Measuring Supply Chain Efficiency and Congestion

Mithun J. Sharma, and Song Jin Yu, *Member, IAENG*

***Abstract*— This paper examines the efficiency of supply chain keeping the essence of processes that knits the stages of supply chain. In order to enhance and extend the variation of data envelopment analysis (DEA) methodology, this paper serves to supplement the DEA literature in its application to supply chain efficiency measurement. In addition an examination of input congestion is carried out indicates that a managerial inefficiency exist in the different process cycles of supply chains. However, presence of congestion indicates the inability to dispose of unwanted inputs without incurring cost. Using the DEA variation, supply chains are partitioned into three levels/stratums namely 'best-in-class', 'average' and 'laggard'. Substantial performance inefficiency is uncovered in the four process cycle dimensions. Relatively, down-stream process cycles of the supply chain exhibit better performance than the up-stream process cycles. The classification of supply chains serve as a guideline for best practices, and projects directly to the best-in-class.**

***Index Terms*— supply chain; efficiency; DEA; congestion; process cycles**

I. INTRODUCTION

THE measurement of efficiency and congestion of a supply chain is crucial to increase co-ordination both across firms and within firms which are members of the chain. Supply chain is a combined system which comprises planning, sourcing, making and development of processes with its constituent parts to include material suppliers, production facilities, distribution centers and customers linked together through the feed forward flow of material as well as feedback flow of information [1]. A typical firm consists of separate departments which manages the different aspects of the supply chain. For instance, purchasing takes care of the suppliers and raw materials inventory, operations takes care of manufacturing and work-in-process inventory and marketing manages demand and finished goods inventory. When these departments lack coordination, there are dramatic effects on supply chain within the firm as well as outside the firm. Thus measuring supply chain performance is the first step towards improvement.

Performance measurement plays an essential role in evaluating production because it can define not only the current state of the system but also its future. According to Dyson [2], performance measurement helps move the system in the desired direction through the effect exerted by the behavioral responses towards these performance measures that exist within the system. Mis-specified performance measures, however, will cause unintended consequences, with the system moving in the wrong direction [2]. The underlying assumption behind this claim is the role or presence of drivers such as efficiency and effectiveness in the composition of performance. To put it in a simple way, efficiency in Dyson's [2] claim is 'doing things right' and effectiveness is 'doing the right thing'. The combination of these two key drivers helps move the system in the right direction by doing the right thing.

The efficiency is determined by using a variation of frontier estimation especially data envelopment analysis (DEA) amidst multiple inputs and outputs. In particular, DEA methodology has proved to be powerful for benchmarking and identifying efficient frontiers especially for single producers or decision making units (DMU). Literature reviews, such as the excellent bibliography in Seiford, [3] reveal that research examining the use of mathematical programming and associated statistical techniques to aid decision-making in supply chain benchmarking is lacking. Liang et al. [4] points out that traditionally most models (deterministic and stochastic) dealt with isolated parts of supply chain systems. Liang et al. [4] developed a Stackelberg co-operative model to evaluate the efficiency of SC members using DEA but their study was neither empirical nor showed any relationship of co-operation among members. An empirical study to evaluate the efficiency of whole supply chain was done by Reiner and Hoffman [5]. They tried to evaluate the processes in a supply chain using the performance measure of SCOR [6]; however they considered various processes of a single supply chain instead of multiple chains. This leaves us with a literature gap and a question on how to measure the performance of supply chain considering each supply chain as meta-DMU. Research is required to find out how to measure the efficiency of a supply chain keeping an eye on key performance metrics that can cover all the interfaces in a supply chain.

Some researchers have tried to evaluate the chain in a serial order while others have tried to use a single performance measure [7]. Some others like Chen and Zhu [8] have provided two approaches in modeling efficiency as a two-stage process. Golany et al. [9] provided an efficiency measurement framework for systems composed of two subsystems arranged in series that simultaneously compute the efficiency of the aggregate system and each subsystem. Zhu [10], on the other hand, presented a DEA-based supply chain model to define and measure the efficiency of a supply chain and that of its members. Fare and Grosskopf [11] and Castelli et al. [12] introduced the network DEA

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model, in which the interior structure of production units can be explicitly modeled.

