Intermediate measures consideration for a value chain or multistage system: an efficiency analysis using DEA approach

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1. Introduction

It has been recognized that performance evaluation is extremely important as the old adage says "you can't improve what you don't measure". Companies using performance measurement were more likely to achieve leadership positions in their industry and were almost twice as likely to handle a major change successfully (Wisner et al., 2004). Today, business performance is evaluated not only in terms of a single business unit but rather the entire value chain. Performance measurement of the entire value chain is a lot more difficult and complex compared to the performance measurement of a single business unit. When managing a value chain, apart from the formidable multiple performance measures problem, assessing the performance of several tiers, e.g., suppliers, manufacturers, retailers and distributors further complicates the matter. Basically, there are two main problems in value chain performance measurement, which are a) existence of multiple measures that characterize the performance of each member, for which the data must be acquired, b) existence of intermediate measures between them, e.g., the output from the upstream can become the input to the downstream which further complicates the performance assessment.

As noted in Wong and Wong (2007 and 2008), DEA is a powerful tool for measuring value chain efficiency. DEA, developed by Charnes et al. (1978), is a well-established methodology used to evaluate the relative efficiency of a set of comparable entities called Decision Making Units (DMUs) with multiple inputs and outputs by some specific mathematical programming models. DEA can handle multiple inputs and outputs and it does not require prior unrealistic assumptions on the variables which are inherent in typical supply chain optimization models (i.e. known demand rate, lead time etc) (Cooper et al. 2006). These advantages of DEA enable managers to evaluate any measure efficiently as managers do not need to find any relationship that relates the measures.

We point out that DEA's vitality, real-world relevance, diffusion and global acceptance are clearly evident, as supported from such literature studies as Seiford (1996) and Gattoufi et al. (2004a and 2004b). There are a number of DEA studies on value chain efficiency; yet, most of them tend to focus on a single chain member. This can be partly due to the lack of DEA models for the entire value chain or multi-stage systems. Note that DEA cannot be directly applied to the problem of evaluating the entire value chain efficiency because the value chain cannot be simply viewed as a simple input-output system as conceptualized in DEA.

Within the context of DEA, there are some recent models, e.g., by Fare and Grosskopf (2000) and Golany et al. (2006), which have the potential to address a value chain in a powerful way. Recently, Liang et al. (2006) developed two classes of DEA-based models for supply chain efficiency using a seller-buyer supply chain setting. They used the game theory approach to analyze the effect of one member having on another. One similarity of the recent models for addressing the chain effect or multilayer system is that they take into consideration the presence of intermediate measures; their differences lie in their mechanic system design. The issue of intermediate measures was initially addressed by Banker and Morey (1986) in a service industry which operates in a single layer. The model separates the inputs/outputs into two groups, i.e., discretionary and non-discretionary; non-discretionary inputs/outputs are exogenously fixed inputs/outputs that are not controllable and their values are predetermined.

The current chapter provides an alternative way to measure value chain or multistage efficiency which is by taking into consideration the effect of the intermediate measures in the system. We draw on previous Banker's model and extend the model construction for value chain. We analyze its dual formulation and explain how it suits the value chain setting. This chapter contributes to the existing value chain or multistage system literature by providing an alternative model to measure value chain or multistage efficiency. This model is simple and easy to understand. Though, this model may not have addressed all the concerns in value chain or multistage system, it can still serve as a tentative solution for measuring the efficiency of these systems.

In the following section, we will review Banker's model by analyzing its dual formulation and then provide the insight on how it can address the value chain or multistage efficiency. Then we present an application study to show the usefulness of the model.

2. Theoretical foundations

In this section, we first discuss the foundations of DEA. Then, we show the dual formulation of the Banker's model and explain how it can better characterize the value chain or multistage system.

2.1 Basic DEA methodology

Build upon the earlier work of Farrell (1957), data envelopment analysis (DEA) is a mathematical programming technique that calculates the relative efficiencies of multiple decision-making units (DMUs) based on multiple inputs and outputs.

Assume S to be the set of inputs and R the set of outputs. J is the set of DMUs. Further assume that DMU$_j$ consumes $x_{sj} \geq 0$ of input s to produce $y_{rj} \geq 0$ of output r and each DMU has at least one positive input and one positive output (Fare et al., 1994). Based on the efficiency concept in engineering, the efficiency of a DMU, says DMU j_0 ($j_0 \in J$), can be estimated by the ratio of its virtual output (weighted combination of outputs) to its virtual input (weighted combination of inputs).

