \leq n) & (8) \end{array}\right\} \; 2.3$$

θ^*_{BCC} is the optimal solution for the problem (2.3). The additional constraint provides that the reference set is formed as a convex combination of DMUs. It also ensures that the composite unit is of similar scale size as the unit being measured (Martic et al. 2009).

2.3 A two stage CCR-BBC models for examinating technical, pure and scale efficiencies

The ratio of the overall technical efficiency to the pure technical efficiency is called scale efficiency (SE).

$$SE = \theta^*_{CCR} / \theta^*_{BCC} \qquad (9)$$

Overall technical efficiency measures inefficiencies due to the input/output configuration as well as the size of operations, where scale efficiency is the component of overall technical efficiency that can be attributed to the size of operations (long term) and pure technical efficiency or managerial efficiency the component that measures inefficiencies due to only managerial underperformance (short term) (Cooper et al. 2011, Kumar et al. 2008)**.**

2.4 Aggregation of indicators using DEA

This section describes a methodology based on DEA for indicators aggregation. This method is widely inspired from the seminal works by Zhou et al. (2007a,b)**.** We consider the case where there are *m* supply chains under evaluation. Suppose we have classified all the indicators into several categories and our aim is to aggregate each category into one indicator called aggregated indicator or composite indicator to evaluate the performance of supply chain i with respect to a given category.

The problem is to aggregate a set of indicators *Iij* (*j*=1,2,... *n*) into a composite indicator *Ii* that can be used to evaluate the performance of supply chain *i* with respect to all the underlying sub-indicators of a given category of indicators. DEA is used to suggest the "best" and the "worst" set of weights for each supply chain which are used to aggregate the sub-indicators into a performance score.

The following method which combines two DEA models (2.5) and (2.6) can be used. To determine the "best" vector of weights w_{ij}^g for each supply chain *i*, the following model can be formulated:

$$\left.\begin{array}{lll} & max \; gI_i = \sum_{j=1}^{n} w_{ij}^{g} \, I_{ij} & \\ \text{Subject to} & \sum_{j=1}^{n} w_{ij}^{g} \, I_{kj} \leq 1 \;, (1 \leq k \leq m) & (10) \\ & w_{ij}^{g} \geq 0 \;, (1 \leq j \leq n) & (11) \end{array}\right\} (2.4)$$

The mathematical model (2.4) is an input oriented DEA model with multiple outputs and constant inputs, which measures how far the evaluated supply chain is from the best practice category under the best possible weights. It provides an aggregated performance score for supply chain i in terms of all the underlying sub-indicators of a given category. By solving (2.4) repeatedly for each supply chain, we will obtain the optimal index gI_i^* for each supply chain i. Let $[gI_1^*, gI_2^*, ..., gI_m^*]$ be the optimal indices vector for these supply chains.

Model (2.5) determines the "worst" vector of weights w_{ij}^{b} for each supply chain *i*, it is very similar to an output oriented DEA model with multiple inputs and constant outputs:

$$\left.\begin{array}{ll} & min\ bI_i = \sum_{j=1}^{n} w_{ij}^{b}\ I_{ij} \\ \text{Subject to} & \sum_{j=1}^{n} w_{ij}^{b}\ I_{kj} \geq 1\ ,(1 \leq k \leq m) \quad (12) \\ & w_{ij}^{b} \geq 0\ ,(1 \leq j \leq n) \quad (13) \end{array}\right\} (2.5)$$

bI_i^* is the optimal solution for the problem (2.5).
The two indexes provided by (2.4) and (2.5) are based on the weights that are most favorables and least favorables for each supply chain. we can combine them into an overall index by the following way:

$$Ii(\alpha) = \alpha.\frac{gIi^{*} - gI^{-}}{gI^{+} - gI^{-}} + (1-\alpha).\frac{bIi^{*} - bI^{-}}{bI^{+} - bI^{-}} \quad (14)$$

Where:

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

$0 \leq \alpha \leq 1$ is an adjusting parameter which reflects the decision maker's preferences. If $\alpha = 1$, I_i will become a normalized version of gI_i^*. If $\alpha = 0$, I_i will become a normalized version of bI_i^*. For other cases, $I_i(\alpha)$ makes a compromise between the two indexes. If the decision maker is neutral $\alpha = 0.5$ is generally used.

