Technical and Scale Efficiency of the Intensive Tiger Shrimp Cultivation Farms in Binh Dai district - Ben Tre - Viet nam An Application of DEA

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DECLARATION OF ORIGINALITY

I declare that the work in this thesis is my best belief and knowledge, my own work, except as acknowledged in the text. The thesis is submitted only to Tromso University and Nha Trang University to fulfill the requirement of Master program in Fisheries and Aquaculture Economics and Management.

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ABSTRACT

While DEA method, a data oriented approach for evaluating the performance of decision making units, has been studied and applied successful in many fields worldwide; in Vietnam, concepts and applications of this method used for accessing the efficiency of aquaculture operations, however, is still a shortcoming. In that context, this study is implemented with two main purposes: (1) reviewing the literature on efficiency and DEA methods, (2) applying certain DEA methods to examine the technical and scale efficiency of the intensive tiger shrimp farms in Binh Dai district, Ben Tre Province, Vietnam. In the thesis, therefore, after literature on efficiency and DEA methods are reviewed, a case study of measuring the performance of shrimp farms in Binh Dai district is implemented. In analyzing the case study, input oriented CRS and VRS DEA models are applied to measure the technical and scale efficiency of shrimp farms. Furthermore, super efficiency is also considered to have better ranking for the farms performance. Then, some hypothesis will be performed and tested to further examine relationships, factors related to used inputs, outputs, scale and technical efficiency of the shrimp farms. Interesting findings have been found from the study. Theoretical literature on efficiency and DEA methods and their worldwide applications reflected that the application of DEA for measuring aquaculture performance in Vietnam absolutely have chances to be applied successfully. For findings from the case study, results from examining the intensive shrimp farming shows that at normal production process, the intensive tiger shrimp farms in Binh Dai district are quite efficient. Purely technical efficiency and scale efficiency level of the shrimp farms are rather high (on average above 90 percent). These results express that as risk factors are controlled, the intensive shrimp farming technology can control quite well the production process, so it could be encouraged to be applied. However, significant possibilities to increase efficiency levels of those farms have been still identified. Inefficiency shrimp farms could improve their performance by eliminating pure technical inefficiencies through the adoption of the best practices of efficient shrimp farms and by operating at optimal scales. Certain types of hypothesis tests has been performed and implemented to test the impacts of farm size to technical efficiency, the existence of scale inefficiency, the relationships between inputs used to the efficiency as well as other potential relationships included in production process. The results of the hypothesis tests are interesting and suggested to be further examined in near future. Overall, this study has focused and solved a certain issues in a limitation of time and finance; the results and information mentioned in the study are expected to be perfect foundations for a further comprehensive study to cover more issues related to aquaculture performance.

LIST OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

AE	Allocative efficiency
AR	Assurance regions
BCC	Input oriented-returns to scale model
CCR	DEA model proposed by Charnes, Cooper and Rhodes
CRS	Constant return to scale
DEA	Data envelopment analysis
DMUs	Decision Making Units
GDP	Gross domestic production
LP	Linear programs
NDRS	Non decreasing return to scale
NIRS	Non increasing return to scale
RE	Revenue efficiency
SE	Scale efficiency
SFAF	Stochastic frontier function approach
TE	Technical efficiency
VIFEP	Vietnam Institute for Fisheries Economic and Planning
VND	Vietnam Dong
VRS	Variant return to scale
WRs	Weight restrictions

1. INTRODUCTION

In the trend of aquaculture development in Vietnam, shrimp farming in Binh Dai district, Ben Tre province has been considerable developed. Many water areas has been transformed in to shrimp farming and provided significant increase in shrimp production of the district. In 2006, around 13.000 ha were used for shrimp farming provided approximately 12.300 tons of shrimp products. Even though the district has got such high achievement, sustainable shrimp farming development still has been identified as an urgent requirement for managers and farmers in the local area.

