Chapter 2

2.0. A CRITICAL REVIEW OF CONCEPTS, METHODS AND STUDIES RELATED TO EFFICIENCY.

2.1. Introduction

This chapter gives an introduction to a DEA-based efficiency measurement by firstly reviewing the basic concept of efficiency and its measurement. This is followed by a brief explanation on two types of economic efficiency i.e. technical efficiency and allocative efficiency. The assumptions of constant returns-to-scale and variable returns-to-scale is also examined in relation to the scale of production of the universities. The following section presents two main methods of efficiency measurement which introduces the basic concept of DEA efficiency measurement. In this chapter, we will also explore the foundations of DEA models, which are the Charnes, Cooper, and Rhodes (1978) CCR version and Banker, Charnes, and Cooper (1984) BCC version. Both models are presented in their input and output orientations plus the dual model for each DEA model explained. A comprehensive review on the previous studies on DEA applications to higher educations wraps up this chapter.

2.2. The Concept and Measurement of Efficiency

When measuring for efficiency, one is actually interested in measuring the rate at which inputs are converted to output. Hence a simple measure of efficiency would be:

$$\text{efficiency} = \frac{\text{output}}{\text{input}} \quad \text{........Equation (1)}$$

and normalize it to be less than or equal to one (Simons, 1995). An efficiency value equals to one means efficiency level is at its maximum. This happens when the same amount of output can be produced by consuming less input or it can produce more output by consuming the same level of input. In the presence of multiple input and output factors, where it is generally the case in all organizations, the efficiency measure would use weighted sum of inputs and outputs:

$$\begin{aligned} \text{efficiency} &= \frac{\text{weighted outputs}}{\text{weighted inputs}} \\ &= \frac{\sum_i u_i x_i}{\sum_j v_j y_j} \end{aligned} \qquad \text{...Equation (2)}$$

where:
u_i = the weight given to output i
x_i = amount of output from unit i
v_j = the weight given to input j
y_j = amount of input from unit j

In this efficiency measurement there are multiple possibly incommensurate inputs and outputs which was addressed by Farrell (1957). But the problem one would raise with regards to weights is how to obtain an agreed common set of weights for the sum of inputs and outputs. A linear programming technique of efficiency measurement has a solution for this and to be addressed later.

In the economic analysis, education takes the form of a production function where the educational institutions is seen as analogous to a company transforming inputs into outputs through a production process (Worthington, 2001). Worthington (2001) in his study of Frontier Efficiency Measurement, citing Farrell (1957), proposed that the efficiency of any given firm consists of two components: *technical efficiency*, the ability of a firm to maximize output from a given set of inputs; and *allocative efficiency*, the ability of a firm to use these inputs in an optimal proportion, given the respective prices. Combining these two measures of efficiency provides the measure of total economic efficiency or cost efficiency or also known as *overall efficiency*.

These two forms of efficiency can be illustrated by Figure 2.1. Here, we consider a set of institution i.e. J, K and L, each producing a single output (Y) using 2 inputs (X_1, X_2) in varying quantities. The example of physical inputs used to produce educational outcome are the number of staff and number of computers and the educational outcome or output here is the number of students. The inputs are normalized so that they can be represented in a two dimensional diagram. These two measures of inputs used per student are plotted for each institution (represented by a dot) of differing sizes as shown in Figure 2.1.