3. Proposed framework for evaluating and approximately dimensioning supply chains

In order to evaluate the performance of supply chains and approximately dimensioning their resources to achieve a given level of production, we introduce the following framework (Fig.1). It's a revised and expanded version of the framework presented by Chorfi et al. (2016b). The present framework generalize the previous one and allows the evaluation of the short term and long term performance of supply chains as well as the derivation of the original inputs and outputs targets by using the computer experiment methodology described in step 6.

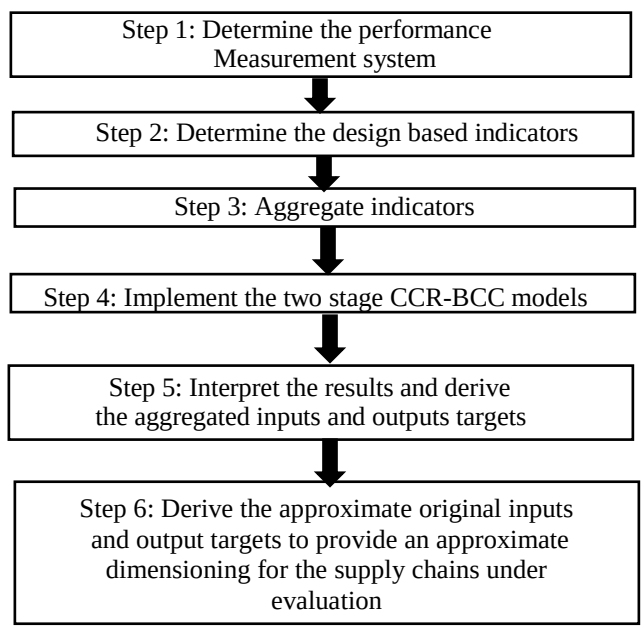

Figure 1. Proposed framework for evaluating and approximately dimensioning supply chains

Step 1: Determine the performance measurement system that best characterize the supply chain's activities. The proposed measurement system must contain both financial and non-financial indicators and align supply chain activities with the whole organization strategy.
Step 2: Complete the performance measurement system by determining the design based indicators**.** Design based indicators are measurements that are related to the design of the supply chain. They are very important to illustrate the strategic decisions made by the organizations in term of facilities and transportation. Facilities and transportation are some of the logistical drivers stated by Chopra and Meindl (2016) as key drivers of supply chain performance. Many indicators can be derived from these two logistical drivers and will be referred to as the designed based indicators.
Step 3: in this step, we suggest to classify all the indicators into several categories and then to aggregate each category into one indicator called aggregated indicator or composite indicator in order to keep the maximum information in a minimum number of inputs and outputs to maintain the discriminatory power of DEA (Dyson et al. , 2001). The resulted aggregated indicators will be used as aggregated inputs and outputs for implementing the CCR-BCC models.
Step 4: In this stage we implement the aforementioned two stage CCR-BCC models to determine the overall technical, pure technical and scale efficiencies of each supply chain with regard to other supply chains.
Step 5: While interpreting the results we can propose a short term performance actions to overcome the managerial underperformance and long term performance actions to achieve optimal scale size. An optimal scale size is identified when the CCR and BCC scores are both equal to one, we say that we are in the most productive scale size (MPSS) (Cooper et al. 2011)**.** We can also deduce the aggregated inputs and outputs targets according to the CCR model in order to take into account inefficiencies due to the input/output configuration as well as the size of operations. We can run the CCR-BCC model to the aggregated inputs and outputs targets to ensure that the resulted model is at the (MPSS).
Step 6: Derive the original inputs and outputs targets by disaggregating the aggregated indicators using the following computer experiment methodology:
Step 6.1: Modelling the problem
1- Define the response to be emulated by computer experiment design**:** The response for the problem of indicators disaggregation can be the variable I_i (α).
2- Define the input variables -original indicators- and the ranges over which they will be explored: The inputs to be determined for a given value of the output or response I_i (α) =C are the I_{ij} , j =1...n such as gI_i^* and bI_i^* calculated by the two models (2.4) and (2.5) yield $I_i(\alpha)$=C**.** The inputs ranges have to be determined by the Decision-Maker.
Step 6.2: Latin hypercube sampling
1- Choose the number of samples for constructing a space filling design by using Latin hypercube sampling. Latin hypercube sampling (LHS) is a statistical method for generating a sample or a collection of points from a multidimensional distribution (McKay et al. 1979). The choice of the number of samples depends on the researcher, but more samples will give more reliable results. If the researcher expects that his predicted error observed in the response is not negligible, then he has to choose a larger sample size.
2- Construct a space filling design for the inputs variables-original indicators- by using the Latin hypercube sampling (LHS).
Step 6.3: Response surface methodology
1- Construct a Metamodel for emulating the response Ii (α) by using the response surface methodology for computer experiment (Douglas & Montgomery, 2012), the surrogate function will be called E (I_i (α)) or R_i .
2- Determine several combinations of the inputs value I_{ij} , j =1...n that yield I_i (α) = C and choose the one with the closest real response to the predicted response E (I_i (α)) . In other words choose the combination of inputs that minimizes the error observed in the response.
For more details about the computer experiment methodology you can refer to Chorfi et al. (2016a).