To manage effectively shrimp farming activities, it is important to evaluate the performance of farms. Unfortunately, in Vietnam, there has been still a shortcoming in applying effectively efficiency analysis methods in analyzing the operations of aquaculture systems. Frequently, managers just focus on analyzing traditional economic factors related to revenue, benefit, and costs. Useful approaches such as data envelopment analysis or econometrics methods, which have been applied widely in many fields worldwide, are still a new concept and have not applied successful by aquaculture managers and farmers.

In that context, this thesis is implemented with two main purposes: (1) reviewing the literature on efficiency and DEA methods, (2) applying certain DEA methods as well as statistic and regression approach to examine the technical and scale efficiency of the tiger shrimp farms in Binh Dai district, Ben Tre Province. Two main problem questions, therefore, will be examined to be answered is that: (a) in what way, do DEA methods measure the performance of a firm? And (b) how efficient are the operations of intensive Tiger shrimp farms in Binh Dai district, Ben Tre province, in term of technical efficiency and scale efficiency?

1.1. Objectives of the research

- To review the literature on efficiency and DEA methods in order to gain an understanding about concepts and applications of DEA.
- To examine technical and scale efficiency of the intensive tiger shrimp farms in Binh Dai district, Ben Tre province
- To investigate the impacts of farm size to efficiency of shrimp farms, as well as the existence of scale inefficiency.
- To examine the relationships of inputs used with efficiency of the shrimp farms.
- To propose applications related to shrimp farming.

1.2. Research framework

After reviewing DEA methods, certain DEA methods are applied to calculate the efficiency of shrimp farms in Binh Dai district.

Input oriented is proposed to be applied in DEA in analyzing the performance of the shrimp farms. Then, CRS DEA and VRS DEA are implemented by applying DEA- Solver-PRO written by Cooper et al. (1999) to identify the technical and scale efficiency.

In the next step, in order to have better ranking performance of farms, super efficiency analysis (done in both cases CRS DEA and VRS DEA) is implemented through applying the DEA Excel solver software written by Zhu.

Finally, statistic approach is applied to test the impacts of farms size to the general technical efficiency and the pure technical efficiency of farms, as well as to test the existence of scale efficiency. Regression approach is also used to examine the relationships between inputs used and efficiency scores. Excel and SHAZHAM software will be used to perform these estimations.

Proposed hypothesis include: (a) In term of capacity utilization, the larger farms the more generally technical efficient or purely technical efficient farms; (b) There is the existence of scale inefficiency in the production process of the shrimp farms; and (c) There are certain relationships between input used and efficiency scores of farms. Details about hypothesis testing procedures will be mentioned in methods and procedures chapter.

1.3. Structure of thesis

This thesis is organized into nine chapters. Following this introduction is the related literature. Next, overview on efficiency analysis in aquaculture is illustrated. Then general information about the study area is described. The next three important chapters are methods and procedures; results; and discussions implications and conclusions respectively.

2. RELATED LITERATURE

2.1. Definitions and measure of efficiency

Productive efficiency is divided into two components: purely technical (physical) component and allocative component (Tewodros, 2001). The purely technical component refers to the ability to avoid waste by using as little input as given level of output or by producing as much as output with a given level of input. These two ways of assessments lead to two orientations in measuring technical efficiency: output augmenting orientation and input conserving orientation. On the other hand, the allocative, or price component refer to the ability to combine output and inputs in optimal proportions with given prevailing prices (Lovell, 1993). According to the formal definition of technical efficiency stated by Koopmans (1951, p.60), a producer is considered to be technically efficient if an increase in any output require a reduction in at least one other output or an increase in at least one input, and if a reduction in any input require an increase at least one other input or a reduction in at least one output. This also means a technically inefficient firm could produce the same outputs with less of at least one input or could use the same inputs to produce more of at least one output.

Regarding the measure of technical efficiency which was introduced by Debreu (1951) and Farrell (1957)[1]; with an orientation of input-conserving, technical efficiency is defined as the maximum equiproportionate (i.e., radical) reduction in all inputs that is feasible with given technology and outputs; as an output-augmenting orientation is considered, then the measure is defined as the maximum radical expansion in all outputs that is feasible with given technology and inputs. In both orientations, a value of unity (1) indicates technical efficiency as no radical adjustment is feasible, and a value different from unity indicates the status of technical inefficiency.