However, a supply chain is a sequence of processes and flows that take place within and between different stages and combine to fill a customer need for a product. The objective of every supply chain is to maximize the overall value generated. The value a supply chain generates is the difference between what the final product is worth to the customer and the effort the supply chain expends in filling the customer's request. For most commercial supply chains, value will be strongly correlated with *supply chain profitability*. *Supply chain profitability* is the total profit shared across all the supply chain stages [14]. All the above mentioned studies evaluated supply chain in stages ignoring the essence of processes that knits the stages of supply chain. By focusing on the process as the unit of analysis, the management of inter-organizational relations in a way which is generally known as network, on performance is analyzed.

In order to enhance and extend the variation of DEA methodology this paper serves to supplement the DEA literature in its application to supply chain. This chapter extends the work published in WCE [14] and proposes a model to evaluate the overall supply chain efficiency. Using the DEA variation of Sharma and Yu [15], the supply chains are partitioned into three levels/stratums namely 'best-in-class', 'average' and 'laggard' [16]. In addition, an examination of input congestion is carried out indicates that a managerial inefficiency [17] exist in 'average' and 'laggard' supply chains. By simply reconfiguring these excess resources it may be possible to increase output without reducing the inputs. Equipped with this knowledge, managers will be better able to determine when large reengineering projects are necessary versus minor adjustments to existing business processes. The object oriented DEA models to classify and measure efficiency and congestion of supply chains are discussed in section II, followed by identifying inputs and outputs of each process cycle of supply chain and the resulting empirical findings in Section III. Finally, Section IV summarizes and concludes the chapter.

II. DEA SUPPLY CHAIN MODELS

A. *DEA Supply Chain Efficiency Models*

There are some issues related to measuring the efficiency of a supply chain using DEA. The first is that supply chain operations involve multiple inputs and outputs of different forms at different stages and second is that the performance evaluation and improvement actions should be coordinated across all levels of production in a supply network. In this chapter, we evaluate supply chain stages in process cycles keeping the essence of processes that knits the stages of supply chain. By focusing on the process as the unit of analysis, the management of inter-organizational relations in a way which is generally known as network, on performance will be analyzed.

DEA models are classified with respect to the type of envelopment surface, the efficiency measurement and the orientation (input or output). There are two basic types of envelopment surfaces in DEA known as constant returns-to-scale (CRS) and variable returns-to-scale (VRS) surfaces. Each model makes implicit assumptions concerning returns-to-scale associated with each type of surface. Charnes et al. [18] introduced the CCR or CRS model that assumes that the increase of outputs is proportional to the increase of inputs at any scale of operation. Banker et al. [19] introduced the BCC or VRS model allowing the production technology to exhibit increasing returns-to-scale (IRS) and decreasing returns-to-scale (DRS) as well as CRS.

A common approach to evaluate supply chain in particular two stage DEA is that the first stage uses inputs to generate outputs that then become the inputs to the second stage. The second stage thus utilizes these first stage outputs to produce its own outputs under CRS and VRS assumptions [20], [21]. However, a supply chain is a sequence of processes and flows that take place within and between different stages and combine to fill a customer need for a product with an objective to maximize the overall value of the supply chain. Previous studies evaluated supply chain in stages ignoring the essence of processes that knits the stages of supply chain. Therefore evaluating supply chain processes and sub processes will help to effectively analyze supply chain as a whole. A detailed description of supply chain processes along with inputs and outputs of each process cycles are discussed in [14].

The BCC Supply Chain Model

The input-oriented BCC model evaluates the efficiency of DMU_o $(o = 1,\dots\dots, n)$ by solving the following envelopment form: (BCC_o)

$$Min_{\theta_B,\lambda}\theta_B$$

Subject to,
$$\theta_B x_o - X\lambda \geq 0$$
$$Y\lambda \geq 0$$
$$e\lambda \geq 0$$

Where θ_B is a scalar.

