CHAPTER 2

REVIEW OF LITERATURE

2.1 Introduction

Essentially, performance measurement analyses the success of work at various levels of activity, such as group, programme or organization, by comparing data on what actually happened to what was planned or intended (Wholey & Hatry, 1992). Performance measurement evaluation is an important aspect that has been studied over the years. This evaluation is important since it may support a variety of management functions whereby it allows a manager to identify operating strength and weaknesses, target areas for improvement and recognize improvement when it occurs (Bond, 1999). To evaluate the performance measurement, an appropriate quantitative approach can be applied. One of the approaches that can be considered to measure the performance is by determining the efficiency of their activities.

To clearly comprehend the concept and measurement of efficiency, this chapter will present two main categories, which are the theoretical and empirical reviews. For the theoretical review, the discussion will expound on the various approaches of measurement in production frontiers that have been proposed by previous authors. While for the empirical review, the discussion discusses the empirical studies based on earlier literature. A blending of both reviews will provide a better understanding concerning efficiency measurement while doing the empirical analysis for this study.

This chapter is organized as follows. Section 2.2 briefly introduces the concept of efficiency. Section 2.3 discusses the traditional measurement approaches. Section 2.4 presents the production frontiers approach, which consists of parametric and non-parametric frontiers. Next, Section 2.5 describes the DEA approach as a method to measure the efficiency. Further, undesirable factors in DEA are extended in Section 2.6. Section 2.7 provides the substance to the theoretical review whereby it reviews various approaches in DEA efficiency measurement with undesirable outputs categorized as indirect and direct approaches. An additional explanation of the concept and measurement of productivity change will be presented in Section 2.8. Later, Section 2.9 reviews the empirical orientation with several issues highlighted including the efficiency and productivity in the manufacturing sector, application of various approaches, the effect of environmental regulations on the environmental efficiency, potential variables and sources of pollution by different industries as well as environmental performance in the Malaysian manufacturing sector. Finally, Section 2.10 summarizes the chapter.

2.2 Concept of Efficiency

The underpinning of efficiency measurement began with from the work of Koopmans (1951) and Debreu (1951). Koopmans (1951) provided a definition of technical efficiency whereby “A possible point in the commodity space is called efficient whenever an increase in one of its coordinates (the net output of one good) can be achieved only at the cost of a decrease in some other coordinate (the net output of another good)”. Fried et al. (2008) interpreted the Koopmans definition with “a producer is technically efficient if an increase in any output requires a reduction in at least one other output or an increase in at least one input, and if a reduction in any input requires an increase in at least one other input or a reduction in at least one output”. In simple words, a point is efficient if the output is maximized by the given inputs. From Koopmans description of technical efficiency, Debreu (1951) introduced a measure of efficiency through the ‘coefficient of resource utilization’. This efficiency measure can be interpreted as a determination of a distance between the produced outputs and the outputs that could have been produced given the inputs. Later, Farrell (1957) extended the work of Koopmans and Debreu in a seminal paper by illustrating the efficiency measurement with the application in the agriculture sector in the United States.

The conventional production theory views an organization as a production system in which inputs are the resources utilized by the organization and transformed into outputs. Economic efficiency based on the production theory implies that organizations should structure their outputs as to achieve the lowest possible use of inputs. In the literature, there are various descriptions of efficiency. The researchers might use different words or look at efficiency measurement from a different angle, however the underlying concept will be the same. Another basic description on the concept of estimating efficiency is by comparing the inputs and outputs of an entity with those of its best performing peers. These peers are measured with respect to an objective whereby it can be measured based on the maximization of output or profit or minimization of cost (Thanassoulis, 2001). A further explanation of efficiency is to determine the frontier of the production function. This can be done by either maximizing outputs produced by any given inputs vector, or minimizing inputs usage to produce any outputs vector (Kumbhakar & Lovell, 2003). From the above descriptions, efficiency can simply be portrayed as the relationship between inputs and outputs in performance measurement.

2.3 Traditional Efficiency Measurement Approaches

One of the simplest and most frequently used estimates of efficiency is the ratio or index analysis (Bikker, 1999). Ratios are measured by the relationship of any two parameters to explain the different aspects of the operation. The limitation of this approach is that it provides a single dimensional image of the figure without any specific reason for good or bad performance (Sherman, 1984). This limitation has led to the development of the frontier approach, which has becomes a popular approach among researchers nowadays. The frontier approach measures the performance of firms with the “best practice” frontiers, which consist of the performance of other firms in the industry. The benefits of applying the frontier approach, are, among others, it is easier to identify best practice firms within the industry, it provides a number of efficiency scores, identifies areas of inputs overuse and/or outputs underproduction and relates the efficiency score with any policy or research interest, especially for the individual who does not have any knowledge concerning the frontier analysis (Berger & Humphrey, 1997).

2.4 Production Frontiers Approach

Over the last two decades several scholars have applied two fundamental approaches of performance measure under the production frontier approach. They are the parametric and the non-parametric approaches. As a brief description, the parametric approach assumes the existence of a specific functional form for the technology or frontier function that determines what maximum amounts of outputs can be produced from different combinations of inputs. A non-parametric approach does not require the specification of any particular functional form to describe the efficient frontier (Murillo-Zamorano & Vega-Cervera, 2001). Berger (1993) is an example of a study using the parametric approach while Seiford and Thrall (1990) prefer the non-parametric approach.

Both the parametric and non-parametric frontier approaches can be further separated into deterministic and stochastic. The deterministic approach assumes away any random factors like random noise or errors in the data. Thus, all observations must lie on or below the frontier. In contrast, the stochastic approach allows for random noise and errors in the data. Therefore, the observations may lie above the frontier, due to either inefficiency or random error (Broek et al., 1980). For the estimation tools, the deterministic frontier functions can be gauged either via mathematical programming or by means of econometric techniques while stochastic specifications can be gauged by means of econometric techniques only (Murillo-Zamorano, 2004). The parametric and non-parametric frontier methods summarized by Hollingsworth et al. (1999) are modified and illustrated in Figure 2.1.

2.4.1 Parametric Frontier Approach

a) Parametric Deterministic Frontiers

For the technical efficiency measurement, Aigner and Chu (1968) provided a deterministic approach, which was extended from the work of Debreu (1951) and Farrell (1957). In their paper, Aigner and Chu (1968) measured a single-output Cobb Douglas frontier production function. This involves the specification of a parametric form for the production technology using linear programming to select parameter values that provide the closest possible envelopment of the observed data. The Deterministic Parametric Frontier requires a priori functional form for the technology of production. By utilizing this approach, the estimation of technical efficiency involving a single-output multiple-input situation may require the definition of a production function.

b) Parametric Stochastic Frontiers

The Stochastic Frontier Approach (SFA) is a starting point in the stochastic production frontier. This approach, which was initiated by Aigner et al. (1977) and Meeusen and Broeck (1977) specifies a functional form for the cost, profit or production function and allows for random error as well. This approach is also known as an econometric approach. The SFA assumes that deviations from the estimated frontier are composed by inefficiencies and random error. It gives a composed error model where inefficiency is assumed to follow a one-sided distribution, usually the half-normal, while the random error follows a symmetric distribution, usually the standard normal. The logic behind this is that the inefficiency must have a truncated distribution because inefficiency cannot be negative. It is quite difficult to separate inefficiency from random error and composed error framework via this method.

As an alternative to the conventional stochastic frontier technique above, Berger (1993) introduced the Distribution-Free Approach (DFA). This approach specifies a functional form for the frontier but separates the inefficiency from random error in a different way. The DFA assumes that the efficiency of each firm is stable over time, whereas random error tends to average out to zero over time (Berger, 1993). The estimation of efficiency for each firm is determined by the difference between its average residual and average residual of the firm on the frontier. This approach is only applicable for panel data.

Another option for the stochastic frontier approach is the Thick Frontier Approach (TFA) by Berger and Humphrey (1991). This approach provides an efficiency measure for the overall organization. Similar to the DFA above, the TFA also attempts to simplify the difficulty of differentiating the two composite error term components. It specifies a functional form and assumes that deviations in predicted cost within the highest and the lowest quartiles represent random error, while deviations in predicted cost between the highest and the lowest quartiles represent inefficiency.

2.4.2 Non-Parametric Frontier Approach

a) Non-Parametric Deterministic Frontiers

Data Envelopment Analysis (DEA) proposed by Charnes et al. (1978) and Free Disposal Hull (FDH) initiated by Deprins et al. (1984) are two approaches frequently used in non-parametric techniques.