4. Application to public pharmaceutical products supply chains

This chapter aims to illustrate the proposed framework for evaluating and approximately dimensioning supply chains by a case study with arbitrary generated data.

4.1 Determination of the performance measurement system

We have used an integrated performance management system to determine all the strategic performance indicators that best describe the pharmaceutical products supply chains. The list of abbreviations for the indicators included in the proposed performance measurement system is defined as follows: TSCMC, BG, CPU, ENR, IT, RLO, OFCT, SB, HSI, POF, STA, CE, CS, and TD.

4.2 Determination of the design based indicators

The design based indicators of pharmaceutical products supply chains related to facilities and transportation are defined as follows: Facilities related indicators are the total capacity and the number of facilities. Transportation related indicator is the distance traveled.

4.3 Aggregating indicators

We propose to categorize the indicators according to the following performance attributes to characterize the inputs and the outputs of DEA: The supply chain cost based indicators (Input 1), the supply chain responsiveness indicators (Input 2), the design based indicators (Input 3), and the supply chain effectiveness indicators (Output 1). By using the aforementioned DEA method for indicators aggregation. The original indicators and the aggregated indicators are listed by categories and are set out in table 2, table 3 and table 4.

4.4 Implementation of the two stages CCR-BCC models

To evaluate the performance of these supply chains, we can consider that each supply chain being evaluated corresponds to a DMU. By this, let's say that DMU (i) = supply chain (i). The aggregated indicators will be used as inputs and outputs of DEA for evaluating the performance of supply chains:
Aggregated inputs indicators: The aggregated cost based indicator, the responsiveness indicator, and the aggregated design indicator.
Aggregated output indicator: The aggregated effectiveness indicator.
The global results obtained by applying the input oriented CCR-BCC models are summarized in the table 1.

4.5 Interpretation of the results and derivation of the aggregated inputs targets

The average efficiency score obtained through the BCC model is higher than that of the CCR model with the average score being 0.922 which means that the management performance of the different Pharmaceutical products supply chains (wise management and employees' engagement) is relatively performant with regards to the size of operations.

The overall sample average BCC technical efficiency (pure technical efficiency) score was 92.2%, meaning that inefficient DMUs could on average reduce by 7.8 % their inputs without changing their current output level. The managers are likely to focus first on removing the managerial inefficiency of these supply chains in the short term without changing the scale of operations. However, the majority of inefficiency is due to the small size of operations, that is, IRS, then these DMUs will need to plan for expansion (Cooper et al. 2011).

Moreover, an average scale efficiency of 89.2 % suggests a great potential to upsize the sector. Expansion can be achieved for example by acquisition and/or mergers within different parts of the supply chains. Three supply chains (DMU1, DMU2 and DMU6) had a scale efficiency of 100% meaning that they were at the optimal size for their particular input/output configuration, meaning that increasing their inputs by a given proportion would result in an increase in their health service outputs by the same proportion. This means that they were operating at their most productive scale sizes (MPSS).The remaining supply chains had scale efficiency scores of less than 100% and were thus deemed scale inefficient. Increasing returns to scale in the three supply chains (DMU3, DMU4 and DMU5), means that increasing their inputs by a given proportion would result in an increase in their health service outputs by a greater proportion. Thus, these DMUs would have needed to increase their size to achieve optimal scale (the region at which there are constant returns to scale in the relationship between inputs and outputs). The long term aggregated inputs targets for individual supply chains (after removing the scale and managerial inefficiencies) are obtained by the CCR model and are set out in Table 5.