The dual multiplier form of this linear program *(BCC_o)* is expressed as

$$Max_{v,\ u,\ u_o} z = uy_o - u_o$$

Subject to
$$vx_o = 1$$
$$-vX + uY - u_o e \leq 0$$

$v \geq 0,\ \ u \geq 0,$ and u_o free in sign,

Where, v and u are vectors and z and $u_o e$ are scalars and the latter, being 'free in sign', may be positive or negative or zero. The equivalent BCC fractional program is obtained from the dual program as:

$$Max\frac{uy_o - u_o}{vx_o}$$

Subject to $\frac{uy_j - u_o}{vx_j} \leq 1 \ \ (j = 1, \dots., n)$

$v \geq 0,\ \ u \geq 0,$ and u_o free.

The primal problem *(BCC_o)* is solved using two-phase procedure. In the first phase, we minimize θ_B and, in the second phase, we minimize the sum of the input excesses and output shortfalls, keeping $\theta_B = \theta_B^*$. An optimal solution for *(BCC_o)* is represented by $\theta_B^*, \lambda^*, s^{-*},\ s^{+*}$, where s^{-*} and s^{+*} represent the maximal input excesses and output shortfalls, respectively.

BCC-Efficiency: If an optimal solution $\theta_B^*, \lambda^*, s^{-*},\ s^{+*}$ obtained in this two phase process for *(BCC_o)* satisfies

$$\theta_B = 1$$

And has no slacks ($s^{-*} = 0\ and\ \ s^{+*} = 0$), then the DMU_o, we define its reference set, E_o, based on an optimal solution λ^* by

$$E_o = \{j|\lambda_j^* \geq 0\}\ \ (j \in \{1, \dots\dots, n\})$$

If there are multiple optimal solutions, we can choose any one to find that

$$\theta_B^* x_o = \sum_{j\in E_o} \lambda_j^* x_j + s^{-*}$$
$$y_o = \sum_{j\in E_o} \lambda_j^* y_j - s^{+*}$$

Thus the improvement path via the BCC projection,

$$\hat{x}_o \Leftarrow \theta_B^* x_o - s^{+*}\ ;\ \hat{y}_o \Leftarrow y_o + s^{+*}$$

The above VRS setting is proposed for a single process of supply chain. In Kao and Hwang [20] model to measure the two-stage processes, they combine the processes in a multiplicative (geometric) manner. In our proposed VRS model we combine the processes in an arithmetic mean approach since the processes are interlinked and not independent. The same averaging method is applied to CCR model.

Input congestion supply chain model

Congestion is said to occur when the output that is maximally possible can be increased by reducing one or more inputs without improving any other input or output. Conversely, congestion is said to occur when some of the outputs that are maximally possible are reduced by increasing one or more inputs without improving any other input or output. For example, excess inventory cluttering a factory floor in a way that interferes with production. By simply reconfiguring this excess inventory it may be possible to increase output without reducing inventory. This improvement represents the elimination of inefficiency that is caused by the way excess inventory is managed. There are many models dealing with congestion but we start with FGL (Fare, Grosskopf and Lovell [22], [23]) because it has been the longest standing and most used approach to congestion in the DEA literature. Fare, Grosskopf and Lovell (FGL) approach proceeds in two stages. The first stage uses an input oriented model as follows (Fare et al. [23]):

$$\theta^* = min\theta$$

Subject to

$$\theta x_{io} \geq \sum_{j=1}^{n} x_{ij}\lambda_{j,}\ \ i = 1,2,\ldots,m \qquad (1)$$
$$y_{ro} \leq \sum_{j=1}^{n} y_{rj}\lambda_{j,}\ \ r = 1,2,\ldots.,s$$
$$\lambda_j \geq 0, \qquad j = 1,2,\ldots.,n$$

Where $j = 1,2,\ldots.,n$ indexes the set to DMUs (decision making units) of interest. Here is the observed amount of input $i = 1,2,\ldots,m$ used by DMU_j and y_{ro} is the observed amount of output $r = 1,2,\ldots.,s$ associated with DMU_o is the $DMU_j = DMU_o$ to be evaluated relative to all DMU_j (including itself). The objective is to minimize all the inputs DMU_o in the proportion θ^* where, because the $x_{io} = x_{ij}$ and $y_{ro} = y_{rj}$ for $DMU_j = DMU_o$ appear on both sides of the constraints, the optimal $\theta = \theta^*$ does not exceed unity and the non-negativity of the λ_j, x_{ij}, and y_{rj} implies that the value of θ^* will not be negative under the optimization in (1). Hence,

$$0 \leq min\theta = \theta^* \leq 1 \qquad (2)$$

We now have the following definition of technical efficiency and inefficiency.