Data Envelopment Analysis (DEA) does not require an explicit specification of the production function form that expresses how inputs are transformed into outputs (Sexton & Lewis, 2012). Lewis and Sexton (2004) describe the handling of decision making units (DMU) in DEA as a 'black box' whereby no assumptions are specified for the production process while observing inputs and outputs. Another advantage of using DEA is that it does not require parametric assumptions, such as normality and equal variance (Talluri et al., 2003). In addition, unlike the parametric approach, DEA is also less data demanding as it works fine with a small sample size (Canhoto & Dermine, 2003; Moffat & Valadkhani, 2011), which is very relevant to this study. In this approach, the efficiency measurement is obtained through the application of mathematical programming techniques. The DEA method is described in greater detail in the next section.

The Free Disposal Hull (FDH) introduced by Deprins et al. (1984) is a special case of the DEA model, in which the convex combinations of the frontier observations are not included in the frontier. In this model, only the strong (free) disposability of inputs and outputs are assumed. Since the FDH is interior to the DEA frontier, the FDH gives larger estimates of average efficiency than the DEA. These two approaches assume no prior assumption regarding the functional form and they do not require random error.

From the various methods that have been developed, the deterministic non-parametric approach, which is the DEA, is considered to be the most developed technique. The next chapter will provide a broader description of the DEA as a substantial part of this study.

b) Non-Parametric Stochastic Frontiers

In the non-parametric stochastic frontier, statistical analysis has been utilized to produce efficiency estimates. For instance, Kneip and Simar (1996) suggested a statistical analysis through kernel regression for estimating the production frontier model. In their study, they make use of panel data to avoid the distributional assumptions while constructing a new stochastic non-parametric frontier estimator.

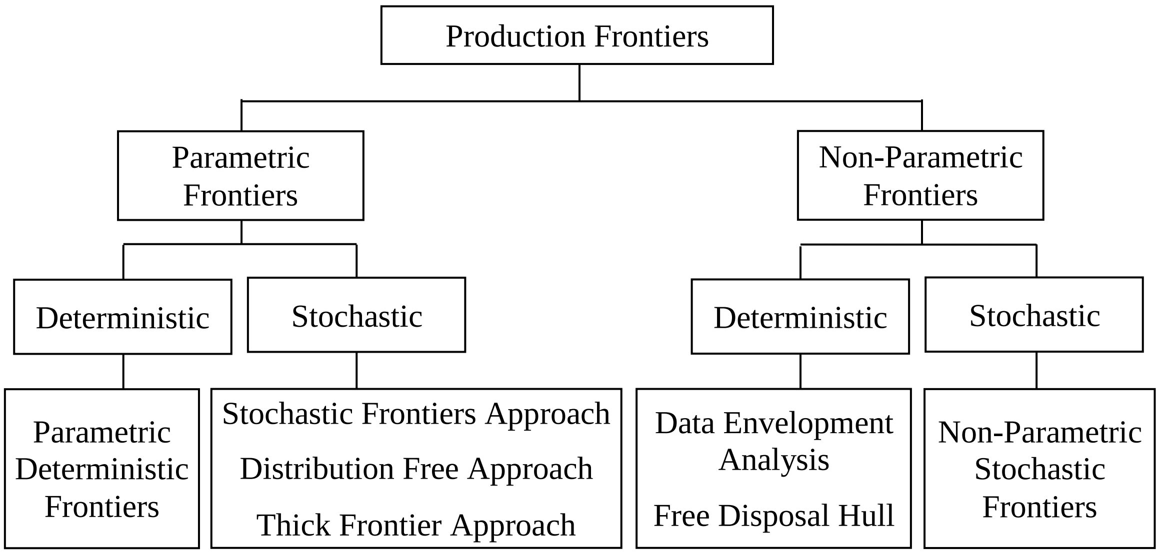

Figure 2.1: Production Frontiers

Source: Hollingsworth et al. (1999)

2.5 Data Envelopment Analysis (DEA)

The DEA, which is a non-parametric frontier approach, is a linear programming technique to measure the relative efficiency of a set of decision making units (DMUs) or units of assessment in their use of multiple inputs to produce multiple outputs. This technique, which originated from the seminal work by Charnes et al. (1978) is developed in the Operation Research/Management Science field and uses mathematical programming techniques and models to solve the problem. DEA identifies a subset of efficient ‘best practice’ DMUs and, for the remaining DMUs, their efficiency level is derived by comparison with a frontier constructed from the ‘best practice’ DMUs. Each DMU is analysed separately to examine whether the DMU under consideration could improve its performance by increasing its output and decreasing its input. Beyond the efficiency measure, DEA also provides other sources of managerial information relating to the DMUs’ performance. DEA identifies the efficient peers for each inefficient DMU. Therefore, DEA can be viewed as a benchmarking technique, as it allows decision makers to locate and understand the nature of the inefficiencies of a DMU by comparing it with a selected set of efficient DMUs with a similar profile.

The state of the art in DEA models can be seen in the diverse fields of the market and non-market sectors. In addition to production in manufacturing (Carbone, 2000; Renuka, 2002b), the applications of DEA include agriculture (De Koeijer et al., 2002; Song et al., 2008), health care (Harrison & Sexton, 2006; Hollingsworth et al., 1999), education (Bougnol & Dulá, 2006; Johnes, 2006), bank systems (Avkiran & Morita, 2010; Charles et al., 2011), transportations (Karlaftis, 2004; McNeil, 2007) and criminal justice (Butler & Johnson, 1997; Lewin et al., 1982) as researchers have focused considerable attention on the significance of the efficiency evaluation in performance measurement.

Before proceeding, it is important to understand the DEA efficiency model as follows:

$$
\begin{aligned}
&\text{Max } \theta_m \\
&\text{Subject to} \\
&\qquad \sum_{n=1}^{N} z_n x_{in} \leq x_{im} \; ; \;\; i = 1,2,\ldots,I \\
&\qquad \sum_{n=1}^{N} z_n y_{jn} \geq \theta_m y_{jm} \; ; \;\; j = 1,2,\ldots,J \\
&\qquad z_n \geq 0 \; ; \;\; n = 1,2,\ldots,N
\end{aligned} \tag{2.1}
$$

Where

z_n = intensity variables

x_{in} = i^{th} input of the n^{th} DMU

x_{im} = i^{th} input of the m^{th} DMU

y_{jn} = j^{th} desirable output of the n^{th} DMU

y_{jm} = j^{th} desirable output of the m^{th} DMU

The DEA output oriented envelopment model seeks a set of z values, which maximizes the θ_m and identifies a point within the production possibilities set whereby output levels of DMU m can be increased as high as possible proportion while input remains at current level (Charnes et al., 1978).

2.6 Undesirable Factors in DEA

The conventional formulation for efficiency measurement in the DEA is based on the isotonicity property whereby increased input may reduce the efficiency while increased output may increase the efficiency (Dyson et al., 2001; Golany & Roll, 1989). In the real cases, the circumstances are more complicated where increased output may also reduce the efficiency while increased input may also increase the efficiency. This is called an anti-isotonic property (Dyson et al., 2001). In anti-isotonic circumstances, the outputs factor need to be minimized while the inputs factor need to be maximized. These are usually referred to as ‘bad’ or ‘undesirable’ factors to input/output variables.

Some examples of undesirable inputs include fines in the case of library systems (Anderson, 2008) and time duration to reconnect electricity supply failure (Munisamy, 2010). On the other hand, examples that can be considered as undesirable outputs from various applications are aircraft noise and delayed flights in airplane systems (Lozano & Gutierrez, 2011), non-performing loans in bank systems (Barros et al., 2012), death of a patient in the course of administering health treatment (Yawe & Kavuma, 2008), number of machine errors, manual errors and other errors in the printed circuit board (PCB) assembling production process (Charles et al., 2012) and pollution in production systems (Färe et al., 1996; Zaim, 2004; Zhou et al., 2008a).

To explain the undesirable factor further, let us consider a pulp and paper mill production where pulp and paper is produced with undesirable outputs of pollutants, such as biochemical oxygen demand and suspended solids (Hailu, 2003). An increase in the emission of a pollutant, which is an undesirable output in production activities will possibly decrease the production efficiency. This performance measured is also referred to as environmental efficiency. The concept of environmental efficiency or eco-efficiency can be described as a measurement of efficiency with the integration of undesirable output, that contributes negatively to the environment[1] (Dyckhoff & Allen, 2001). In addition, Koskela and Vehmas (2012) provided five definitions of eco-efficiency. The first definition refers to the numerous productions with limited amount of environmental impact. The second definition refers to the relationship between environmental and economic performance. The third definition refers to the ratio of economic performance to environmental influence. The fourth definition is eco-efficiency as a management strategy, and fifth, is an adjustment to the management strategy definition.