Table 1. The efficiency summary of the public pharmaceutical products supply chains.

Supply chains	CCR efficiency	BCC efficiency	SE	Return to scale
DMU1	1,000	1,000	1,000	CRS
DMU2	1,000	1,000	1,000	CRS
DMU3	0,862	1,000	0,862	IRS
DMU4	0,293	0,532	0,552	IRS
DMU5	0,936	1,000	0,936	IRS
DMU6	1,000	1,000	1,000	CRS
Mean	**0,849**	**0,922**	**0,892**	-

Table 2. The Data of the public pharmaceutical products supply chains operations: Cost based indicators

DMUs	Cost based indicators						Aggregated cost based indicator
	TSCMC	BG	CPU	ENR	IT	RLO	
DMU1	19000000	0,05	9,5	16	0,65	0,012	0,500
DMU2	20000000	0	10	15	0,59	0,024	0,500
DMU3	21000000	0,05	10,5	12	0,48	0,025	0,500
DMU4	22000000	0,1	11	13	0,88	0,032	0,937
DMU5	23000000	0,15	11,5	9	0,77	0,014	0,500
DMU6	24000000	0,2	12	10	0,64	0,019	0,696

Table 3. The Data of the public pharmaceutical products supply chains operations: Responsiveness and Design indicators

DMUs	Responsiveness indicator	Design indicators			Aggregated design indicator
	OFCT	Number of facilities	Total storage capacity	Distance traveled	
DMU1	1	1285	24,8	703005	0,500
DMU2	2	1234	30,4	569000	0,286
DMU3	3	1214	28,4	656000	0,722
DMU4	4	1254	34,2	590000	1,000
DMU5	5	1265	25,4	601000	0,384
DMU6	6	1200	27,5	600000	0,000

Table 4. The Data of the public pharmaceutical products supply chains operations: Effectiveness indicators

DMUs	Effectiveness indicators							Aggregated effectiveness indicator
	SB	HSI	POF	STA	CE	CS	TD	
DMU1	15896000	4,7	0,75	0,98	0,97	0,77	5,9	0,577
DMU2	14004000	4,2	0,97	0,87	0,89	0,88	6	0,500
DMU3	16000014	5,4	0,96	0,85	0,74	0,85	7	0,500
DMU4	15105477	3,9	0,78	0,90	0,91	0,89	1	0,318
DMU5	10006800	5,6	0,94	0,72	0,90	0,92	9	0,500
DMU6	16010024	4,6	0,84	0,79	0,98	0,9	11	0,528

Table 5. Aggregated inputs targets for the inefficient DMUs according to the input oriented CCR model (long term)

DMUs	Aggregated input	Actual value	Target value
DMU1	Aggregated cost based indicator	0,500	0,5
	Responsiveness indicator	1	1
	Aggregated design indicator	**0,500**	0,5
DMU2	Aggregated cost based indicator	0,500	0,5
	Responsiveness indicator	2	2
	Aggregated design indicator	**0,290**	0,29
DMU3	Aggregated cost based indicator	0,500	0,431
	Responsiveness indicator	3	0,862
	Aggregated design indicator	**0,720**	0,431
DMU4	Aggregated cost based indicator	0,936	0,276
	Responsiveness indicator	4	0,552
	Aggregated design indicator	**1**	**0,276**
DMU5	Aggregated cost based indicator	0,500	0,468
	Responsiveness indicator	5	1,471
	Aggregated design indicator	**0,384**	0,356
DMU6	Aggregated cost based indicator	0,700	0,7
	Responsiveness indicator	6	6
	Aggregated design indicator	**0**	0

4.6 Approximate dimensioning of the supply chains operations

This section aims to derive the approximate original inputs for DMU4 with regard to the targeted value of the aggregated design indicator by using the aforementioned computer experiment methodology (step 6).

A. Modelling the problem

Suppose we have 6 supply chains under evaluation called Decision-making units (DMUs), each DMU has 3 sub-indicators aggregated into one composite index by using the aforementioned DEA methodology for indicators aggregation. We aim to find one combination of sub-indicators I_{7j} (j=1..3) for a fictional supply chain 7 such as the composite index I_7 (0,5) =0,276 .