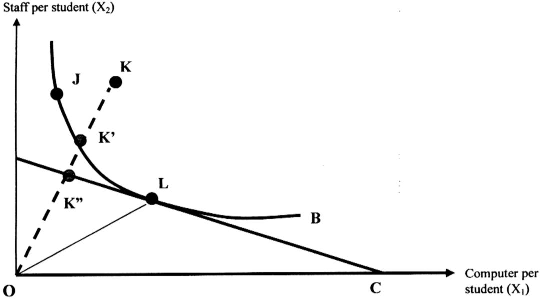

Figure 2.1 : Technical and Allocative Efficiency

Institutions which lie on Line B i.e. J and L in the above diagram indicates technically efficient institutions as such they are using the least amount of inputs per outputs. This fitted line creates an envelope convex to the origin and build a *frontier* from which the inefficiency in other institutions can be evaluated. In economics, this line is referred as the *isoquant*. For example, institution K uses more staff per student and computers per student than both institutions J and L. The extent to which institution K is inefficient can be measured by tracing its way back to the efficient combinations i.e. moving along the dotted line towards the *isoquant*. Technical efficiency measures the extent to which physical inputs are efficiently allocated. In economics, measures related to cost is termed as *isocost* as depicted by Line C in Figure 2.1. This line represents the different input combinations that can be purchased from a fixed budget.

From Figure 2.1 above, point K could be regarded as technically efficient if it lies on the *isoquant* i.e. at point A. Thus, the technical efficiency of institution K can be measured by $\frac{OK'}{OK}$. When cost factors are considered, K is also not totally efficient because it lies above the *isocost* line. It can operate at an efficient level by reducing it number of staff and increasing the number of computers that is equivalent to moving along the isocost approaching towards point L. Therefore, the allocative efficiency of K can be measured by $\frac{OK''}{OK'}$. From these two efficiencies, the overall efficiency of K is $\frac{OK''}{OK}$. An example of the institution which is both technically and allocatively efficient is institution L. It is because Institution L actually lies on both the isoquant and isocost lines. Thus, institution L is also said to be overall efficient or economically efficient. The fact that institution K can operate at an efficient level by approaching towards point L, institution K can actually attempt to emulate institution L in order for it to be efficient. Hence, institution L is a peer referent or a benchmark for institution K. The concept of peer referent or benchmark will be explained in a greater detail in the later section.

As has been noted earlier, the process within education institutions takes the form of a production function transforming inputs into outputs. The transformation is often characterized in relation to the concept of returns-to-scale. A basic production function would normally characterize the transformation by a constant returns-to-scale (CRS) (Thanassoulis, 2001).

CRS is a condition whereby doubling the inputs would result in a doubling of the output. The implication of CRS assumption means that the ratio of $\frac{Y}{X}$ is not dependent on scale of production. The economic theory suggests, in the long run, institutions would achieve their optimal size when they are operating at constant returns-to-scale (CRS) and as such that they achieve a level of scale efficiency. Scale efficiency is the other type of efficiency evident in many empirical studies of higher education (Salerno, 2003). It relates the extent to which institutions are operating at increasing or decreasing returns-to-scale. This, in turn, will help the institutions in determining the optimal size of an institution.

Operating at a decreasing returns-to-scale (DRS) is when doubling inputs results in a less than equal increase in outputs of an institution, and vice-versa as for increasing returns to scale (IRS). The condition of an institutions experiencing either decreasing or increasing returns to scale is termed as variable returns-to-scale (VRS). The concept of returns-to-scale in the organizations' operation will be discussed in relation to the CRS and VRS modeling in the later part of this chapter.

2.3. Main Methods of Efficiency Measurement

In general, there are two major techniques in efficiency measurement, i.e. the parametric or regression-based estimation; and the non-parametric or mathematical programming technique. For efficiency measurement of the higher educations, the most popular parametric and non-parametric techniques applied are stochastic frontier analysis (SFA) and data envelopment analysis (DEA), respectively (Salerno, 2003).

DEA appeals as a tool for the efficiency analysis of public operating institutions as DEA does not require price information and can easily aggregate multiple inputs and outputs (McMillan *et al* 1998). DEA was originally applied to the not-for-profit organizations (Charnes, Cooper and Rhodes (CCR), 1978) and evidently applied to the educational institutions, essentially due to its advantages towards the nature of such non-profit or public sector organization (Charnes, 1981). This is particularly because market prices or relative values of these organizations are not readily available (Avkiran, 2001). DEA is also most suited to those organizations when there is no obvious objective way of aggregating either inputs or outputs into a meaningful index of efficiency, Therefore, in this study we utilize DEA as the tool to measure the relative efficiency of a group of public universities in Malaysia.