To avoid the arbitrariness in assigning the weights for inputs and outputs, Charnes et al. (1978) developed an optimization model known as the CCR model in ratio form to determine the optimal weight for DMUj_0 by maximizing its ratio of virtual output to virtual input while keeping the ratios for all the DMUs not more than one. The fractional form of a DEA mathematical programming model is given as follows:

$$\max \frac{\sum_{r \in R} u_r y_{rj_0}}{\sum_{s \in S} v_s x_{sj_0}}$$

$$\text{s.t.} \quad \frac{\sum_{r \in R} u_r y_{rj}}{\sum_{s \in S} v_s x_{sj}} \leq 1 \tag{1}$$

$$u_r, v_s > 0 \qquad s \in S,\ r \in R$$

where u_r and v_s are the weights for the output r and input s respectively.
The objective function of Model (1) seeks to maximize the efficiency score of a DMUj_0 by choosing a set of weights for all inputs and outputs. The first constraint ensures that, under the set of chosen weights, the efficiency score of the observed DMU is not greater than 1. The last constraint ensures that the weights are greater than 0 in order to consider all inputs and outputs in the model. A DMUj_0 is considered efficient if the objective function of the associated Model (1) results in an efficiency score of 1, otherwise it is considered inefficient.
Using the Charnes-Cooper transformation, this problem can be further transformed into an equivalent "output maximization" linear programming problem as follows:

$$\max \sum_{r \in R} u_r y_{rj_0}$$

$$\text{s.t.} \quad \sum_{r \in R} u_r y_{rj} - \sum_{s \in S} v_s x_{sj} \leq 0, \quad j \in J \tag{2}$$

$$\sum_{s \in S} v_s x_{sj_0} = 1$$

$$u_r, v_s > 0 \qquad s \in S,\ r \in R$$

Model (2) is known as the CCR model in multiplier form. If the objective function value of (2) is equal to 1, it implies that the DMU concerned is relatively efficient since we can find a weight combination to make its efficiency score to be equal to one. Despite the linear form of (2), efficiency score is usually calculated based on its dual problem:

$$
\begin{aligned}
&\min \ \theta \\
&\text{s.t.} \quad \sum_{j \in J} x_{sj} \lambda_j \le \theta x_{sj_o}, \quad s \in S \\
&\qquad \sum_{j \in J} y_{rj} \lambda_j \ge y_{rj_o}, \quad r \in R \\
&\qquad \lambda_j \ge 0, \qquad\qquad j \in J
\end{aligned}
\tag{3}
$$

Model (3) is known as the input-oriented CCR in envelopment form or the Farrell model, which attempts to proportionally contract DMUj_0's inputs as much as possible while not decreasing its current level of outputs. The λ_j values are the weights (decision variables) of the inputs/outputs that optimize the efficiency score of DMU j_0. These weights provide measures of the relative contributions of the inputs/outputs to the overall value of the efficiency score. The efficiency score will be equal to one if a DMU is efficient and less than one if a DMU is inefficient. The efficiency score also represents the proportion by which all inputs must be reduced in order to become efficient. In a similar way, we can also derive the output-oriented CCR in envelopment form if efficiency is initially specified as the ratio of virtual input to virtual output. A large number of extensions to the basic DEA model have appeared in the literature as described by Ramanathan (2003) and Cooper et al. (2006). We shall limit our discussion to this basic model as this is sufficient to lead us to the explanation of the following model to address a value chain or multistage system.

2.2 The DEA analysis of value chain efficiency.

Consider a value chain relationship as follows, e.g., supplier – manufacturer with inputs and outputs as described in Figure 1. This may also be viewed in terms of a multistage process, e.g., a product has to go through two stages of a manufacturing process: assembly (stage 1) and testing (stage 2). We may further categorize the inputs and outputs into two types, i.e., direct and indirect or intermediate. *Direct* inputs/outputs are associated with a single stage or member only and they do not affect the performance of other stages / members. For example, supplier cost and supplier revenue are direct inputs and outputs for the supplier only, they have no impact on the manufacturer. *Intermediate*s are those inputs/outputs that are associated with two or more stages/members. For instances, ontime delivery is the performance of the supplier in delivering its products; it is also a cost measure to the manufacturer which relates to inventory holding cost.