The response for the problem is taken to be I_7 (0,5). Let's put R_1=E(I_7(0,5)) the approximate function of I_7 (0,5). The response function can be expressed as I_7 (0,5) = f (I_{71}, I_{72}, I_{73}) where function f is known but has no analytic expression. For this example the inputs values are taken to be (I_{71}, I_{72}, I_{73}).

The inputs and the output values for running computer experiment are illustrated in Table 6.

In this example we want to predict the relationships between the inputs variables (I_{71}, I_{72}, I_{73}) and the response I_7 (0,5) and to find one inputs-combination (I_{71}, I_{72}, I_{73}) minimizing the error observed in the response. The response target is I_7 (0,5)=0,276

Table 6. The original and the aggregated design based indicators for supply chains

	Number of facilities (I_{i1})	**Total storage capacity (I_{i2})**	**Distance traveled (I_{i3})**	**I_i(0,5)**
DMU_1	24,8	1285	703005	0,5
DMU_2	30,4	1234	569000	0,29
DMU_3	28,4	1214	656000	0,72
DMU_4	34,2	1254	590000	1
DMU_5	25,4	1265	601000	0,384
DMU_6	27,5	1200	600000	0
DMU_7	**?**	**?**	**?**	**0,276**

B. Latin hypercube sampling

Suppose, the inputs for our computer experiment design are varying in the following ranges:

I_{71} = A = [24, 35]

I_{72} = B = [1200, 1285]

I_{73} = C = [569000, 703005]

In this study, we have decided to study 30 samples in the Latin hypercube sampling (LHS).

C. Response surface modeling for computer experiments

After constructing a space filling design by using LHS, the resulting data is used to construct response surface approximation models using regression analysis.

The results from a statistical software for fitting the response I_7 (0,5) according to the inputs variables (I_{71}, I_{72}, I_{73}) are addressed in Table 7 and Table 8.

Table 7. Summary statistics for the response R_1

Model Summary Statistics

Source	Std. Dev.	R-Squared	Adjusted R-Squared	Predicted R-Squared	PRESS	
Linear	0,20	0,8808	0,8670	0,8459	1,34	
2FI	0,19	0,9082	0,8843	0,8611	1,21	
Quadratic	0,13	0,9582	0,9394	0,9148	0,74	Suggested
Cubic	0,13	0,9820	0,9479	0,8336	1,45	
Quartic					+	Aliased

Table 8. Parameter estimates for the response R_1

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	8,34	9	0,93	50,97	< 0.0001	significant
A-A	*2,38*	*1*	*2,38*	*131,08*	*< 0.0001*	
B-B	*3,27*	*1*	*3,27*	*179,73*	*< 0.0001*	
C-C	*1,01*	*1*	*1,01*	*55,72*	*< 0.0001*	
AB	*0,22*	*1*	*0,22*	*12,20*	*0,0023*	
AC	*0,053*	*1*	*0,053*	*2,93*	*0,1022*	
BC	*0,045*	*1*	*0,045*	*2,48*	*0,1312*	
A^2	*0,32*	*1*	*0,32*	*17,73*	*0,0004*	
B^2	*7,982E-003*	*1*	*7,982E-003*	*0,44*	*0,5153*	
C^2	*0,22*	*1*	*0,22*	*11,88*	*0,0026*	
Residual	0,36	20	0,018			
Cor Total	8,71	29				

The R squared gives information about the goodness of fit of a model. It measures how well the regression line approximates the real data points. An *R* squared of 1 indicates that the regression line perfectly fits the data. Notice that the quadratic model fit nicely our response R_1.The difference between ‘‘predicted R-squared’’ and the ‘‘adjusted R-squared’’ is less than 0.2 which means that they are in reasonable agreement.

Based on the above analysis, table 8 shows that there are many insignificant terms (Those with p-value inferior or equal to the level of significance α=0,05). In this case A, B, C, AB, A^2, C^2 are the only significant model terms. The parameter estimates for the reduced model (without insignificant terms) are shown in table 9.