2.4. Data Envelopment Analysis (DEA)

DEA is a non-parametric linear-programming procedure developed by Charnes, Cooper and Rhodes (1978) to measure relative efficiency of several homogeneous organizational units called decision making units (DMUs) that use multiple inputs to produce multiple outputs. It is a relative efficiency measurement because its measurement is with reference to some set of units comparing with each other. The characterization of the organizational units as "decision making" implies that it has control over the process it employs to convert its resources into outcomes (Thannasoulis, 2001).

There are two forms of DEA analysis options available, namely the input orientation (or also termed as input minimization) and the output orientation (or also termed as output maximization) (Avkiran, 2001). Whether input oriented or output oriented measure of efficiency is to be employed will depend on the DMU's discretion over its input or output variables. If it has more control over the input levels, and it targets to save cost in attempt to increase productivity, input orientation would be the best analysis option because DEA would suggest for input reduction. If it is the case where the inputs are being the uncontrollable variables, output orientation would, then, be the best form of analysis whereby outputs are raised without increasing the inputs.

The following section presents the basic DEA models for assessing the input and output efficiency in a context of multi-input multi-output. The extensions to the models are also presented in this coming section.

2.4.1. The Basic DEA Models

2.4.1.1. Charnes, Cooper and Rhodes (CCR) Version

The first model is the distinguished model introduced by Charnes, Cooper and Rhodes (CCR)(1978). CCR (1978,1979,1981) laid down the following ratio form of DEA assuming constant returns to scale.

$$\text{maximize:} \quad h_o = \frac{\sum_{r=1}^{s} u_r y_{ro}}{\sum_{i=1}^{m} v_i x_{io}} \qquad \text{...Equation (3)}$$

$$\text{subject to:} \quad \frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \leq 1;$$

$$\frac{u_r}{\sum_{i=1}^{m} v_i x_{io}} \rangle \varepsilon;$$

$$\frac{v_i}{\sum_{i=1}^{m} v_i x_{io}} \rangle \varepsilon;$$

$$\varepsilon \rangle 0$$

In this model, the relative efficiency of a decision making unit (DMU), designated as DMU$_j$ is to be evaluated based on observed performance of j DMUs. y_{rj} and x_{ij} represents the observed amount of rth output and ith input of the jth decision making unit. For example, DMU$_j$ used i inputs to produce r outputs. One of the j DMUs is singled out for evaluation, and placed in the objective function to be maximized in Equation (3) while also leaving it in the constraints. Then, it follows DMU$_j$'s efficiency score will be h_o^*. The numerator in the objective function of the model of Equation (3) represents a collection of resources used to produce the outputs while the denominator represents a collection of resources used to obtain those outputs. (The definitions of the variables for the efficiency models are given in Table 2.1)

Table 2.1

Definitions of the variables

h_o	=	the DEA efficiency score
o	=	a specific distribution organisation to be evaluated ($1 \leq o \leq n$)
i	=	the subscript of inputs (i = 1, 2, …., m)
j	=	the subscript of distribution organisation (j = 1, 2, …., n)
r	=	the subscript of outputs (i = 1, 2, …., s)
x_{ij}	=	the ith input of the jth distribution organisation
y_{rj}	=	the rth output of the jth distribution organisation
v_i	=	the weighting variable for the ith input
u_r	=	the weighting variable for the rth output
s_i^-	=	the slack variable for the ith input
s_r^+	=	The slack variable for the rth output
λ_j	=	a non-negative value related to the jth distribution organisation
ε	=	a small non-Archimedian (positive number)

The value h_o^* (* indicates optimum efficiency) obtained from the ratio will satisfy $0 \leq h_o^* \leq 1$, and in terms of efficiency rating, $h_o^* = 1$ represents full efficiency and $h_o^* \leq 1$ indicates inefficiency is present. To obtain this ratio form of scalar measurement, there is no weights need to be specified as a priori. When solutions are available from (3), the optimal value of u_r^*, v_r^*, which are the weights will be determined. The h_o^* obtained from (3) is also the highest rating that the data allow for a DMU. Thus, a condition of optimality for some j is as such,

$$\frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} = 1$$

Thus, the model in equation (3) generalises the normal single output to single input efficiency measures used in these disciplines in a way that accommodates the case of multiple outputs and the multiple inputs.