[1] In the case of undesirable output that do not impact the environment, the efficiency is considered to be operational or technical efficiency

It would be incomplete to measure the efficiency without considering the undesirable inputs or outputs. This is because undesirable inputs (outputs) are present in the inputs (outputs) set along with the desirable inputs (outputs). In fact, the efficiency scores may be biased when only desirable inputs (outputs) are considered. Therefore, the undesirable and desirable inputs (outputs) should be incorporated in an efficiency measurement but with different treatment between the two.

Since the elements of undesirable inputs are very limited, this study will focus on undesirable outputs rather than undesirable inputs. In fact, currently, more and more researchers are concentrating on the undesirable outputs in their studies. In addition, later, for the empirical section, environmental performance has been chosen as the area of application for this research study. Environmental performance can be seen as a dominant application among others when dealing with undesirable output in efficiency measurement. The reason for this domination is because the issue of environmental performance seems very relevant to the element of undesirable output in production activities. Furthermore, these days, environmental performance has become a major issue regarding global warming and climate change at every level of many countries.

2.7 Various approaches in DEA with undesirable output

Pittman (1983) initiated the earliest effort to include the undesirable outputs in productivity measurement. By using the multilateral productivity index, he calculated the shadow prices for the undesirable output value. In DEA efficiency measurement, there are several approaches to handle undesirable outputs. An evaluation pertaining to this topic has been discussed previously by several researchers. (See for example; Amirteimoori et al., 2006; Bian, 2008; Färe et al., 2007; Hua & Bian, 2007; Hua et al., 2007; Song et al., 2012; Sueyoshi & Goto, 2011a; for a review). Their reviews are more of a comparison of the efficiency score rather than a discussion on the development of the various approaches. Since numerous approaches have been proposed in recent times, there is a need to gather and review the development of these approaches.

There are various approaches for incorporating undesirable output into the DEA model, which can be divided into two categories – indirect and direct approaches (Scheel, 2001). The indirect approach means that the data for the undesirable output variables are transformed into the desirable output. This approach manipulates the undesirable output value so that they can be included in the standard DEA model along with the desirable output. In contrast, the direct approach means that the undesirable output data are applied directly into the modification of the DEA model in order to treat the undesirable output appropriately. In DEA efficiency measurement, generally, there are two types of measure, namely, radial and non-radial. According to Zhu (1996), radial measures are the models that adjust all inputs, or alternatively all outputs of a DMU by the same proportion, such as constant return to scale and variable return to scale models, whereas, a non-radial DEA measure allows for non-proportional reductions in each positive input, or augmentations in each positive output. The non-radial measures take into account the slacks in the model i.e. slack based measure and range adjusted measure (Jahanshahloo et al., 2012).

2.7.1 Indirect approach

The first indirect approach for incorporating undesirable outputs into the model is by transforming it using the additive inverse method. To incorporate undesirable outputs as desirable outputs, the value of undesirable outputs are multiplied by -1. This method was suggested by Koopmans (1951) and applied by Berg, Førsund and Jansen (1992).

The second indirect approach is an approach where the undesirable outputs are considered as input. In this approach, the undesirable output variables are moved from the output side to the input side of the model. Thus, a reduction in the inputs may reduce the undesirable outputs as well. The technology set defined by this approach is the same as the one defined by additive inverse. The only difference is the sign of the undesirable outputs. This approach was suggested and tested by Tyteca (1997). However, treating the undesirable outputs as inputs opposses the physical laws and standard production theory. It also leads to conceptual confusion and will not reflect the true production process in the DEA result (Seiford & Zhu, 2002).

The next approach is the translation invariance in the sense of Iqbal Ali and Seiford (1990) in which a large scalar is added to each of the undesirable output values, such that the resulting output values are positive. The transformed data are regarded as normal outputs. The drawback of this approach is that it moves the zero to a different position and the choice of the scalar can alter the efficient frontier.

Another indirect approach is the multiplicative inverse suggested by Golany and Roll (1989) in which each undesirable output is incorporated as a desirable output using its reciprocal. Then the data of the undesirable outputs are included with the data of the desirable outputs. The drawback of this approach is that it destroys the ratio of the interval scales of the original data. In addition, the inverse of zero values does not exist. When choosing inversion, the efficiency classification can differ from the alternative approaches.

Based on a review of the above indirect approaches, Scheel (2001) suggested that the undesirable outputs and desirable outputs can be joint, as one constraint, with the undesirable outputs bearing a negative sign which decreases the undesirable outputs when the desirable outputs decrease (but without modifying the classical DEA assumption of strong disposability). However, in this "non-separating" outputs approach, the efficiency score and ranking obtained are different from the measurement of the efficiency score with separation on the output approach. This approach is limited to the situation where there is only one negative output or undesirable output.

Another alternative approach to treat the undesirable outputs in the DEA model can be employed using the linear monotone decreasing transformation approach. This approach was developed by Seiford and Zhu (2002) using a linear monotone decreasing transformation, $\bar{u}_k = -u_k + v \geq 0$. All the undesirable outputs are multiplied by –1 and then added with v, a proper translation vector for the undesirable outputs. This translation will transforms negative data to non-negative data. A DMU is efficient if the θ_m value is equal to one. Based on this transformation, the efficiency score can be formulated as below:

$$
\begin{aligned}
&\text{Max } \theta_m \\
&\text{Subject to} \\
&\qquad \sum_{n=1}^{N} z_n x_{in} \leq x_{im}\,; \;\; i = 1,2,\dots,I \\
&\qquad \sum_{n=1}^{N} z_n y_{jn} \geq \theta_m y_{jm}\,; \;\; j = 1,2,\dots,J \\
&\qquad \sum_{n=1}^{N} z_n \bar{u}_{kn} \geq \theta_m \bar{u}_{km}\,; \;\; k = 1,2,\dots,K \\
&\qquad z_n \geq 0\,; \;\; n = 1,2,\dots,N
\end{aligned}
\tag{2.2}
$$

Where $\bar{u}_{kn}$ and $\bar{u}_{km}$ are the transformation of k^{th} undesirable output of the n^{th} and m^{th} DMU, respectively.

In addition, Portela, Thanassoulis and Simpson (2004) claimed that handling the negative data is similar to the treatment of undesirable output. The reason for the similarity is because both negative and undesirable output data need to be removed from the efficiency measurement. Therefore, they proposed the range direction model (RDM), which is based on the directional distance function approach in which the direction is the range of possible improvement (defined as maximum output minus observed output, or observed input minus minimum input). Their efficiency measure also has the same geometric interpretation as radial measures in DEA (Portela et al., 2004). Their suggestion for the RDM model may overcome the drawback of the original additive model in that it tends to project the DMUs on the furthest point of the production frontier. However, it does not provide an efficiency measure for the DMUs by which they can be compared and ranked.

In many real life applications, the transformation of the data may no longer make sense which motivates the researcher to explore other direct approaches in which no transformation is done to the data set, and they are employed with necessary modifications in the modelling assumptions.