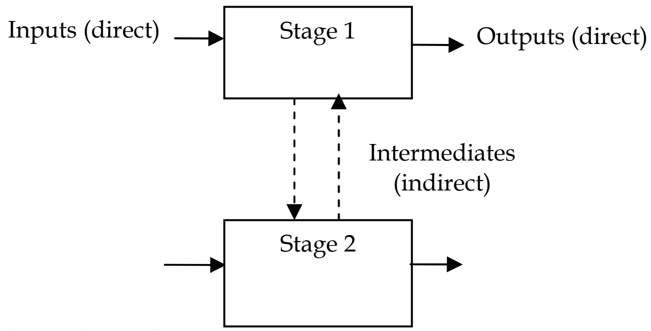

Fig. 1. A simple chain relationship

Note that if the intermediate measures are treated as both inputs and outputs in the model, all the DMUs (decision making units) will become efficient. This does not necessarily indicate efficient performance in an individual chain member. Due to the presence of intermediate measures in the value chain or multistage system, the performance of one member will affect the performance or efficiency status of the other members.

Alternatively, we may consider the effect of the intermediate measures using Banker's model. We will now elaborate how the value chain or multistage efficiency will be characterized if we take into consideration the intermediate (indirect) measures.

Let's use a simple scenario; for example, there are two value chains, i.e. DMU A and DMU B, and each of them is a dual-channel (supplier-manufacturer) system. Let's say that the manufacturers of A and B are the same. Also, let's assume that supplier A is very efficient while supplier B is less efficient compared to A. Note that the efficiency of the individual supply chain member can be obtained using the DEA CCR model as explained earlier. Recall that the best practice of one channel does not mean that it fits the other channel. In this case, the impact from the performance of the supplier may affect the efficiency status of the manufacturer in such a way that the manufacturer A may seem to be less efficient compared to the manufacturer B; by right, they should be equally good because they are the same manufacturer. This shows that a member's inefficiency may be caused by another's efficient operations.

In order to better characterize the value chain, we have to 'discount' or remove the impact of the performance improvement of one supply chain member that affects the efficiency status of the other. We will illustrate how this discounting concept can be realized using the intermediate (indirect) measures in Banker's model. From the basic DEA model in fractional (ratio) form, let's denote *IS* as the set of intermediate inputs, *DS* as the set of direct inputs, x_{tj} as the t^{th} intermediate input of DMU j and x_{tj_0} as the t^{th} intermediate input for the observed DMU j_0. Note that $DS \cup IS = S$.

$$\max \frac{\sum_{r\in R} u_r y_{rj0} - \sum_{t\in IS} v_t x_{tj0}}{\sum_{s\in DS} v_s x_{sj0}}$$

$$\text{s.t.} \quad \frac{\sum_{r\in R} u_r y_{rj} - \sum_{t\in IS} v_t x_{tj}}{\sum_{s\in DS} v_s x_{sj}} \le 1 \tag{4}$$

$$u_r > 0, \quad r \in R$$

$$v_s > 0, \quad s \in DS$$

$$v_t \ge 0, \quad t \in IS$$

where v_t is the weight for the intermediate variables.

All the other notations used have been previously defined in Section 2. Note that the weights for the intermediate variables may be zero, but for the direct variables, the weights must always be positive. Note also that the difference between (4) and (1) is the subtraction of the intermediate term. This term represents the performance of one chain member (e.g. the upstream channel) that feeds into the other chain member (e.g. the downstream channel). By subtracting the intermediate term in such a way is analogous to 'discounting' the impact of one's performance that affects the other. From Model (4), it is obvious that the impact of the indirect factor is removed; and the efficiency obtained in this model will be the best case efficiency. Though the 'discounting' concept may not have fully addressed all the issues in a value chain or multi stage system, it can serve as a tentative solution to measure the chain or multistage efficiency.

Model (4) can be further transformed into its equivalent linear form as shown in Model (5) (the primal model) and Model (6) (the dual model).