These efficiency ratings are more than just index numbers which indicate a ranking of DMUs based on their efficiency. The value of h_o^* has operational significance in that 1-h_o^* provides an estimate of the inefficiency for each DMU$_o$ being evaluated. Thus, this characterization makes it possible to identify the sources and amounts of inefficiency in each output for every one of the DMU$_o$ being evaluated.

Equation (3) is a linear fractional model and it needs to be transformed in an ordinary linear program to be solved. The transformed model that is equivalent to linear programming model, assuming CRS, in the input oriented is given as Equation (4) and its corresponding dual is given as Equation (5) in Table 2.2. The linear programming model in the output orientation and its corresponding dual is given in Table 2.3.

Table 2.2

The CCR Input Orientation Model.

Primal Model	Dual Model
maximize: $h_o = \sum_{r=1}^{s} u_r y_{ro}$ ...Equation (4) subject to: $\sum_{i=1}^{m} v_i x_{io} = 1$; $\sum_{r=1}^{s} u_r y_{rj}$ - $\sum_{i=1}^{m} v_i x_{ij} \leq 0$, $u_r, v_i \geq \varepsilon$;	minimize: θ - $\varepsilon \left[\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+ \right]$ ....Equation (5) subject to: $\sum_{j=1}^{n} x_{ij}\lambda_j + s_i^- = \theta\, x_{io}$ $\sum_{j=1}^{n} y_{rj}\lambda_j - s_r^+ = y_{ro}$ $\lambda_i \geq 0$ $s_i^-, s_r^+ \geq 0 \;\forall\; i$ and r, θ free

Table 2.3

The CCR Output Orientation Model

Primal Model	Dual Model
minimize: $\frac{1}{h_o} = \sum_{i=1}^{m} v_i x_{io}$ ...Equation (6) subject to: $\sum_{r=1}^{s} u_r y_{ro} = 1$; $\sum_{i=1}^{m} v_i x_{ij}$ - $\sum_{r=1}^{s} u_r y_{rj} \;\geq\; 0$, $u_r, v_i \geq \varepsilon > 0$	maxmize: θ + $\varepsilon \left[\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+ \right]$ ....Equation (7) subject to: $\sum_{j=1}^{n} x_{ij}\lambda_j + s_i^- = \theta\, x_{io}$ $\sum_{j=1}^{n} y_{rj}\lambda_j - s_r^+ = y_{ro}$ $\lambda_i \geq 0$ $s_i^-, s_r^+ \geq 0 \;\forall\; i$ and r, θ free

The constraints in the primal model in Equation (4) and (6) aggregate the virtual inputs or outputs (the product of the input level and the optimal weight for that input; or likewise for the virtual output) to 1 (or 100%) for each unit. These virtual inputs and outputs of each DMU reveal the relative contribution of each input and output to its efficiency rating (Sarrico & Dyson, 2000). Hence, the input efficiency measure h_o^* yielded by the model in Equation (4) and the output efficiency measure $\frac{1}{h_o}$ yielded by model (6) in respect of DMU_j are equal. This also has been acknowledged by Avkiran (2001) who cited a study by Drake & Howcroft (1994) stating that "under the CRS, input and output orientation form of analysis will provide the same relative efficiency scores, provided all inputs are controllable."

2.4.1.2. Banker, Charnes, and Cooper (BCC) Version

While CCR version bases the evaluation on constant returns to scale, the Banker, Charnes, and Cooper (1984) version assumes variable returns to scale, thus it is more flexible. In the CCR model, a DMU is only considered as efficient if it is both scale and technical efficient. But in a BCC model, a DMU is already considered as efficient provided it is technically efficient. Under the assumption of VRS, the linear models with inputs and output orientation and their corresponding duals are as shown in Table 2.4 and Table 2.5 below.