2.7.2 Direct approach

a) Hyperbolic Efficiency (HE) model

Färe et al. (1989) proposed the direct approach when attempting to modify the multilateral productivity using the HE measure. This HE measure treats desirable and undesirable output differently. The concept of this approach is to increase the desirable output while decreasing the undesirable output where the desirable outputs are strongly disposable (i.e. the waste can be released without cost) and the undesirable outputs are weakly disposable (i.e. the waste needs to be released with cost). The HE technique requires data on the quantities of the undesirable output rather than the shadow price in order to measure the following model.

$$
\begin{aligned}
&\text{Max } \theta_m \\
&\text{Subject to} \\
&\qquad \sum_{n=1}^{N} z_n x_{in} \leq \theta_m{}^{-1} x_{im}\,; \;\; i = 1,2,\dots,I \\
&\qquad \sum_{n=1}^{N} z_n y_{jn} \geq \theta_m y_{jm}\,; \;\; j = 1,2,\dots,J \\
&\qquad \sum_{n=1}^{N} z_n u_{kn} \geq \theta_m{}^{-1} u_{km}\,; \;\; k = 1,2,\dots,K \\
&\qquad z_n \geq 0\,; \;\; n = 1,2,\dots,N
\end{aligned} \tag{2.3}
$$

In this approach, z denotes the intensity variable vector while the optimal value of θ_m measures the same proportion of increasing the desirable outputs and decreasing the undesirable outputs simultaneously for each DMU m. Since this alternative is based on non-linear programming, many researchers experience a difficult solution to solve this model. Therefore, the empirical study using this approach is limited.

b) Directional Distance Function (DDF) model

An alternative approach is to treat the undesirable outputs by adjusting the distance measurement in order to restrict the expansion of the undesirable outputs. This original approach, suggested by Chung et al. (1997), considers the desirable and undesirable outputs jointly and replaces the strong disposability of outputs, by the assumption that undesirable outputs are weakly disposable. This means that their production can only be reduced at the expense of a joint reduction in some other outputs, or a joint increase in the use of some inputs. The linear programming of the Directional Distance Function (DDF) model to gauge the efficiency is formulated as follows:

$$
\begin{aligned}
&\text{Max } \beta_m \\
&\text{Subject to} \\
&\qquad \sum_{n=1}^{N} z_n x_{in} \le x_{im} \, ; \;\; i = 1,2, \dots, I \\
&\qquad \sum_{n=1}^{N} z_n y_{jn} \ge y_{jm}(1 + \beta_m) \, ; \;\; j = 1,2, \dots, J \\
&\qquad \sum_{n=1}^{N} z_n u_{kn} = u_{km}(1 - \beta_m) \, ; \;\; k = 1,2, \dots, K \\
&\qquad z_n \ge 0 \, ; \;\; n = 1,2, \dots, N
\end{aligned}
\tag{2.4}
$$

The detailed explanation on the DDF model will be discussed further in the methodological chapter.

The application using DDF has become more popular than the other approaches. This model seems to be a more popular model because it allows one to consider non-proportional changes in outputs and makes it possible to expand desirable outputs while contracting the undesirable outputs. However, there is also a major drawback using this model in that there are no standard techniques on how to determine the direction vector. The direction vector to the production boundary is fixed arbitrarily, and thus, may not provide the best efficiency measure. A different direction vector may provide a different efficiency score (Bian, 2008). In addition, the DDF model omits the non-zero input and output slacks in the efficiency measurement, and thus, fails to account for the non-radial excesses and shortfall (Jahanshahloo et al., 2012).

c) Slack Based Measure (SBM) model

Based on the Slack Based Measure (SBM) model proposed by Tone (2001), Zhou et al. (2006) extended the model so that it can incorporate undesirable output. This model makes an attempt to minimize the ratio of the average undesirable output reduction to the average desirable output increase. In this model, z_n are positive multipliers used for computing a linear combination of the DMU. The proposed model is formulated as follows:

$$\text{Min} \frac{1-\frac{1}{I}\sum_{i=1}^{I}\frac{s_i}{x_{im}}}{1+\frac{1}{J}\sum_{j=1}^{J}\frac{s_j}{y_{jm}}}$$

Subject to

$$\sum_{n=1}^{N} z_n x_{in} + s_i = x_{im} \; ; \; i = 1,2, \ldots, I$$

$$\sum_{n=1}^{N} z_n y_{jn} - s_j = y_{jm} \; ; \; j = 1,2, \ldots, J$$

$$\sum_{n=1}^{N} z_n u_{kn} = \lambda u_{km} \; ; \; k = 1,2, \ldots, K$$

$$z_n, \; s_i, \; s_j \geq 0 \; ; \; n = 1,2, \ldots, N \qquad (2.5)$$

Where s_i and s_j are the slack values of the i^{th} input and j^{th} desirable output, respectively. This non-radial model combines environmental and economic inefficiencies. Thus, it is treated as a composite index for modelling economic environmental performance. Compared to radial efficiency measurement, this model provides a higher discriminating power in modelling environmental performance (Zhou et al., 2006).

d) Additive model

Later, Bian (2008) attempted to present an alternative approach to efficiency measurement with the incorporation of undesirable output in the analysis. In his study, Bian extended the additive DEA model introduced by Charnes et al. (1985) by taking into account the slack variables. To measure the efficiency by incorporating the undesirable output in the analysis, a basic additive model has to add another constraint, which is to release *k* undesirable output (u_{1j}, u_{2j},….u_{tj}). The undesirable output slack (s_k^-) follows the same manner as input slack whereby the objective is to maximize the opportunity to improve efficiency in the amount of excesses produced by the DMU in the evaluation of the comparison with other DMUs. The proposed model is as below:

$$
\begin{aligned}
&\text{Max } \sum_{i=1}^{I} s_i + \sum_{j=1}^{J} s_j + \sum_{k=1}^{K} s_k \\
&\text{Subject to} \\
&\quad \sum_{n=1}^{N} z_n x_{in} + s_i = x_{im}\,; \quad i = 1,2,\dots,I \\
&\quad \sum_{n=1}^{N} z_n y_{jn} - s_j = y_{jm}\,; \quad j = 1,2,\dots,J \\
&\quad \sum_{n=1}^{N} z_n u_{kn} + s_k = u_{km}\,; \quad k = 1,2,\dots,K \\
&\quad z_n,\ s_i,\ s_j,\ s_k \ge 0\,; \quad n = 1,2,\dots,N
\end{aligned}
\tag{2.6}
$$

Where s_i, s_j and s_k are the slack values of the i^{th} input, j^{th} desirable output and k^{th} undesirable output, respectively. The advantage of this model is that it does not require any data transformation or user specified direction vectors (Bian, 2008).

e) Range Adjusted Measure (RAM) model

A similar concept was proposed by Zhou et al. (2006) who extended the basic original model to incorporate the undesirable output in DEA, Sueyoshi et al. (2010) also did it in the same way. Even though the method of RAM was introduced by Cooper et al. (1999) more than a decade ago, the application for efficiency measurement with the incorporation of undesirable output has only recently been implemented. Sueyoshi et al. (2010) made an attempt to extend the basic model of RAM with the incorporation of undesirable output. This model measures the efficiency by maximizing the distance from the efficient frontier. At the same time, output will be maximized and input will be minimized. In the first model, they construct the RAM model with desirable outputs to evaluate the operational performance of DMU.

$$
\begin{aligned}
&\text{Max}\,\frac{1}{I+J}\left(\sum\nolimits_{i=1}^{I}\frac{s_i}{R_i^x}+\sum\nolimits_{j=1}^{J}\frac{s_j}{R_j^y}\right)\\
&\text{Subject to}\\
&\qquad\sum_{n=1}^{N} z_n x_{in} + s_i = x_{im}\,;\ \ i = 1,2,\dots,I\\
&\qquad\sum_{n=1}^{N} z_n y_{jn} - s_j = y_{jm}\,;\ \ j = 1,2,\dots,J\\
&\qquad z_n,\ s_i,\ s_j \geq 0\,;\ \ n = 1,2,\dots,N
\end{aligned}
\tag{2.7}
$$

I and J in the above model indicate the number of input and desirable output variables. R_i^x and R_j^y are the range value of the i^{th} input and j^{th} desirable output, respectively. The range (R) is calculated by the maximum and minimum value over all n for each variable. For instance, R_i^x can be computed by $\hat{x}_{in} - \check{x}_{in}$ $(i = 1,\dots,I)$. The symbol of "$\frown$" and "$\smile$" denote the maximum and minimum value over all n for each i (Sueyoshi et al., 2010).