<u>CCR multiplier model</u>

$$\max \sum_{r\in R} u_r y_{rj0} - \sum_{t\in IS} v_t x_{tj0}$$

$$\text{s.t.} \quad \sum_{r\in R} u_r y_{rj} - \sum_{t\in IS} v_t x_{tj} - \sum_{s\in DS} v_s x_{sj} \le 0, \qquad j \in J$$

$$\sum_{s\in DS} v_s x_{sj0} = 1 \tag{5}$$

$$u_r > 0, \quad r \in R$$

$$v_s > 0, \quad s \in DS$$

$$v_t \ge 0, \quad t \in IS$$

CCR envelopment model

$$
\begin{aligned}
&\min \Omega \\
&\text{s.t.} \quad \sum_{j \in J} \lambda_j x_{sj} \le \Omega \; x_{sj_o}, && s \in DS \\
&\sum_{j \in J} \lambda_j x_{tj} \le x_{tj_o}, && t \in IS \\
&\sum_{j \in J} \lambda_j y_{rj} \ge y_{rj_o}, && r \in R \\
&\lambda_j \ge 0, && j \in J
\end{aligned}
\tag{6}
$$

Note that all the notations used have been previously defined in the above section. Note that Model (6) is an input oriented model whereby it aims to reduce the inputs as much as possible while not decreasing the level of the outputs. Note that the third constraint (i.e. for the outputs) can actually be separated into two constraints, i.e., one for direct and another for indirect terms. Since the indirect term for the output will not affect the objective function, we did not explicitly write it into two separate constraints; for conciseness purpose of the model, we combined them into one constraint.

Given Model (6), one way to evaluate the entire value chain or multistage efficiency, is to estimate the efficiency, Ω as the normalized (weighted) efficiency of all the members or stages. That is,

$$
\Omega^* = \frac{\sum_{i \in I} w_i \Omega_i^*}{\sum_{i \in I} w_i}
\tag{7}
$$

where Ω^* is the optimal efficiency score of the value chain or multistage system, I is the set of members or stages in the system, Ω_i^*, $i \in I$, is the optimal efficiency score for a specific chain member (channel) or stage and w_i is the weight reflecting the extent of each channel or stage contributing to the evaluation of the entire value chain or multistage efficiency. These weights can be estimated using various methods such as AHP (Analytic Hierarchical Process), Delphi method and Pareto analysis (Clemen and Reilly, 2001; Kirkwood, 1997). In this research, we consider all channels (stages) have equal contribution to the value chain (multistage) system performance. As the indirect effect, i.e., the performance improvement of one channel affecting another channel has already been removed or discounted from Model (6), the weight measures proposed in such a way would be reasonable and the 'double counting' effect on the performance of the entire value chain will not be very significant. Note that in this study we set $w = 1$.

From Model (6), a chain or multistage system is efficient if $\Omega^* = 1$. Note that it is possible among all DMUs, the highest value of Ω^* is < 1. In this case, it means that none of the DMUs is efficient. Comparing Model (6) to (3), as the values of Ω^* and θ^* have to be greater than 0 and less than or equal to 1, and as Model (6) has less restriction on the intermediate inputs, the value of Ω^* from Model (6) will always be less than or equal to the value of θ^* from Model (1) i.e. $\Omega^* \leq \theta^*$.

Proposition 1. *The efficiency score, Ω^* of (6) for any DMU j_0 is less than or equal to the corresponding efficiency score from θ^* (3).*

To prove this proposition, we first note that $\theta^* \leq 1$ in the optimal solution of (1) because DMU j_0 is itself one of the $j_0 \in J$ referent observations. By comparing the constraint sets in the two linear programs, we see that any optimal solution to (3) is a feasible solution for (6); hence, $\Omega^* \leq \theta^*$.

Model (6) yields the target values on the performance measures for an inefficient supply chain to reach the best practice by using its slack information. The model assumes that the inputs could be reduced while maintaining all the outputs at the same level. The target values are obtained as follows. We denote $x^*_{sj_o}$ and $x^*_{tj_o}$ as the direct and indirect input targets i.e., $x^*_{sj_o} = \Omega^{a*} x_{sj_o} - s^-_{sj_o}$ and $x^*_{tj_o} = x_{tj_o} - e^-_{tj_o}$

where $s^-_{sj_o}$ and $e^-_{tj_o}$ are the direct and indirect input slacks respectively.