Technical efficiency is achieved by DMU_o if and only if $\theta^* = 1$

Technical inefficiency is present in the performance of DMU_o if and only if $0 \leq \theta^* \leq 1$.

Next, FGL then go on to the following second stage model,

$$\beta^* = min\beta$$

Subject to $x_{io} = \sum_{j=1}^{n} x_{ij}\lambda_{j,}\ \ i = 1,2,\ldots,m$ (3)

$$y_{ro} \leq \sum_{j=1}^{n} y_{rj}\lambda_{j,}\ \ r = 1,2,\ldots.,s$$
$$\lambda_j \geq 0, \qquad j = 1,2,\ldots.,n$$

Note that the first $i = 1,2,\ldots,m$ inequalities in (1) are replaced by equation (3). Thus slack is not possible in the inputs. The fact that only the output can yield non-zero slack is then referred to as weak disposal by Fare et. al., [22]. Hence, we have $0 = \theta^* \leq \beta^*$. FGL use this property to develop a measure of congestion,

$$0 \leq C(\theta^*, \beta^*) = \frac{\theta^*}{\beta^*} \leq 1 \qquad (4)$$

Combining model (1) and (3) in a two-stage manner, FGL utilizes this measure to identify congestion in terms of the following conditions,

(i) Congestion is identified as present in the performance of DMU_o if and only if

$$C(\theta^*, \beta^*) < 1 \qquad (5)$$

(ii) Congestion is identified as not present in the performance of DMU_o if and only if

$$C(\theta^*, \beta^*) = 1$$

Our proposed congestion model will use arithmetic mean of the congestion scores of each process cycle to check the presence or absence of congestion in the overall supply chain θ^{o*}/β^{o*}.

Supply chain classification model

Classification of supply chain is required to standardize the sets of efficient and inefficient supply chains for step-wise improvement, otherwise not possible with the traditional DEA. To classify the set of supply chains, we modify the algorithm developed by Sharma and Yu[15] to segment the supply chains into three classes namely, best-in-class, average, and laggard chains. The modified algorithm is as follows:

Assume there are $n\, DMUs$, each with m inputs and s outputs. We define the set of all DMUs as J^1, $J^1 = DMU_j, j = 1,2,\ldots,n$ and the set of efficient DMUs in J^1as E^1. Then the sequences of J^1 and E^1 are defined interactively as $J^{l+1} = J^l - E^l$ where $E^l = DMU_p \in J^l | \phi_p^l = l$, and ϕ_p^l is optimal value to the following linear programming problem:

$$max_{\lambda_i,\phi}\, \phi_p^l = \phi$$

Subject to, $\sum_{i\in F(j^l)} \lambda_i x_{ji} - x_{jp} \leq 0 \qquad \forall j$

$$\sum_{i\in F(j^l)} \lambda_i y_{ki} - \phi y_{kp} \geq 0 \qquad \forall k$$
$$\lambda_i \geq 0, \quad i \in F(j^l)$$

Where $k = 1\ to\ s,\ j = 1\ to\ m,\ i = 1\ to\ n,\ y_{ki}$= amount of output k produced by DMU_i; x_{jp}= input vector of DMU_p, x_{ji}= amount of input j utilized by DMU_i; y_{kp}=

output vector of DMU_p. $i \in F(j^l)$ in other words $DMU_i \in j^l$, i.e. $F(.)$ represents the correspondence from a DMU set to the corresponding subscript index set. The following algorithm accomplishes subsequent stratum.

Step 1: Set $l = 1$. Evaluate the set of DMUs, j^l, to obtain the set E^1, of the first level frontier DMUs (which is equivalent to classical CCR DEA model), i.e. when $l = 1$, the procedure runs a complete envelopment model on all n DMUs and E^1 consists of all of the DMUs on the resulting overall best-practice efficient frontier.

Step 2: Exclude the frontier DMUs from future DEA runs and set $J^{l+1} = J^l - E^1$.