Then, they formulate the second RAM model for undesirable output. In this approach, the undesirable output has been specified in the context of environmental performance. The following model is basically similar to (2.7) but with undesirable output.

$$
\begin{aligned}
&\text{Max}\,\frac{1}{I+K}\left(\sum\nolimits_{i=1}^{I}\frac{s_i}{R_i^x}+\sum\nolimits_{k=1}^{K}\frac{s_k}{R_k^u}\right)\\
&\text{Subject to}\\
&\qquad\sum_{n=1}^{N} z_n x_{in} - s_i = x_{im}\,;\ \ i = 1,2,\dots,I\\
&\qquad\sum_{n=1}^{N} z_n u_{kn} + s_k = u_{km}\,;\ \ k = 1,2,\dots,K\\
&\qquad z_n,\ s_i,\ s_k \geq 0\,;\ \ n = 1,2,\dots,N
\end{aligned}
\tag{2.8}
$$

Here s_k is the slack variables related to undesirable outputs while R_k^u is the range value related to the undesirable output variables. It is important to note that the signs of the slack in the constraints of Model (2.7) are the opposite of those of Model (2.8). The differences are because the projection of an inefficient unit in Model (2.7) is the opposite of that of Model (2.8). Moreover, using both models, the operational and environmental efficiency scores can be measured separately. Later, a combination of both models desirable and undesirable outputs provides a unified efficiency score for operational and environmental performance. The combined formulation becomes:

$$\text{Max} \frac{1}{I+J+K}\left(\sum_{i=1}^{I} \frac{s_i^+ + s_i^-}{R_i^x} + \sum_{j=1}^{J} \frac{s_j}{R_j^y} + \sum_{k=1}^{K} \frac{s_k}{R_k^u}\right)$$

Subject to

$$\sum_{n=1}^{N} z_n x_{in} - s_i^+ + s_i^- = x_{im} \; ; \; i = 1,2,\dots,I$$

$$\sum_{n=1}^{N} z_n y_{jn} - s_j = y_{jm} \; ; \; j = 1,2,\dots,J$$

$$\sum_{n=1}^{N} z_n u_{kn} + s_k = u_{km} \; ; \; k = 1,2,\dots,K$$

$$z_n, \; s_i^+, \; s_i^-, \; s_j, \; s_k \geq 0 \; ; \; n = 1,2,\dots,N \qquad (2.9)$$

Concerning the range adjusted measure model, which is still new, some drawbacks have been identified by the authors themselves. For instance, its efficiency score is larger than those of the radial DEA models and the results of the efficiency scores obtained are close to unity (Sueyoshi et al., 2010). In addition, this model also fails to provide a valid ranking of performance and it is biased against large DMUs.

f) Alternative models

In addition to the various approaches discussed above, there are also other alternatives that have been suggested by researchers. Among others, Liu et al. (2006) provide a solution to treat the undesirable factor for input and output variables. An additive DEA model has been derived to handle undesirable input and output variables. Treating desirable and undesirable factors for both input and output are considered while identifying the preference in the input output space, production possibility set and performance measurement (Liu et al., 2006). Later, the ideas utilized in Liu et al. (2006) were extended by Liu et al. (2010) wherein they extend the standard strong disposability to extended strong disposability in the presence of undesirable factors. By assuming extended strong disposability they disclose that it is equivalent with standard strong disposability in developing the production possibility set when handling undesirable inputs and outputs as desirable inputs and outputs (Liu et al., 2010)

Another solution is the hybrid measure proposed by Tone and Tsutsui (2011). This measure resolves the efficiency in the presence of radial and non-radial inputs or outputs with no separation of desirable and undesirable outputs. According to Tone and Tsutsui (2011), the drawback of the radial approach is the neglect of the non-radial input or output slacks while the non-radial approach, which addresses slacks directly, neglects the radial characteristics of inputs and/or outputs. Therefore, from the weaknesses above, the authors propose a hybrid measure, which follows the original model of the slack based measure. In the hybrid measure, both the desirable and undesirable outputs have been addressed in a unified framework under condition in which certain non-separable associations between some inputs and outputs exist.

In addition to the two alternatives above, Gomes and Lins (2007) propose the zero sum gains DEA (ZSG-DEA) model to treat equilibrium models, where the sum of the quantities produced by all decision-making units can be set as the upper admissible bound. This model has been applied to evaluate the carbon dioxide (CO_2) emissions while measuring eco-efficiency.

Another recent development is an approach proposed by Wu et al. (2013) to measure the congestion between desirable and undesirable outputs based on additive framework. In their suggestion, the method of Seiford and Zhu (2002) is combined with the method of Wei and Yan (2004) to develop the new framework for measuring congestion with undesirable outputs.

2.8 Concept and Measurement of Productivity Change

Efficiency and productivity are important aspects of economic performance. The concept and measurement of efficiency have been discussed previously. This section will discuss the concept and measurement of productivity change.

The productivity of a unit is defined as the relation between outputs and inputs, and can be regarded as a natural measure of performance (Coelli et al., 2005). A firm can accomplish productivity increases by using either a minimum amount of input to produce a given level of output or by producing greater output from a given level of input. In this case, the productivity of a firm can be defined as the ratio of the output(s) produced to the input(s) used (Avkiran, 2001).

The measurement of productivity is widely used to assess the changes in economic efficiency over the period of time besides the variation in efficiency at a particular time. Productivity may vary over time due to differences in production technology, i.e. technological change and due to changes in the efficiency of the production process, i.e. efficiency change.

A Malmquist index of productivity change, initially defined by Caves et al. (1982) and extended by Färe et al. (1992) by merging it with Farrell’s (1957). Efficiency measurement has received increasing interest among researchers studying firm performance. The Malmquist productivity index is constructed from the ratios of distance functions. The formulation of this index in terms of distance functions leads to the straightforward computation by exploiting the relation between distance functions and Debreu-Farrell measures of technical inefficiency.

However, if the technology has a feature that joints the production of desirable and undesirable outputs, the Malmquist index may not be computable (Chung et al., 1997). The Malmquist Luenberger productivity index is formulated to measure the productivity change in which the undesirable outputs are produced together with desirable outputs. The Luenberger productivity index is defined by Chambers et al. (1996) as the difference in values of the directional distance functions. In the primal Luenberger productivity index, the shortage function (directional distance function), which accounts for both input contractions and output improvement is used (Luenberger, 1992; Sarkis, 2006). The formulation for this Malmquist Luenberger Productivity index will be elaborated upon in the methodology chapter.

2.9 Empirical Orientation

A number of empirical works have been carried out, taking into consideration the undesirable output in efficiency measurement using the DEA approach. A review by Zhou et al. (2008b) presents a literature survey on the application of DEA onto energy and environmental performance. Another paper by Tyteca (1996) reviews an analysis of environmental inefficiencies from industrial activities. Inspired by these reviews, this section reviews the efficiency measurement with and without the incorporation of undesirable output in the previous empirical studies on the manufacturing sector. The particular motivation behind this review is to integrate the methodological development orientation discussed earlier as well as the empirical analysis in the previous literature.

This review highlights several issues including technical efficiency and eco-efficiency as well as productivity change in the manufacturing sector, the application of various approaches in different levels of studies, the effect of environmental regulation on the environmental efficiency, potential sources of pollution by different industries and followed by a discussion on productivity growth and environmental performance in the context of the Malaysian manufacturing sector. The information gathered is very useful in guiding the rest of the chapters in this research work as well as the enhancement of the research gap that has been identified in previous literature.

2.9.1 Technical efficiency and productivity change in manufacturing sector

The terms efficiency and productivity are interrelated. The efficiency measurement can be an indicator of productivity performance while productivity performance can be a determinant of a country's economic growth. Economic growth is the result of an improvement in the quantity and quality of the factors of production that a country has available. In all countries, productivity growth plays a significant role in economic development.

In the last decade, many studies can be found in the literature that analyse the technical efficiency of the manufacturing sector. For instance, Martin-Marcos and Suarez-Galvez (2000) examined the technical efficiency of Spanish manufacturing firms during the period 1990 to 1994. Hailu and Veeman (2000) measured technical efficiency in the Canadian pulp and paper industry from 1959 until 1994. Mini and Rodriguez (2000) measured the technical efficiency of Philippine manufacturing firms in 1994. Kaynak and PagÁn (2003) estimated the technical efficiency for the United State manufacturing industry and Wadud (2004) studied the efficiency in the Australian textile and clothing firms.

More recently, Faruq and Yi (2010) estimated the technical efficiency of firms in Ghana across six manufacturing industries between 1991 and 2002. From the results, they found that manufacturing firms in Ghana are significantly less efficient than their counterparts in other countries. Meanwhile, Mok et al. (2010) investigated the technical efficiency of 287 clothing manufacturing firms in Southern China. The results indicate that Guangdong province is more technically efficient than others. Later, in another study, Pham et al. (2010) estimated the technical efficiency for manufacturing enterprises in Vietnam for 2003. The empirical results reveal that an average manufacturing enterprise is operating at nearly 62 percent of its technically efficient frontier with an estimated standard deviation of around 16 percent.