3. An application study

In this section, we discuss an application study on the proposed approach. First, we explain the conceptual configuration of the value chain or multistage setting which comprises the variables or metrics used in the study. Then, we provide some descriptions of the data, followed by results discussion of the empirical analysis.

3.1 Configuration

To illustrate our proposed approach, we model a value chain setting based on the global value chain system of multinational semiconductor corporations. There are three levels in the proposed setting, e.g., supplier, manufacturer and retailer. This can also be viewed in terms of a multistage process, e.g., first stage (assembly), second stage (testing) and third stage (final inspection/packaging). We use the supply chain operations reference (SCOR) to determine the value chain performance metrics. The metrics used are the financial and operational measures. Table 1 shows the categorization of the metrics.

Direct Inputs	**Cost (including labor , variable, and capital components) ($)**
Intermediates	**Fill rate (%), on-time delivery (%), cycle time (days)**
Direct output	**Revenue ($)**

Table 1. Metrics categorization

A brief definition for each measure is given below. For financial measures, the elements are cost and revenue; for operational measures, the elements include fill rate, on-time delivery and cycle time.

Financial measures:

a. Revenue - This is a common measure of efficiency in various profit-oriented organizations. In value chain studies, emphasis is often placed on the final revenue, i.e., revenue of the final product. In our experiment we consider the effect of revenue of one member affecting another's performance is minimal.

b. Cost - This is the performance attribute for value chain costs, i.e. the total cost associated with operating the value chain. The total cost comprises labor, variable and capital components. We consider the total cost of each member separately.

Operational measures:

a. Fill rate – This is a performance attribute for value chain reliability. In the broadest sense, fill rate refers to the service level between two parties. It is usually a measure of shipping performance expressed in percentage. Being an output to the upstream channel, the upstream channel will always desire to have a high fill rate so that it is able to satisfy customer demand. However, for the downstream channel, a high fill rate means additional storage and holding cost. Therefore, fill rate affects two parties; hence, it is generally viewed as an intermediate measure. An optimal level of fill rate is usually determined from the tradeoff between the rate of customer order fulfillment and inventory level.

b. On-time delivery rate - This is another common performance attribute for value chain delivery reliability. It is usually expressed in percentage; it refers to the performance of the value chain in delivering the correct product, to the correct place, at the correct time, in the correct condition and packaging, in the correct quantity, and with the correct documentation to the correct customer. It affects two members; as an output, the member will want this to be as high as possible; alternatively, as an input, it can be viewed as a cost to the associated member.

c. Cycle time - This is the performance attribute for 'production flexibility'. It refers to the agility of a value chain in responding to marketplace changes to gain or maintain competitive advantage. It is also known as the 'upside production flexibility'. It refers to the number of days required to achieve an unplanned, sustainable, a certain percent increase in production. One of the common constraints to cycle time is material availability. Cycle time affects the performance of one member with another, e.g., if the supplier cycle time is high, then, the manufacturer will not be able to meet its production and will be seen as inefficient and vice versa.

In short, we consider all the operational measures as intermediate measures because they affect the performance of one member with another. Note that, the particular setting may not be applicable to all types of industries or systems, as different industries or multistage systems may have different types of configuration. In our case, the value chain configured is sufficient to evaluate the model.

3.2 Data descriptions

The analysis uses observational data from the semiconductor companies based in Malaysia. As one of the requirements of DEA is to have a homogenous set of DMUs for fair comparison, the companies selected are based on a similar logistic distribution network and business. The data required, e.g., the total costs and revenues, are obtained from the companies' annual reports. Total cost comprises three components, i.e., labor, variable and capital components. Specifically, labor relates to the number of employees working directly for a particular channel or stage and the price of labor is measured using the average wages of the employees. As capital comprises buildings, facilities and other peripheral equipment, it is impossible to allocate the capital costs to individual components. According to Arnold (2004), stocks (inventory) play an important role in an operation activity and the costs associated with them are related with each individual capital component. We thus used the value of capital (or capital stock) as a proxy to the amount of physical capital used in the value chain. The value of capital can be obtained through the division of net operating income by the return on capital asset (ROA). On the other hand, the revenue figures may include revenue generated from other businesses; however, as the selected companies for the study have been filtered and ensured of having a similar logistic distribution network, the impact of revenue generated from other businesses would be minimal.