Step 3: If $J^{l+1} = 3\ E^{l+1}$, then stop. Otherwise, evaluate the remaining subset of inefficient DMUs, J^{l+1}, to obtain the new best-practice frontier E^{l+1}.

Stopping rule: The algorithm stops when $J^{l+1} = 3\ E^{l+1}$.

III. APPLICATION

As already mentioned at the outset, a supply chain is a sequence of processes and flows that take place within and between different stages and combine to fill a customer need for a product with an objective to maximize the overall value of the supply chain. Previous studies evaluated supply chain in stages ignoring the essence of processes that knits the stages of supply chain. Therefore evaluating supply chain processes and sub-processes will help to effectively analyze supply chain as a whole. Davenport and Short [24] define 'processes a set of logically related tasks performed to achieve a defined business outcome and suggest that processes can be divided into those that are operationally oriented (those related to the product and customer) and management oriented (those that deal with obtaining and coordinating resources).

The processes of a supply chain are divided into a series of cycles, each performed at the interface between two successive stages of a supply chain. A cycle view of the supply chain clearly defines the processes involved and the owners of each process. This view is very useful when considering operational decisions because it specifies the roles and responsibilities of each member of the supply chain and the desired outcome of each member of the supply chain and the desired outcome for each process. To evaluate the efficiency of supply chain we will consider four process cycles namely – customer order cycle, manufacturing process cycle, replenishment process cycle, and procurement process cycle. A detailed description of these cycles is provided by Sharma and Yu [14]. The inputs and outputs of each of these cycles are taken from Sharma and Yu's studies [14].

A. *BCC supply chain model application*

Table I shows the efficiency results of the CCR and BCC model for 11 supply chain sub-processes of a particular product (e.g. detergent). First, the efficient supply chains, in each process cycle are: customer order cycle (1, 4, 7, 9, and 11) replenishment process cycle (1, 2, 5, 6, 8, 11), manufacturing process cycle (2, 4, 6) and procurement process cycle (5, 6, 9). The same table shows the efficiency results of RTS. The RTS efficiency score is calculated as the ratio of CCR efficiency score to BCC efficiency score. Table I indicates that, customer order cycle, the BCC efficient but not scale-efficient process, cycles were operating on an increasing returns to scale (IRS) frontier. For customer order cycle, five BCC-efficient retail chains were operating on IRS and four on decreasing returns to scale (DRS) frontiers. Of the BCC-inefficient supply chains, 64% and 20% were in the IRS region in cycle 1 and cycle 2, respectively. As economists have long recognized, an IRS frontier firm would generally be in a more favorable position for expansion, compared to a firm operating in a constant returns to scale (CRS) or DRS region. Note that the concept of RTS may be ambiguous unless a process cycle is on the BCC-efficient frontier, since we classified RTS for inefficient process cycles by their input oriented BCC projections. Thus, a different RTS classification may be obtained for a different orientation, since the input-oriented and the output-oriented BCC models can yield different projection points on the VRS frontier. Thus, it is necessary to explore the robustness of the RTS classification under the output oriented DEA method. Note that an IRS DMU (under the output-oriented DEA method) must be termed as IRS by the input oriented DEA method. Therefore, one only needs to check the CRS and DRS supply chain processes in the current study. Using the input oriented approach, we discover only two DRS supply chain processes in replenishment cycle (DMUs 2, 4, 6 and 9) and seven DRS (DMUs 1, 3, 4, 5, 6, 7, and 9) in the manufacturing cycle. These results indicate that (i) in general; the RTS classification under different process cycle is independent of the orientation of DEA model; and (ii) there are serious input deficiencies in manufacturing cycle at the current usage quantities derived from engineering and process design. The overall supply chain of one chain i.e. DMU 2 is found to be efficient in both the CCR and BCC setting. However, there is one chain found efficient in BCC setting i.e. DMU 6.