Table 9. Parameter estimates for the reduced model of 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	8,22	6	1,37	65,14	< 0.0001	significant
A-A	*2,35*	*1*	*2,35*	*111,80*	*< 0.0001*	
B-B	*3,35*	*1*	*3,35*	*159,31*	*< 0.0001*	
C-C	*1,03*	*1*	*1,03*	*48,88*	*< 0.0001*	
AB	*0,25*	*1*	*0,25*	*11,88*	*0,0022*	
A^2	*0,31*	*1*	*0,31*	*14,71*	*0,0008*	
C^2	*0,17*	*1*	*0,17*	*8,11*	*0,0091*	
Residual	0,48	23	0,021			
Cor Total	8,71	29				

The software provides a difference between the predicted R-squared=0,9083 and the adjusted R-squared= 0,9299 for the reduced model less than 0.2 which means that the reduced model can be used to navigate the design space.
The software also provides a model to predict the response I_7 (0,5) called R_1 over the experimental region by keeping only the significant model terms, the prediction equation is:

$$R_1= -114936{,}63*10^{-4} -65720{,}39*10^{-5}\ A-198{,}56*10^{-4}\ B+7397{,}46*10^{-8}\ C+112412{,}34*10^{-8}\ AB-110744567{,}21*10^{-10}A^2 -5{,}45*10^{-11}\ C^2 \quad (15)$$

In order to find the inputs combinations that target a single response subject to upper and lower boundaries on the inputs we have used an experimental design and optimization software. The software provides several combinations

of the inputs values (I_{71}, I_{72}, I_{73}) such as the predicted response of I_7 (0,5) is equal to 0,276 we choose the one with the closest real response to the predicted response.
We find that the input combination I_{71}=33,1; I_{72}=1218,19 and I_{73}=575309 gives a real response I_7(0,5) of 0,251 while the expected response is equal to 0,276 which yields an error of 0,025

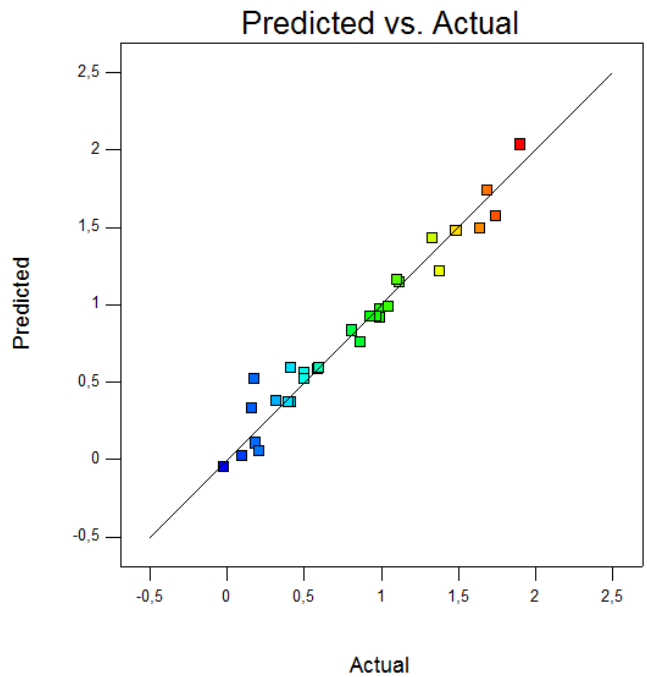

Figure 2. Accuracy of prediction for the response I_7 (0,5)

To see the importance of the prediction, the predicted response was run in several random points over the inputs design range. Figure 2 shows that predictions match well with the real response.
We can improve our results by increasing the Latin hypercube sample size in order to extend our prediction over more design points.

5. Conclusion

The overarching objectives of this research are to propose a framework for assessing and providing approximate dimensioning of Supply Chains.The outcome of this study will assist the supply chains managers in comparing their supply chains against peers and dimensioning their resources to achieve a given level of productions. Data envelopment analysis is first used to aggregate a set of performance indicators into one composite indicator and then to measure the relative technical, pure technical and scale efficiencies of supply chains. Decomposing technical efficiency scores into pure technical efficiency and scale efficiency provides guidance on what can be achieved in the short and long term. The efficiency scores have been calculated under Constant Return to Scale (CRS) and Variable Return to Scale (VRS) with an input orientation which aims to reduce the amount of inputs for a given level of outputs.Finally the proposed approach allows the derivation of the aggregated inputs and outputs targets and then the derivation of the original inputs and outputs targets by using computer experiment.
These results show that, the proposed experimental approach can approximately help Decision-makers disaggregate one composite indicator into several underlying indicators by the mean of prediction. Thus, it provides only an approximate dimensioning for the supply chains operations. Hence future researches are needed to overcome this shortcoming.

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