Table 2.4

The BCC Input Orientation Model

Primal Model	Dual Model
maximize : $\sum_{r=1}^{s} u_r y_{ro}$ - w_o ...Equation (8)	minimize $\theta - \varepsilon \left[\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+ \right]$ ...Equation (9)
subject to: $\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} - w_o \leq 0$	subject to: $\sum_{j=1}^{n} x_{ij} \lambda_j + s_i^- = \theta\, x_{io}$
$\sum_{i=1}^{m} v_i x_{io} = 1$	$\sum_{j=1}^{n} y_{rj} \lambda_j - s_r^+ = y_{ro}$
$u_r, v_i \geq \varepsilon$;	$\sum_{j=1}^{n} \lambda_j = 1$
	$\lambda_i \geq 0$
	$s_i^-, s_r^+ \geq 0 \ \forall\ i$ and r, θ free

Table 2.5

The BCC Output Orientation Model

The Primal Model	The Dual Model
minimize : $\sum_{i=1}^{m} v_i x_{ij} + w_o$ ...Equation (10)	maximize: $\theta + \varepsilon \left[\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+ \right]$ ....Equation (11)
subject to: $\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} - w_o \leq 0$	subject to: $\sum_{j=1}^{n} x_{ij} \lambda_j + s_i^- = x_{ij}$
$\sum_{r=1}^{s} u_r y_{rj} = 1$	$\sum_{j=1}^{n} y_{rj} \lambda_j - s_r^+ = \theta\, y_{ro}$
$u_r, v_i \geq \varepsilon$	$\sum_{j=1}^{n} \lambda_j = 1$
	$\lambda_i \geq 0$
	$s_i^-, s_r^+ \geq 0 \ \forall\ i$ and r, θ free

For the model in Equation (8), the w_o^* (*denotes optimal value) indicates the return to scale possibilities. $w_o^* < 0$ implies local increasing returns to scale. If $w_o^* = 0$, it implies local constant returns to scale. Finally, if $w_o^* > 0$, this implies local decreasing return to scale. As for model in Equation (9), the constraint $\sum_{j=1}^{n} \lambda_j = 1$ is added to the CCR model also will provide information on the local economies of scale. If the observed λ is > 1, the organization is operating at a decreasing, λ < 1 indicates an increasing returns-to-scale, and λ = 1 shows a condition of constant returns-to-scale. In general, efficient firms will have $\sum_{j=1}^{n} \lambda_j = 1$. This is why when this constraint is introduced to the CRS model (relaxing the CRS assumption), some firms that are not efficient in the CRS model, may become efficient in the VRS model.

From both CCR and BCC models explained above, we conclude that the BCC model allows variable to scale and measures only technical efficiency for each DMU. Thus, for a DMU to be considered BCC efficient, it only needs to be technically efficient. However, for a DMU to be considered as CCR efficient, it must be both scale and technical efficient.

In summary, the CRS efficiency score represents technical efficiency, which measure inefficiencies due to input and output configuration and as well as size of operations, whereas the VRS scores represents pure technical efficiency, i.e. a measure of efficiency without scale efficiency. By estimating both CRS and VRS efficiency, it is possible to determine the amount of scale efficiency by taking the ratio $\frac{\text{CRS}}{\text{VRS}}$ (Salerno, 2003).

The CRS and VRS efficiency frontier is illustrated as shown by Figure 2.2. The figure exhibits the observed performance of five DMUs, denoted by P_1, P_2, P_3, P_4 and P_5, each with one input and one output. The bold line connecting points P_1, P_2, P_3, and P_4, represents the VRS frontier where all these points are efficient under the BCC model. The dotted line represents the CRS frontier where it indicates that P_2 is both technical and allocatively efficient under both BCC as well as CCR model. DMU P_5, nevertheless, is observed to be inefficient in both aspects.