B. *Input congestion supply chain model application*

In table II, we focus on the points for DMUs 3, 6, 7, and 8, of customer order cycle which are the only ones that satisfy the condition for congestion specified in equation (5). For DMUs 3, 6, 7, and 8 in the table 3 and coupling this value we obtain congestion efficiency as 0.91, 0.96, 0.97 and 0.98 respectively. Around 36% of the supply chains have exhibited input congestion under VRS technologies. The inputs technological functionality and sales order by FTE in a VRS technology shows the congestion of sales order by FTE is 18.36% of the corresponding technological functionality input level.

Around 45% of the supply chains have exhibited input congestion under VRS technologies in the replenishment process cycle. In the replenishment process cycle we focus on DMUs 2, 3, 6, 7, and 11. We obtain congestion efficiencies of 0.98, 0.97, 0.66, 0.98 and 0.96 for these supply chains. The inputs technological functionality and sales order by FTE same as the customer order cycle, in a VRS technology shows the congestion of sales order by FTE is 26.66% of the corresponding technological functionality input level.

In the manufacturing cycle, the focus DMU points are 3, 4, 5, 6 and 7 which are the ones that satisfy the conditions of congestion specified in equation (5). The congestion efficiencies for these DMUS are 0.66, 0.87, 0.79, 0.77, and 0.66 respectively. The inputs bill-of-materials (BOM), usage quantity, independent demand ratio shows congestion by 15.2%, 22.4%, and 2.5% respectively. The residual score in manufacturing cycle largely indicates the scope for efficiency improvements resulting from less efficient work practices and poor management, but also reflect differences between operating environments in these five supply chains.

The DMUS 2, 3, 5, 8 and 10 of the procurement cycle exhibits the presence of congestion. The congestion efficiency for these supply chains is found to be 0.94, 0.94, 0.66, 0.93, and 0.90 respectively. The inputs purchased item shows congestion by 23.3% of the corresponding input direct material cost.

Starting with input (in the form of technological functionality, order by FTE, BOM, usage quantity, independent demand ration, purchased items, direct material cost) at $x = 0$ the output, y_o, measured in fill rate, cycle inventory, inventory replenishment cycle time, finished product cycle time, end time, on time ship rate and DSA, can be increased at an increasing rate until x_o is reached at output y_o. This can occur, for instance, because an increase in the technological functionality, usage quantity, and purchased items makes it possible to perform tasks in a manner that would not be possible with a smaller number of inputs. From x_o to x_1 however, total output continues to increase, but at a decreasing rate, until the maximum possible output is reached at y_1. Using more input results in a decrease from this maximum so that at x_2 we have $y_2 < y_1$ and $y_1 - y_2$ is the amount of output lost due to congestion. Under congestion, the inability to dispose of unwanted inputs increases costs.

The overall supply chain congestion $\frac{\theta^{o*}}{\beta^{o*}}$ with 1 indicates absence of any congestion found in supply chains 1, 2, and 9. The rest of the supply chain exhibits at least some amount of congestion. Although in a few chains the congestion is negligible for instance the DMUs 8, 10, and 11. The highest amount of congestion is in DMU 6 followed by DMU 5.

C. Supply Chain Classification model application

We analyzed the aggregated metrics of the companies using the modified algorithm of Chen et al. [21] to determine whether their performance ranked as best-in-class (36%), average (27%), or laggard (37%). In addition to having common performance levels, each class also shared characteristics in four process cycles: (1) customer order cycle (balances customer demand with supply from manufacturers); (2) replenishment process cycle (Balances retailer demand with distributor fill rate); (3) manufacturing cycle (balances the percentage mix of demand for an item from independent (outside sources) vs. dependent (inside sources) across all supply chain stages); (3) procurement process cycle (balances Delivery Schedule adherence (DSA) for the timeliness of deliveries from suppliers). The characteristics of these performance metrics serve as guideline for best practices, and correlate directly with best-in-class performance. Based on the findings in table III derived from the context dependent DEA algorithm (modified), the best-in-class supply chains reveal the optimal utilization of technological functionality along with the use of state-of-art technology.

The average and laggard supply chains on the other hand must upgrade their technological functionality towards fast, responsive, and structured supply chains where customer responsiveness and collaboration are necessary ingredients for continued and relentless inventory, margin, working capital, and perfect order-related success.