As known, China is one of the countries that has been maintaining a high rate of economic growth (Liao et al., 2007; Wang et al., 2012). Supporting the above statement discovery, Pandey and Dong (2009) examined the productivity in the manufacturing sector for two developing countries – China and India. From the outcome obtained, they found that the productivity of the manufacturing industry in China improved substantially compared to India over the 1998–2003 period. Similar results are documented in the study by Zheng et al. (2009) who agree that economic transition has resulted in sustained high growth in China. Nevertheless, they suggest that China needs to adjust its reform programme towards a sustained increase in productivity. Market and ownership reforms, and open door policies have improved the conditions under which

Chinese firms operate, however, further institutional reforms are required to consolidate China's move to a full-fledged market economy.

Another paper on the productivity growth in the Korean manufacturing industry is Oh (2011). Based on the time period of 1993 to 2003, he summarizes that, after the financial crisis in 1997, productivity and efficiency have declined. In addition, a competitive market condition, R&D activities, export activities and innovativeness are the determinants of the productivity growth.

Nowadays, the topics of technical efficiency and productivity growth have been improved. One of the improvements is the inclusion of undesirable output in the analysis. As has been discussed in the previous section, the conventional efficiency measurement only considers the input and output variables. However, in real life situations, production activities also produce undesirable output that can contribute to poor productivity performance. This undesirable output is a very important factor and must be taken into account in any related study.

For instance, numerous papers which addressed the issues relating to performance measurement and production efficiency, solely consider input or resources used by a firm and the desirable outputs or operational products that are the result of input utilization. Other production variables, such as pollution, scrap, rework as well as service characteristics that lead to dissatisfied customers are not included in the traditional model formulation of efficiency measurement which derives from technical efficiency. The inclusion of only desirable output might not provide a true picture of the efficiency of a decision making unit and the evaluation of performance may ignore real world considerations. Thus, the efficiency measurement can provide misleading results and unfair assessments. That is the reason why many researchers admit that it is not accurate to measure the efficiency and productivity without the incorporation of undesirable output.

2.9.2 Eco-efficiency analysis in the manufacturing sector

Having discussed the technical efficiency studies and the productivity change above, further discussion ensues on the eco-efficiency studies in the manufacturing sector. There has been an increasing trend of previous studies employing elements of pollutants. Most of the studies agreed that undesirable outputs may influence the efficiency level and that efficiency levels can be biased when only desirable outputs are considered. Some of the previous results are discussed below.

A study conducted by Watanabe and Tanaka (2007) exploited the DDF model to measure the efficiency of the industrial sector in China. In their paper, two efficiencies were measured whereby one is a traditional efficiency measure that considers only desirable outputs, while the other considers both desirable and undesirable outputs simultaneously. In their study, they found that five coastal provinces/municipalities that have attracted a large amount of foreign direct investment manage to obtain a high score in efficiency when only desirable output is incorporated and also when both desirable and undesirable output are incorporated. However, from the comparison, they concluded that efficiency levels are unfair if the analysis only incorporated the desirable output. The incorporation of undesirable outputs becomes important in estimating efficiency levels, especially when the discharge of environmental pollutants has to be considered.

Another paper, published by Zhang (2009) claimed that ignoring the production of by-products, such as pollution, would result in failure to provide information concerning the assessment of environmental performance. In his study, the geometric means of eco-efficiency show that if inputs and desirable output did not change, the undesirable output would have the potential to be decreased by about 60 percent in the whole of China. In conclusion, both technical efficiency and eco-efficiency have the potential to be improved in China.

More recently, Riccardi et al. (2012) evaluated the impact of carbon dioxide emissions on the efficiency score of the cement industry. The analysis compares the results with and without the incorporation of carbon dioxide emissions. The evaluation concludes that carbon dioxide emissions influence the efficiency score and the emissions need to be included when measuring the efficiency score in the cement sector. In their hypothesis testing, the finding also implies that excluding the carbon dioxide, which is undesirable output, may results with a biased efficiency measurement.

In addition, Mandal (2010), who studied energy efficiency, also concurs that analysing the efficiency measurement without considering undesirable outputs may lead to bias in the efficiency score. Mandal (2010) applied DEA to evaluate the energy efficiency of Indian cement industry. The findings disclose that the average energy efficiency measure when incorporating both desirable and undesirable outputs exhibit higher than when only desirable output is incorporated. Next, by conducting the Wilcoxon Rank Sum test, he found that it is statistically significant and that the energy efficiency result may be biased when undesirable output is ignored in the analysis. Another example on energy efficiency with the same finding where omitting undesirable output may cause a biased outcome are Wu et al. (2012) and Zhou and Ang (2008).

Another important finding is the study conducted by Zhang et al. (2008). Zhang et al. (2008) carried out a study on 30 provinces in China and made a conclusion about the eco-efficiency in China. Among others, the results demonstrate a positive relationship between eco-efficiency and economic development level in which provinces with higher GDP per capita also show greater eco-efficiency as well.

To measure the performance over time, the Malmquist Luenberger Productivity Index (MLPI) has been widely used to evaluate the productivity change. Färe et al. (2001) employed MLPI to observe the productivity change of the manufacturing sector in United States between 1974 and 1986. The results reveal that, when incorporating the undesirable output of emission factors, average annual ML productivity growth was 3.6 percent. The results show that technical change is the main contributor of productivity growth. However, when emission factors are omitted, the average annual productivity growth is only 1.7 percent, which was largely due to technical change. Technical change drops from a 1.3 percent average annual increase when emission factors are incorporated to 0.77 percent when emission factors are not incorporated. In conclusion, they conclude that the results might be biased when the emission factors are not incorporated in productivity growth.

The study by Kumar (2006) found that the value of standard Malmquist is similar to the Malmquist Luenberger Index calculated using the DDF model. The average Malmquist index value of 0.9998 indicates that the annual productivity declines about 0.002 percent, which is due to technical change. The average change in the ML productivity index by the assumption that CO_2 is weakly disposable, was 0.02 percent and was due to technological change.

2.9.3 The application of various approaches in different levels of study

Various papers evaluate efficiency with undesirable factors, some of which employed the indirect approaches like Athanassopoulos and Thanassoulis (1995) and Knox Lovell and Pastor (1995), who employed multiplicative inverse, and Lu and Lo (2007) who employed linear monotone decrease transformation. Examples of studies that treat undesirable output as input include Korhonen and Luptacik (2004) and Tyteca (1997) who studied the European and United State countries at firm level, respectively, while Yang and Pollitt (2009) and Zhang et al. (2008) studied China at firm level and regional level, respectively.

Further researches utilizing direct approaches include Boyd and McClelland (1999), Hernandez-Sancho et al. (2000), Taskin and Zaim (2001), Zaim and Taskin (2000b) and Zofío and Prieto (2001) who applied the Hyperbolic Efficiency (HE) model. Boyd and McClelland (1999) conducted time series analysis for the year 1988 to 1992 for the US Bureau of the Census data on economic inputs, outputs, and environmental investments. Zaim and Taskin (2000b), Zofío and Prieto (2001) and Taskin and Zaim (2001) are among the papers that studied at the country level. Both Zaim and Taskin (2000b) and Zofío and Prieto (2001) applied the analysis for OECD countries while Taskin and Zaim (2001) utilized a sample of 47 countries consisting of high, middle and low income countries. Another example that utilized the HE model at firm level is that of Hernandez-Sancho et al. (2000).

As for the application of Directional Distance Function (DDF) technique, this includes Arcelus and Arocena (2005), Boyd et al. (2002), Färe et al. (2005), Färe et al. (2006), Kumar (2006), Lee et al. (2002), Macpherson et al. (2010), Mandal and Madheswaran (2010), Murty and Kumar (2002), Picazo-Tadeo et al. (2012), Picazo-Tadeo and Prior

(2009), Picazo-Tadeo et al. (2005), Wang et al. (2012), Watanabe and Tanaka (2007), Zha and Zhou (2009), Zhang (2009), Zhou et al. (2012) and many more. From all the DDF applications, Arcelus and Arocena (2005) and Kumar (2006) are examples of country level studies while Domazlicky and Weber (2004) and Picazo-Tadeo and Prior (2009) are at the firm level. Other studies like Hu et al. (2010), Kaneko et al. (2010), Lozano and Gutierrez (2008), Macpherson et al. (2010), Wang et al. (2012), Watanabe and Tanaka (2007), Zhang (2009) and Zha and Zhou (2009) are conducted at state and/or regional level. All the researchers prefer their own country as their application area. Out of these eight studies, only two were conducted in the United States while the rest were conducted in China. China is one of the countries that has maintained a high rate of economic growth. In addition, China is also one of the countries that does not perform well in environmental performance with high volumes of pollution being released into the air. Hence, China is a good sample for those who wish to study about economic growth and the impact of environmental performance.