It is quite interesting that the Debreu-Farrell measures are related to the Koopmans definition, and both are related to the structure of production technology. Production technology can be represented by the production set: $S = \{\mathbf{q}: (\mathbf{x}, \mathbf{q}): \mathbf{x} \text{ can produce } q\}$[2]. Then the Koopmans's definition of technical efficiency can now be stated formally as $(q, x) \in S$ is technical efficient if, and only if, $(q', x') \notin S$ for $(q', -x') \geq (q, -x)$.

[1] An argument has been noted that the concepts introduced by Koopmans and Debreau (1951) may be more often to be considered as relating to general pareto efficiency; and that Farrell could be seen as starter dealing with such efficiency concerns.

[2] x, q denote for input, output respectively

Technology can also be represented by input sets L (**q**) = {**x**: (**q, x**) $\in$ **S**}. This set, for every q$\in$ $\mathbf{R}_+^{\mathbf{M}}$ **,** have input isoquants: I (q) = {x: x $\in$ L(q), λx $\notin$ L(q), λ<1} and the input efficient subsets E (q) = {x : x $\in$ L(q), x' $\notin$ L(q); x' $\leq$ x }. The three sets satisfy E(q) $\subseteq$ I(q) $\subseteq$ L(q). Base on the definition and concepts of technical efficiency, Shephard (1953) established the input distance function that can be used to represent production technology. The form of the input distance function is: D_I (q, x) = max {λ: (x/λ) $\in$ L (q)}.

It should be noted that, for x $\in$ L (q), D_I (q, x) $\geq$ 1 and for x $\in$ I (q), D_I (q, x) = 1. With the given standard assumption on S, the input distance function D_I (q, x) is non-increasing in q and is non-decreasing, homogeneous of degree +1, and concave in x.

Regarding the concept of distance function, the Debreu-Farrell input oriented measure of technical efficiency TE_I can be illustrated in a more formal form in a type of function:

$$TE_I(q, x) = \max\{\lambda: (x/\lambda) \in L(q). \qquad (2.1.1)$$

So, from the distance function, we have TE_I (q, x) = $[D_I (q, x)]^{-1}$

For x $\in$ L(q), TE_1 (q, x) $\leq$ 1, and for x $\in$ I(q), TE_I (q, x) = 1

In reality, there has been many concerns about output orientation, and theoretically production technology can also be represented by output sets: P(x) = {**q**: (**x, q**) $\in$ **S**}. This set, for every x $\in$ $\mathbf{R}_+^{\mathbf{N}}$ **,** have output isoquants: I (x) = {q: q $\in$ P(x), λq $\notin$ P(x), λ>1} and output efficient subsets: E (x) = {q : q $\in$ P(x), q' $\notin$ P(x); q' $\geq$q}. The three sets satisfy E(x) $\subseteq$ I(x) $\subseteq$ P(x). The output distance function, which was introduced by Shephard (1970), is D_0(x, q) = min {λ: (q/λ) $\in$ P(x). If q $\in$ P(x), D_o (x, q) $\leq$ 1, and if q $\in$ I(x), D_o (x, q) = 1. Given standard assumptions on T, the output distance function D_o (x, q) is non-increasing in x and is non-decreasing homogeneous of degree +1, and convex in q.

The output oriented measure of Debreu-Farrell about technical efficiency can be represented by a more formal form as in the function:

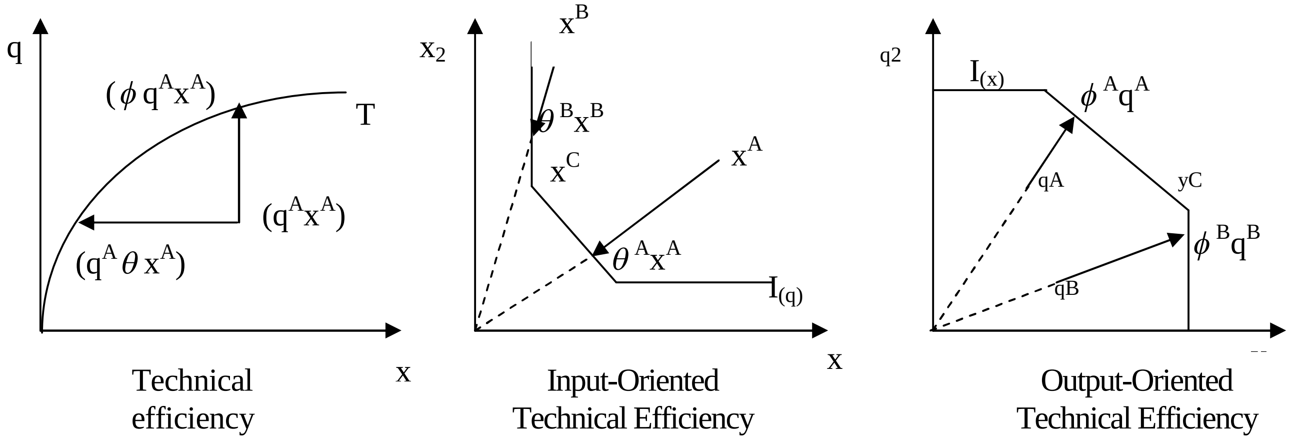
$$TEo(x, q) = \max\{\phi: \phi\, q \in P(x)\}. \qquad (2.1.2)$$

So, from the property of the distance function, we have: TEo(x, q) = $[D_0(x, q)]^{-1}$

If q $\in$ P(x), TE_o (x, q) $\geq$ 1, and if q $\in$ I(x), TE_o (x, q) = 1. Given standard assumptions on S, the output distance function D_o (x, q) is nonincreasing in x and is nondecreasing homogeneous of degree +1, and convex in q.

Assume that M >1 and N > 1 then, in the single input case, we have: D_I (q, x) = x/g(q)$\geq$ 1 <=> x $\geq$ g(q) where g(q) = min {x: x $\in$ L(q)}is an input requirement frontier that defines the minimum

amount of scalar input x required to produce output vector q. The input oriented measure of technical efficiency in this case can be illustrated by the ratio of minimum to actual input: TE_I (q, x) = 1/ D_I (q, x) = g(q)/x $\leq$ 1.
In the output case: $D_0(x, q) = q/f(x) \leq 1 \Leftrightarrow q \leq f(x)$ where f(x) = max $\geq$\{q: q $\in$ P(x)\}is a production frontier that defines the maximum amount of scalar output that can be produced with input vector x. The output oriented measure of technical efficiency, in this case, can be represented by the ratio of maximum to actual output: $TEo(x, q) = [D_0(x, q)]^{-1} = f(x)/q \geq 1$.
The technical efficiency measures are figured out in figure 2-2.



Source: Fried et al. (2008)

Figure 2-1. Technical efficiency measures[3]

The measure of technical efficiency proposed by Debreu-Farrell is widely applied as they satisfy many nice properties (Fried et al., 2008). The most important properties that should be considered are:

- TE_I (q, x) is homogeneous of degree -1 in inputs while $TE_o(x, q)$ is homogeneous of degree – 1 in output
- TE_I (q, x) is weakly monotonically decreasing in inputs, Whilst $TE_o(x, q)$ is weakly monotonically decreasing in outputs
- TE_I (q, x) and $TE_o(x, q)$ are invariant with respect to changes in inputs of measurement.