It is also difficult to obtain a full set of data due to some data, e.g., fill rate and cycle time, are considered confidential by most of the companies. To overcome this hurdle, we gathered the required data via several methods; site interviews with managers were conducted and experts' judgments were collected to gauge the mean value of these uncertain variables. Note that Wong et al. (2008) developed a method called the Monte Carlo DEA to measure the efficiency when there are uncertainties in the data. This method is based on the Bayesian framework where they used the distribution of the inputs/outputs to estimate the distribution of the efficiencies. In this chapter, we will apply the DEA Model (6) in a deterministic setting, which is, we assume that all data are finally available for the experiment. Table 2 shows the data used for the numerical experiment. All the monetary values are denominated in current US dollars.

DMU	Cost (stage 1) *$Million* USD	Cost (stage 2) *$Million* USD	Cost (stage 3) *$Million* USD	Fill rate (stage 1) %	On time delivery (stage 1) %	Cycletime (stage 1) days	Fill rate (stage 2) %	On time delivery (stage 2) %	Cycletime (stage 2) days	Revenue *$Million* USD
1	115	195	154	95	84	11	80	83	6	499
2	105	170	211	86	79	3	77	95	5	504
3	131	148	132	95	88	4	78	87	4	423
4	170	140	175	82	74	3	81	80	3	497
5	125	63	113	85	83	3	72	84	5	359
6	196	121	164	83	89	2	79	82	7	528
7	177	165	124	77	89	3	93	89	8	526
8	151	164	112	84	79	8	79	90	5	455
9	149	108	154	92	87	11	86	94	7	428
10	101	183	178	95	93	8	81	74	6	526
11	169	194	146	93	93	7	88	83	5	558
12	180	131	111	85	98	8	98	84	4	457
13	150	174	161	81	91	4	82	79	8	514
14	143	133	102	88	90	8	98	98	5	404
15	166	121	147	77	83	3	83	89	6	503
16	182	165	107	90	86	10	89	82	6	492
17	189	112	156	93	95	5	96	86	6	478
18	84	125	104	77	74	9	89	84	10	300
19	167	126	196	96	90	1	92	83	7	537
20	179	106	115	82	72	5	79	81	10	414

Table 2. Data

Note that for the semiconductor industry, the gross profit margin is approximately 8% and the net profit margin is approximately 4% of the total revenue. We evaluate a total of 20 value chains (multistage). For confidential purposes, the names of the companies have been omitted and some of the information has been disguised. The results are analyzed using MS Excel and its linear optimization solver.

3.3 Empirical analysis

The ultimate purpose of the experiment is to provide an insight on the importance of characterizing a value chain or multistage system. We will show from the results that, by considering the presence of intermediate measures in the value chain of multistage system, there are potential input savings in the system. We present the DEA efficiency results in Table 3.

DMU	CCR model (Model 3)				Banker's model (Model 6)			
	Stage1 (θ_1^*)	Stage 2 (θ_2^*)	Stage 3 (θ_3^*)	Average (θ^*)	Stage1 (Ω_1^*)	Stage 2 (Ω_2^*)	Stage 3 (Ω_3^*)	Chain (Ω^*)
1	1.000	0.865	0.988	0.951	0.944	0.428	0.839	0.737
2	0.883	1.000	1.000	0.961	0.874	1.000	1.000	0.958
3	0.875	0.880	1.000	0.918	0.771	0.491	0.811	0.691
4	0.524	1.000	1.000	0.841	0.516	1.000	1.000	0.839
5	0.743	1.000	1.000	0.914	0.729	1.000	0.688	0.806
6	0.501	1.000	1.000	0.834	0.497	1.000	1.000	0.832
7	0.554	1.000	1.000	0.851	0.551	1.000	0.953	0.835
8	0.600	0.974	1.000	0.858	0.597	0.815	0.985	0.799
9	1.000	1.000	0.876	0.959	0.722	0.978	0.603	0.768
10	1.000	0.822	1.000	0.941	1.000	0.410	1.000	0.803
11	0.661	0.839	1.000	0.833	0.602	0.477	1.000	0.693
12	1.000	1.000	1.000	1.000	0.595	1.000	1.000	0.865
13	0.666	0.951	0.986	0.868	0.665	0.652	0.823	0.713
14	0.690	1.000	1.000	0.897	0.690	1.000	0.877	0.856
15	0.560	1.000	0.965	0.841	0.549	1.000	0.851	0.800
16	0.588	0.871	1.000	0.820	0.539	0.648	1.000	0.729
17	1.000	1.000	0.922	0.974	0.547	1.000	0.695	0.747
18	1.000	1.000	1.000	1.000	1.000	1.000	0.624	0.875
19	1.000	1.000	0.932	0.977	0.610	1.000	0.680	0.764
20	0.495	1.000	1.000	0.832	0.487	1.000	0.779	0.755