More recently, Wang et al. (2013) estimated a total factor of CO2 emissions performance index using the DDF approach. The study evaluated CO2 emission performance, emission reduction potential and influences of regulatory policies in Chinese provinces. In addition, Yu-Ying Lin et al. (2013) measured environmental efficiency (EE) in 63 countries and analyzed whether the adoption of the Kyoto Protocol is accompanied by an increase in environmental efficiency. The study reveals that high income countries managed to obtain the highest progress in their average environmental efficiency while lower-middle income countries indicate a negative growth in their average EE. Other recent publications of DDF approach on eco-efficiency measurement are written by Beltrán-Esteve et al. (2013) and Halkos and Tzeremes (2013).

Studies that have utilized the Slack Based Measure (SBM) model include Zhou et al. (2007) who studied for OECD countries and Choi et al. (2012) and Li and Hu (2012) who studied provinces in China. As for the Range Adjusted Measure (RAM) model, this includes Sueyoshi and Goto (2010a; 2010b; 2011a; 2011b) who mostly studied eco-efficiency at the firm level in Japan.

From all the studies, it is found that the DDF approach is a popular approach among researchers. The reason for this popularity might be because it is simple, intuitive and can be easily put into practice while expanding desirable output and contracting the undesirable output simultaneously. Further discussion on the DDF approach will be included in the methodology chapter as this method is a main concern in this research study.

2.9.4 The effect of environmental regulation on the environmental efficiency

From all the studies that have been reviewed, a number of studies emphasize environmental efficiency measurement towards environmental regulation (Banerjee, 2007; Hernandez-Sancho et al., 2000; Kumar Mandal & Madheswaran, 2010; Mandal, 2010; Murty & Kumar, 2003; Murty, Kumar, & Paul, 2006; Picazo-Tadeo et al., 2005; Sueyoshi et al., 2010; Telle & Larsson, 2007; Wang et al., 2011; Yörük & Zaim, 2008; Zofio & Prieto, 2001).

The studies by Hernandez-Sancho et al. (2000) and Piczo-Tadeo et al. (2005) evaluated the impact of environmental regulation on the Spanish furnishing industry and Spanish ceramic tile industry, respectively. When environmental regulation is assumed, Hernandez-Sancho et al. (2000) found that firms would have to decrease some desirable outputs in order to reduce waste from input resource utilization. This finding is supported by Picazo-Tadeo et al. (2005) in that when firms face environmental regulation the potential to increase desirable outputs drops. Another study, by Murty et al. (2006) concluded that firms in the sugar industry in India also have to reduce the production of sugar or incur additional input cost to reduce pollution according to the environmental regulations.

Contrastingly, there are studies that argue that environmental regulation can increase environmental efficiency and productivity growth. Telle and Larsson (2007) determined the relationship between environmental regulations and productivity growth. From their analysis, they found that when the emission factor is included in the analysis, there is a positive significant relationship on the effect of environmental regulation towards productivity growth. However, when the emission factor is excluded in the analysis, there is a negative relationship on the effect of environmental regulation towards productivity growth. Their finding exhibits that environmental regulation may not decrease productivity growth.

Another study, by Banerjee (2007), investigated whether environmental regulation has the potential to stimulate higher efficiency levels for Indian cement manufacturing firms. The results obtained show that environmental efficiency increases during the initial phase of regulation implementation which reflects the idea that the firms are more concerned with the initial phase of implementation of regulation eventhough the level of gains in efficiency level decreases over time. In addition, Wang et al. (2011) also reported that the efficiency indicator achieved a significant improvement when implementing the stricter regulation in Shandong Province’s pulp and paper industry, China, while Yörük and Zaim (2008) concluded that the regulations have a positive effect on environmental performance.

2.9.5 Potential variables and sources of pollution by different industry

To measure the efficiency of environmental performance, the identification of the potential input and output factors is also important after deciding on the methodology to be used. From the total number of publications that have been reviewed, the variables that have been identified were based on the production activities of the sector. For instance, the studies on electric utility industry which was written by Burnett and Hansen (2008) and provinces in China which was written by Watanabe and Tanaka (2007) used operating cost and capital for their inputs. Based on the previous studies on efficiency and productivity, it is typical to use operating expenditure and capital as inputs since these two elements are required during the production process (Ball et al., 2004; Färe et al., 2006; Telle and Larsson, 2007). Besides operating cost and capital, labour also has been utilized as an input variable. Labour is a resource that is necessary in production process to produce goods. Examples of studies that employed labour as an input include Choi et al. (2012), Kumar Mandal and Madeshwaran (2010) and Seiford and Zhu (2002) who studied the 30 provinces in China, 20 cement industry in China and 30 paper mills production in United State, respectively.

For desirable output variable, many papers exploited value added as an indicator for output production in manufacturing sector since value added can be represented as the industry's gross income (Domazlicky and Weber, 2004; Watanabe and Tanaka, 2007; Wu et al., 2012; Zhang et al., 2008). Besides value added, gross domestic product (GDP) also has been exploited as an indicator for output production. GDP is more appropriate indicator if the analysis studies on the country level. Examples of studies that employed GDP as desirable output include Ke and Hu (2011), Scheel (2001) and Zhou et al. (2008a) who studied the 15 OECD countries, 13 selected European countries and 8 world regions (OECD, Middle East, Former USSR, Non-OECD Europe, China, Asia, Latin America and Africa), respectively.

With regard to the source of pollution, generally, the classification of factors is connected to the application of industry. Different industrial sectors emit different types of pollution. Carbon dioxide (CO_2), nitrogen oxide (NO_X), sulfur oxide (SO_X) and carbon monoxide (CO) are among the preferred sources of pollution because these elements contribute towards the impact of environmental performance. CO_2 is a major contributor to global warming while NO_X reduce plant growth and causes damage to plant crops, as well as contributes to acidification and the formation of ground-level ozone (Färe et al., 2004). In addition, sulphur oxide can result in negative health and environmental effects. For example, asthmatic children and adults who are active outdoors will suffer severe breathing problems. Furthermore, according to Färe et al. (2004), the main sources of the pollutants, which were discussed earlier, come from the production of electricity, combustion in industry and other non-industrial combustion.

Factors that contribute towards poor environmental performance come from various sectors. The manufacturing sector is one of the largest contributors to poor environmental performance. Emission factors, such as NO_x, CO_2, CO and SO_2 are among the pollution factors that are produced and are damaging the environment.

The studies by Burnett and Hansen (2008), Cuesta et al. (2009) and Tyteca (1997) used electric utilities for their application. The undesirable output for these analyses is SO_2. Even though SO_2 is not an inclusive indicator of environmental performance, it is an extremely important pollutant in the electric utility industry (Burnett & Hansen, 2008). For the cement industry, CO_2 has been employed as an undesirable output (Mandal &

Madeswaran, 2010; Riccardi et al., 2012) while NO_X has been utilized in the glass industry (Boyd et al., 2002; Boyd & Pang, 2000). CO_2 and NO_X are among the preferred undesirable output variables since CO_2 is a major contributor to global warming while NO_X reduces plant growth and contributes to acidification and the formation of ground-level ozone (Färe et al., 2004).

Besides the element of air pollutants as an undesirable output, there are also examples considering the element of water pollutants in the literature. Brannlund et al. (1998), Chung et al. (1997), Hua et al. (2007), Seiford and Zhu (2002) and Telle and Larsson (2007) analysed the pulp and paper industry in their studies. According to Telle and Larsson (2007), the pulp and paper industry is among the most energy intensive manufacturing sectors and also a major contributor to the emissions of water pollutants in Norway releasing biological oxygen demand (BOD) and total suspended solid (TSS). Brannlund et al. (1998) also agreed that the pulp and paper industry destroys the marine environment in Sweden. Picazo-Tadeo et al. (2005), Picazo-Tadeo and Prior (2009) and Domazlicky and Weber (2004) found another example of water pollutant, which is watery mud released by the ceramic tile industry.

2.9.6 Productivity growth and environmental performance in the Malaysian manufacturing context

In the context of the Malaysian manufacturing sector, it is not excluded from being analysed in terms of its efficiency. Nevertheless, since Malaysia is just a young developing country, the studies on this matter are quite limited. Table 2.1 below briefly list the empirical studies devoted to efficiency measurement on the manufacturing sector in Malaysia.