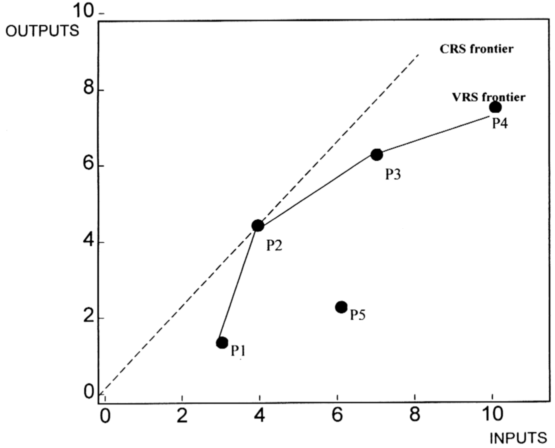

Figure 2.2

CRS and VRS efficiency frontier

2.5. The Empirical Studies Concerning Efficiency Measurement of Universities

Data Envelopment Analysis (DEA) was first proposed as a performance measurement tool by Farrell (1957) and then popularized by Charnes, Cooper and Rhodes (CCR) in 1978 for applications to organizations that lacked profit motivations such as non-profit and governmental organizations. Later it became a popular tool to evaluate private sector organizations as well. In fact, a large number of empirical studies have utilized the DEA framework and have extended it to measure the performance of organizations like the health service, transportation, banking and insurance, military and defense, elementary and secondary and also higher education and many others (Bowlin, 1999).

Empirical studies adopting DEA framework in efficiency measurement of higher educational institutions abroad are numerous. The earliest DEA application to the education sector was to public schools in 1981. Then, Charnes, Cooper and Ahn (1988), utilized the DEA methodology to analyse the performance of IHLs . This seminal paper focused on the efficiency measurement of public and private IHLs. From then on many more studies have been conducted.

Worthington, (2001) and Salerno, (2003) provide two comprehensive literature reviews on DEA studies in IHLs. Salerno laid down three different levels of analysis made on higher education institutions, i.e. at institution level, academic departments level, and lastly, at the level of non-academic or auxiliary units within institutions.

Appendix 2.1 provides a summary of DEA applications to higher institutions of learning. In this study, a review of some DEA studies in IHLs has been conducted. Although there are numerous applications of DEA on IHLs in the international arena, there is a dearth of studies in the Malaysian context. One of the handful Malaysian DEA-based study on higher education was carried out is by Abdullah and Hussain, (2000) who assessed the relative efficiency of academic research projects conducted in the National University of Malaysia. However, there is no Malaysian DEA-based study on the relative efficiency of Malaysian universities.

The literature on IHLs efficiency considered several issues. The first issue concerns how DEA can be used as a tool in educational assessment. The studies of Johnes & Johnes, (1995); Beasly, (1995); Coelli, (1996);. Avkiran, (2001), and McMillan & Datta, (1998) all demonstrated the wide applicability of DEA to educational assessment. For example a study by Johnes & Johnes (1995) concluded that DEA has a positive contribution to make in the development of meaningful indicators of university performance. McMillan & Datta (1998) in their study of relative efficiency of Canadian universities, also concluded that DEA provides insight to university productivity in Canada.

The second issue revolves around the impact of educational reforms to IHLs performance. C.N. Ying & K.L. Sung (2000) examined the research performance of the higher education institution by computing individual institutions' efficiency and studied the effectiveness of Education Reform implemented in the mid 1980s. From their study, it was found that research performance of institutions across regions have improved, although the institutions as a whole remained inefficient from 1993 to 1995. A similar study that analyzed the impact of changes to education systems, was also conducted by Madden & Savage (1997). They concluded that there was substantial reduction in inefficiency within the 24 economic departments of Australian universities evaluated after the changes to education system were implemented.

The efficiency comparison between public and private IHLs is the third area of concern pertaining to efficiency measurement in higher education. Calhoun (2003) brought out the idea of analyzing the efficiency of public and private IHLs with regards to the source of revenue (either restricted or unrestricted) obtainable by each type of institution. Restricted funds are obtained with specific objectives attached while unrestricted funds can be used at the institution's discretion. Specifically, a new way to differentiate the institutions, put forth by Calhoun (2003) is based upon the percentage of unrestricted revenue received by the institution as a proportion of total revenue. In his two stage DEA modeling, he postulated those IHLs with smaller percentage of unrestricted revenue received are generally more efficient than those with higher ones. Persuasively, he implied that the restricted nature of the revenue serves as an accountability and efficiency control measure on managers and institutions, by attempting to eliminate managerial inefficiencies.