Note: θ_i^* , i ={1, 2, 3} refers to the efficiency score obtained using CCR.
Table 3. Value chain efficiency

We compare Banker's Model (6) with the original CCR model; the original CCR model is applied separately on each stage and the value chain efficiency is obtained by taking the average. Note that the value chain efficiency from Model (6) (Banker's model) is always less than or equal to the value chain efficiency from the CCR model. The reduction of the value chain efficiency score in Model (6) is due to the removal of the impact from the indirect (intermediate) measures.

From the analysis, none of the value chain is efficient. We further interpret the target adjustments for the inefficient DMUs. As an example for discussion, we select DMU 3, which is the least efficient DMU.

DMU 3	Original value	Target value	% Change
Stage 1 cost	131	101.00	-22.9
Stage 2 cost	148	72.67	-50.9
Stage 3 cost	132	107.05	-18.9
Fill rate _stage 1	95	95	0
On time delivery _stage 1	88	92	4.5
Cycle time_stage 1	4	4	0
Fill rate _stage 2	78	78	0
On time delivery _stage 2	87	89	2.3
Cycle time_stage 2	4	4	0

Table 4. Target values for inputs, outputs and intermediate variables for DMU 3.

For example, for DMU 3, its average efficiency is 0.918 and the value chain efficiency (using Banker's model) is 0.691. The values of $\Omega_1^* = 0.771$, $\Omega_2^* = 0.491$ and $\Omega_3^* = 0.811$ for DMU 3 (from Table 4) indicate that all the three channels (stages) are inefficient. In order to reach the best practice, each channel, i.e., stage 1, 2 and 3 could reduce their inputs while maintaining the same level of outputs (based upon Ω_1^*, Ω_2^* and Ω_3^*, which are less than 1). In the case of DMU 3, all its direct input slacks have zeros values. Thus, the cost for stage 1 could be reduced to 101; while the cost for stage 2 and 3 could be reduced to 72.67 and 107.05 respectively. This is equivalent to a 22.9% reduction of cost for stage 1, 50.9% reduction of cost for stage 2 and 18.9% reduction of cost for stage 3. In addition, the on time delivery between stage 1 and 2 could be increased to 92% from the current rate of 88%; and the on time delivery between stage 2 and 3 could be increased to 89% from the current rate of 87%. These solutions indicate that based upon the best practice, the associated channels (stages) would be able to maintain the on time delivery rates, i.e., 92% and 89% respectively while cutting down costs. These are the potential savings that can be realized from the value chain or multistage system if it is characterized in a better way. Similarly, the adjustment for other DMUs and their system potential savings could be interpreted using the same way.

4. Conclusions

This chapter draws on previous DEA models and advances the construction of the models for measuring the entire value chain or multistage efficiency. The chapter contributes to the existing value chain (multistage system) literature by providing a simple alternative model to measure the efficiency of the system. This model removes the indirect effect of one's channel performance which affects the efficiency status of another channel. The results show if we characterize the value chain through consideration of the impact of intermediates measures, potential savings can be realized in the system. Though, this model may not have addressed all the concerns in value chains or multistage systems, it can serve as a tentative solution for measuring the efficiency of these systems. This model can be further enhanced by analyzing how different settings of weights affect the overall value chain or multistage performance. In addition, future research can also look into how to adapt the model in uncertain environments, e.g., by utilizing the Monte Carlo method. Lastly, this chapter serves as an exposition to the awareness on the potential of simple conventional models to address more complex problems.

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