TABLE I
CCR, BCC RESULTS OF SUPPLY CHAIN PROCESS CYCLES

DMU ID	Customer Order Cycle			Replenishment Cycle			Manufacturing Cycle			Procurement Cycle			Overall Efficiency	
	CCR	BCC	RTS	CCR	BCC	RTS	CCR	BCC	RTS	CCR	BCC	RTS	CCR	BCC
1	1.00	1.00	CRS	1.00	1.00	CRS	0.08	0.19	DRS	0.63	0.98	DRS	0.677	0.792
2	1.00	1.00	CRS	1.00	1.00	CRS	1.00	1.00	CRS	1.00	1.00	CRS	1.000	1.000
3	0.45	0.49	DRS	0.76	0.82	IRS	0.06	0.09	DRS	0.17	0.18	IRS	0.360	0.395
4	1.00	1.00	CRS	0.45	0.61	IRS	0.46	1.00	DRS	0.64	0.92	DRS	0.637	0.882
5	0.51	0.54	IRS	1.00	1.00	CRS	0.13	0.39	DRS	0.44	1.00	DRS	0.520	0.732
6	0.43	1.00	IRS	0.66	1.00	IRS	0.27	1.00	IRS	0.64	1.00	DRS	0.500	1.000
7	0.97	1.00	DRS	0.69	0.70	DRS	0.02	0.03	DRS	0.12	0.12	IRS	0.450	0.462
8	0.52	0.53	IRS	1.00	1.00	CRS	0.10	0.10	CRS	0.28	0.30	IRS	0.475	0.482
9	0.90	1.00	IRS	0.45	0.95	IRS	0.43	0.75	DRS	1.00	1.00	CRS	0.695	0.925
10	0.74	0.94	DRS	1.00	1.00	CRS	0.01	0.02	IRS	0.09	0.11	IRS	0.460	0.517
11	0.76	1.00	DRS	0.96	1.00	DRS	0.01	0.02	IRS	0.06	0.07	IRS	0.447	0.522

*CRS: constant returns to scale; DRS: Decreasing returns to scale; IRS: Increasing returns to scale

TABLE II
CCR, BCC RESULTS OF SUPPLY CHAIN PROCESS CYCLES

DMU ID	Customer Order Cycle			Replenishment Cycle			Manufacturing Cycle			Procurement Cycle			Overall Congestion
	θ^*	β^*	$\frac{\theta^*}{\beta^*}$	θ^*	β^*	$\frac{\theta^*}{\beta^*}$	θ^*	β^*	$\frac{\theta^*}{\beta^*}$	θ^*	β^*	$\frac{\theta^*}{\beta^*}$	$\frac{\theta^{o*}}{\beta^{o*}}$
1	1.00	1.00	1.00	1.00	1.00	1.00	0.19	0.19	1.00	0.98	0.98	1.00	1.000
2	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.000
3	0.45	0.49	0.91	0.80	0.82	0.97	0.06	0.09	0.66	0.17	0.18	0.94	0.870
4	1.00	1.00	1.00	0.61	0.61	1.00	0.87	1.00	0.87	0.92	0.92	1.00	0.967
5	0.51	0.51	1.00	1.00	1.00	1.00	0.31	0.39	0.79	0.66	1.00	0.66	0.862
6	0.60	0.62	0.96	0.66	1.00	0.66	0.77	1.00	0.77	1.00	1.00	1.00	0.847
7	0.97	1.00	0.97	0.69	0.70	0.98	0.02	0.03	0.66	0.12	0.12	1.00	0.902
8	0.52	0.53	0.98	1.00	1.00	1.00	0.10	0.10	1.00	0.28	0.30	0.93	0.977
9	1.00	1.00	1.00	0.95	0.95	1.00	0.75	0.75	1.00	1.00	1.00	1.00	1.000
10	0.74	0.74	1.00	1.00	1.00	1.00	0.02	0.02	1.00	0.10	0.11	0.90	0.975
11	0.76	0.76	1.00	0.96	1.00	0.96	0.02	0.02	1.00	0.07	0.07	1.00	0.990

*CRS: constant returns to scale; DRS: Decreasing returns to scale; IRS: Increasing returns to scale