Table 2.1: Empirical studies on efficiency measurement of manufacturing sector in Malaysia

Author and Year	Input (I) and output (O) variables	Methodology	Data set
Renuka (2002a)	I – capital, labour O – value added	Stochastic Production Frontier	28 manufacturing sub-industries (1981 – 1996)
Renuka (2002b)	I – capital, labour O – value added	Data Envelopment Analysis	28 manufacturing sub-industries (1981 – 1996)
Renuka (2002c)	I – capital, labour O – value added	-Stochastic Production Frontier -Data Envelopment Analysis	28 manufacturing sub-industries (1981 – 1996)
Elsadig (2006b)	I – capital, labour, material O – growth rate	Divisia Translog Index	Manufacturing sector (1971 – 2001)
Idris and Rahmah (2006)	I – capital, labour O – value added	Data Envelopment Analysis	7 manufacturing sub-industries (1984 – 2000)
Rahmah (2009)	I – capital, labour, wages O – value added	Data Envelopment Analysis	Food based industries (1985 – 2003)
Idris and Rahmah (2009)	I – capital, labour O – value added	Data Envelopment Analysis	Small and medium scale industries (1985 – 2005)
Nordin and Fatimah (2010)	I – cost of input, labour, fixed asset O – value added	Data Envelopment Analysis	32 food manufacturing sub-industries (2002 – 2007)

In Table 2.1, it can be seen that the studies on the manufacturing sector, particularly in efficiency measurement through a frontier approach, are very limited in the Malaysian context. As for input and output variables, most papers employ the same variables, which are capital, labour and value added. These variables are common elements when running the analysis in the manufacturing sector. The two dominant frontier approaches that were employed in these studies include Data Envelopment Analysis (DEA) from a non-parametric approach and Stochastic Production Frontier (SPF) from a parametric approach to measure the efficiency. Nearly all of the studies employed preferred industries in the manufacturing sector.

Renuka (2002a) analyses the productivity growth by using the SPF approach. Renuka (2002a) pointed out that growth in the Malaysian manufacturing sector is driven by input growth and the Total Factor Productivity (TFP) in Malaysian manufacturing improved over the period of 1981 to 1984 and yet declined over the period of 1987 to 1996. Two factors have been identified that influence the turn down of TFP – negative contribution towards technological progress and the considerable worsening of technical efficiency. In the following year, once again Renuka (2002b) applied a similar data set to the DEA approach to approximate the TFP. It is found that TFP grows positively over a period of time. According to her, the main influence of this trend is due to the catching up effect (technical efficiency change). In addition, she also pointed out that TFP growth is driven by technical efficiency instead of technical change.

Later, in another paper, Renuka (2002c) compared both approaches, DEA and SPF while estimating TFP growth. Different approaches have presented different results. Using DEA, the TFP growth rate is consistently positive. In contrast, using SPF, the TFP growth rate is consistently negative. However, the similarity is that both models exhibit low TFP growth and decline over a period of time. Elsadig (2006b), in his paper also agrees with Renuka (2002a) in that the productivity growth of the Malaysian manufacturing sector is input driven rather than TFP growth driven.

A subsequent paper written by Idris and Rahmah (2006) also analysed the technical efficiency of the manufacturing sector in Malaysia. The analysis, conducted from 1984 to 2000, shows that the food, wood, chemical and iron industries provide a higher efficiency score, which is above one compared to the textile, paper and non-metallic industries. This paper also shows a similar finding to Renuka (2002a) in that the trend of TFP growth is influenced by the technological progress.

Meanwhile, Rahmah (2009) investigated the TFP growth in the components of technical efficiency and technical change in the Malaysian food based industry. From the results obtained, Rahmah (2009) found that the technical efficiency during the time period of study is not high between 35 percent (1995) and 62 percent (1986). She also noticed that the efficiency level for the food-based industry was not affected by the 1985-1986 economic crisis. Nevertheless, in 1995, when the economic growth slightly increased, the technical efficiency reduced. She assumed that, the reason for this decline might be because of the lower participation of this industry in the international market.

In addition to the studies mentioned above, Idris and Rahmah (2009) tested the effect of technical progress on labour productivity in small and medium scale industries in the Malaysian manufacturing sector. They concluded that there is a positive relationship between technical progress and labour productivity. As for the TFP growth, it reveals a negative result due to the negative contribution from technical progress. This result exhibits that small and medium scale industries are quite slow in adapting to technological change.

In a very recent article, Nordin and Fatimah (2010) examined TFP growth through technological change and technical efficiency change in 32 Malaysian food manufacturing sub-industries. The average of technical efficiency between 2002 and 2007 was 71 percent. They also documented that technical efficiency did not improve in line with technological progress. From their highlighted observations, the manufacturing of tea obtained the highest TFP growth while pineapple canning obtained the lowest TFP growth.

Other papers studying the productivity growth of manufacturing sector regardless of DEA efficiency measurement in the Malaysian context include Rahmah and Idris (2000), Kalirajan and Tse (2007), Menon (1998) and Oguchi et al. (2002).

On the topic of productivity growth and environmental performance, the research done by Elsadig (2006a) led the way in the Malaysian manufacturing context. His paper contributes to the available literature of growth accounting methods in the area of calculating the real TFP and TFP per unit of labour growth by internalizing CO_2 emissions and CO_2 emissions intensity in addition to the conventional input terms in the production function. From the results obtained, he found that industrial activities are related to the growth rate of carbon dioxide emissions generated by the manufacturing sector. This finding is based on the slowdown in the productivity growth of the manufacturing sector when CO_2 is included in the productivity indicator.

In the following year, Elsadig (2007) demonstrated the impact of organic water pollutant BOD emissions on the productivity growth of Malaysia's manufacturing sector. The results exhibit that BOD emissions have a negative impact on the TFP growth during the period of study. Thus, this consequence raises a connection with his previous research whereby by including the air pollution indicators may slowdown the TFP growth. Both papers, presented by Elsadig (2006a) and Elsadig (2007) employed the non-frontier model of Divisia Translog Index approach to study the three periods of analysis, whereby, 1971 – 1979 witnessed the birth of Malaysia's era of export oriented economy, 1980 – 1986 saw further diversification of the economy into industrial sectors while 1987 – 2001 witnessed further development of the economy into more advanced industries.

2.10 Conclusion

This chapter sets out to provide a review of the development of an efficiency measurement with and without the incorporation of undesirable output, specifically, in the DEA framework. Papers that utilize the models have also been acknowledged. At the same time, the advantages or/and disadvantages from the models have also been identified in the theoretical section earlier.

In considering all the approaches that have been identified in the DEA frontier approach, the various methods have been classified into two categories which are indirect and direct approaches when incorporating the undesirable output in the efficiency measurement. Through the indirect approach, the data of the undesirable output variables have been manipulated so that they can be included in the standard DEA model with desirable output. On the other hand, the direct approach applies the method directly with the undesirable output variable in order to treat the undesirable output appropriately.

As for the review of empirical literature, the papers on technical efficiency without undesirable output were discussed first. Later, the efficiency with undesirable output was reviewed. Environmental performance can be seen as a dominant application among others when dealing with undesirable output in efficiency measurement. The reason for this domination is because the issue of environmental performance seems very relevant to the element of undesirable output in production activities. Furthermore, in recent times, environmental sustainability has become a major issue regarding global warming and climate change at every level of many countries.

The information from the theoretical and empirical review presented in this chapter contributes to the identification of issues that deserve further attention. The first issue that has been identified from this review is that the body of knowledge is lacking theoretical based studies compared to empirical based studies. Although empirical studies are important, it is hoped that this study can initiate future research, introducing a new outstanding technique while filling the weaknesses of previous models, with regards to efficiency measurement incorporating undesirable output in DEA. Based on the advantages or/and disadvantages that have been identified from the models, a new development for DDF model is a research direction in this study. The DDF model incorporating undesirable output using slack-based measure may overcome the drawback of the original DDF model whereby the direction vector to the production boundary is fixed arbitrarily and omits non-zero slacks in the efficiency measurement. This development on comprehensive efficiency measurement which will be discussed further in the model development chapter is a very significant contribution for future research in the DEA framework.

The second issue is inadequacy in the application of eco-efficiency in Malaysia. The above studies in the Malaysian context are very limited while incorporating the undesirable output in the manufacturing framework. Therefore, it is hoped that this study may contribute to the available literature with a new dimension of the frontier approach concerning efficiency measurement in the Malaysian context, particularly in the manufacturing sector, wherein both desirable and undesirable outputs are considered in the analysis and thus provide a bearing on eco-efficiency study.