The next issue identified from the list of studies is the type of efficiency measure within IHLs. In the context of higher education institutions, there are four different forms of efficiency which are often evaluated, namely technical efficiency, allocative or cost efficiency, overall efficiency, and finally, scale efficiency (Salerno, 2003). Flegg *et al* (2004) studied the causes of variations in efficiency and decomposed technical efficiency into pure technical efficiency, congestion analyses and scale efficiency.

While a number of studies explored technical efficiency, others investigated cost efficiency. Casu & Thanassoulis (2003) examined the expenditure on central administration so as to identify cost efficient and inefficient universities in this area in a set of UK universities.

The choice on input and output measures is another area of controversy in many DEA studies. In deciding the input and output measures to be used to compare universities efficiency, one need to have a conceptual view of what the inputs and outputs are for a university and also to consider that the data which are actually available (Beasley, 1995). The selection of input and output variables of a university should be defined primarily according to the services it provides in terms of teaching, research, consultancy and other educational services (Flegg *et al* 2004). Teaching and research activities are the two main activities which have been agreed upon as the dimension of higher educational quality assessment (Green, 1994).

Two most commonly selected inputs for DEA institutional efficiency models are the number of academic staff and expenditures. Four studies which have specifically employed the number staff (a combination of either academic, non-academic and/or researchers) as the input measure to their efficiency models are Johnes & Johnes, (1993) and (1995), Avkiran, (2001), Madden *et al*, (1997), and Abott *et al*, (2003). In some other studies, specifically the cost-based efficiency studies, expenditure variables are employed as the input specifications (Anthanassapoulos & Shale,1997; McMillan *et al*, 1998).

In terms of the teaching output measures, Salerno (2003) highlighted that in nearly all empirical studies of higher education, the most popular outputs were the physical headcounts of full time equivalent enrolments, FTE (Johnes & Johnes, 1993 and 1995, Avkiran, 2001, Madden *et al*, 1997, Abott *et al*, 2003). Anthanassapoulos & Shale (1995), on the other hand, use the number of successful leavers as the output variable as they argued such measure would give an insight into how effective the universities are, with the given resource allocation and the abilities of their students to achieve the outcomes as graduates. Other equivalent teaching outputs evidently employed are the number of graduating students (Madden & Savage, 1997) and the number of degrees awarded (Calhoun, 2003).

For research outputs, publication counts, citations, or research expenditure/funding are mainly used as indicators in empirical studies (Ahn *et al*, 1978 and McMillan & Datta, 1998). Salerno's excerpt is "those who advocate journal articles as research output argue that research expenditure neglects the quality aspect of research. On the other hand those who favour research expenditure claim not all research output is in the form of journal articles. Plays, musical scores, patents are also considered in the same category". In the context of this study, the Science University of Malaysia considers items like film, cassette, modules, program scripts, thesis and video as publications (USM, 2004) which will form research expenditure as output. As Cohn (1989) argues "the ability of an higher institution to generate such funds is closely related with its research output, at least insofar as it is perceived by sponsor." Conclusively, there is a wide range of inputs and outputs variables used. This shows that there is no firm consensus on how to model the basic function of universities.

2.6. Conclusion

The concept of DEA-based efficiency measurement in higher education has long been explored and is deemed as a potentially useful approach. In contrast to the vast use of DEA applications in measuring efficiency of higher education institutions aboard, DEA application in the Malaysian universities has been neglected. The extensive discussions on many constructive issues of DEA performance modeling should be captured and used in the development of a suitable performance model for the higher educations in the Malaysian context. The measurement of higher education performance has already become an international trend. We should not delay in moving in the same direction with an attempt to develop "a model" for the Malaysian public universities.