In table III, best-in-class supply chains processes sales order by full time employees 24 - 32% more than the average and laggard chain in the replenishment process cycle. As well as the fill rate and the time required to deploy the product to the appropriate distribution center is 28% higher than the average and laggard supply chains. In the manufacturing cycle front the inventory optimization goals are well served by best-in-class chains. They work closely with their trading partners, including suppliers, distributor, and retailers to reduce the pressure of increased lead times and potentially lower inventory levels for the chain. Due to this close collaboration, the finished product cycle time (average time associated with analyzing activities, such as: package, stock, etc.) and end item (the final product sold to a customer) less relative to average and laggard supply chains by 34.5%. On time ship rate (percent of orders where shipped on or before the requested ship date) and delivery schedule Adherence (DSA) (a business metric used to calculate the timeliness of deliveries from suppliers) in the procurement cycle does not show any significant difference among the best-in-class, average and laggard supply chains. There is only a 5% difference in the performance of this supplier manufacturer interface.

TABLE III
RESULTS OF SUPPLY CHAIN CLASSIFICATION

	Best-in-Class (E^1)	Average (E^2)	Laggard (E^3)
Classes of efficient supply chains	36 %	27%	37%
Customer Order Cycle	Balances customer demand with supply from manufacturers		
	66%	53%	48%
Replenishment Process Cycle	Balances retailer demand with distributor fill rate		
	55%	31%	23%
Manufacturing Process Cycle	Balances the percentage mix of demand for an item from independent (outside sources) vs. dependent (inside sources) across all supply chain stages		
	65%	44%	36%
Procurement Process Cycle	Balances Delivery Schedule Adherence (DSA) for the timeliness of deliveries from suppliers		
	52%	48%	45%

IV. CONCLUSION

This chapter analyzes the process cycles of 11 supply chains using an innovative DEA model. Close to 45% of the supply chains were inefficient in four process cycles namely – customer order cycle, replenishment process cycle, manufacturing cycle and procurement cycle. Further, most supply chains exhibited DRS in manufacturing cycle and procurement cycle, while some of them exhibited IRS in customer order cycle and replenishment process cycle. This suggests that up-stream components of the supply chain may have a negative effect on finished product cycle time and end item. Having examined performance at process cycle of a supply chain, the current study employs a procedure by FGL[12 with modification to identify the presence of congestion in the chains that may hinder improvement projection of the inefficient chains incurring some cost. Then a context-dependent DEA model is used to classify the chains into three categories - best-in-class, average, and laggard chains. The characteristics of these performances metrics serve as guideline for best practices, and correlate directly with best-in-class performance. Finally, our examination of supply chain data set indicates that the gap in performance is higher in the down-stream relative to up-stream.

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Mithun J Sharma (M'10) was born in Guwahati, Assam, India on the 27th of November 1978. Mr. Sharma holds a Masters in Business Administration (MBA) degree from the Department of Shipping Management, Korea Maritime University, Busan, South Korea. He completed his MBA in 2006 specializing in operations research.

He is an Assistant Professor in the Centre for Management Studies, Dibrugarh University, Dibrugarh, Assam, India. Prior to Dibrugarh University, he worked as a researcher in the University of Venice, Venice Italy. He also has industrial experience with Hyundai Motors and Nisshinbo Automotive Manufacturing. He has published in reputed journals such as EJOR, AMC, ESWA etc. His current research interest includes optimization techniques, supply chain management and game theory.

Mr. Sharma holds membership in professional bodies like NOFOMA, IAENG and KASL. He has been awarded Certificate of Merit for Best Paper in the World Congress on Engineering, London, U. K, 2010. He has also received NURi best paper award, 2006.

Song Jin Yu received the B.S. in management policy, M.S. in industrial management and Ph.D degrees in industrial engineering from Korea Advanced Institute of Science and Technology (KAIST), Daejon, in 1994, 1997 and 2002, respectively.

He is currently associate professor at division of shipping management, Korea maritime university. His current interests include the application of artificial intelligence, especially machine learning or neural network methodologies, to the design of knowledge-based systems for various management principles. He has expanded his research domain into SCM, B2B EC, CRM, and Security. He has published in the areas of data mining, quality information systems, B2B EC, and financial engineering in reputed journals such as EJOR, AMC, ESWA etc.