Fried et al. (2008) has stated that Debreu-Farrell measures of technical efficiency do not coincide with Koopmans's definition of technical efficiency. Meanwhile Koopmans's definition requires the absence of coordinatewise improvements; the Debreu-Farrell measure requires only the

[3] A, B are considered firms

absence of radical improvement. Therefore, besides identifying correctly the technically efficient producers as identified by Koopmans definitions, the Debreu-Farrell measures also defined other technically efficient producers located on an isoquant outside the efficient subset. As a result, for Debreu-Farrell measure, it is necessary but not sufficient for Koopmans technical efficiency. This can be illustrated in figure 2-2 where $\theta^B x^B$ and $\theta^B q^B$ satisfy the Debreu-Farrell conditions but not the Koopmans requirement as slacks remain at the optimal radical projections. There have been many studies about the slack issues; however, as stated also by Fried et al. (2008), these issues depend on the numbers of observations lie outside the cone spanned by the relevant efficient subset. These problems will be solved as econometric analysis is applied (the parametric function is used to estimate the production technology). If nonparametric form of the frontier is estimated in the measure procedure, to eliminate the slack issues it is possible to identified Debreu-Farrell efficiency scores and slacks separately. Instead of doing this, certain strategies have been considered as following:

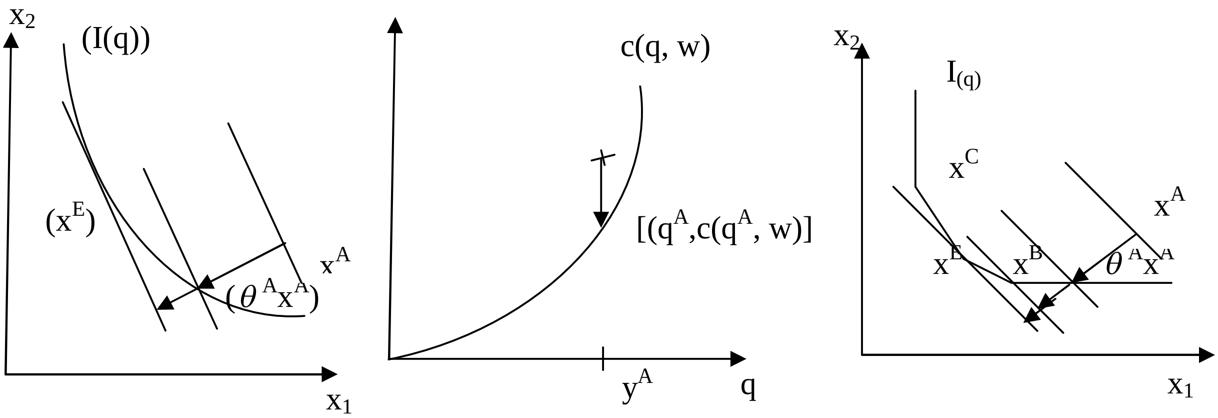
- Use a non-radical measure that project to efficient subsets instead of using the radical Debreu-Farrell measures (Färe and Lovell, 1978). This way, however, may violate the homogeneous property.
- Developing a measure that includes slack and the radical component into a technical efficiency measure (Cooper et al., 1999). This method satisfies the indication property but it has its own problems related to the possibility of negative values (Fried et al., 2008).

Concerning the economic efficiency, it is stated that, there has been no distinction between definitions and measures of economic efficiency (Fried et al., 2008). Generally economic defining and measures impacted by economic objectives and information related to relevant prices. If cost minimization is the objective of a production unit, the measure of cost efficiency is the ratio of minimum feasible cost to actual cost. This measure depends on input prices. As the measure reaches the maximum value of unity, the producer is cost efficiency. Then the measure of input allocative efficiency is defined by the ratio of the measure of cost efficiency to the input oriented measure of technical efficiency. To express the economic efficiency related to cost efficiency, suppose that producers face input prices $w = (w_1, w_{2......}\ w_N) \in R^N_{++}$ and their behavior is cost minimization. A minimum cost function (cost frontier) can be defined as:

$$c\ (q, w) = \min_x \{w^S x : D_I\ (q, x) \geq 1\} \qquad (2.1.3)$$

The measure of cost efficiency CE then can be defined as the ratio of minimum cost the actual cost: $CE\ (x, q, w) = c(q, w)/w^S x$

Or the measure of input allocative efficiency AE_1 can be defined as AE_I (x, q, w) = CE (x, q, w)/TE_I (q, x). Following is the three alternatively views to examine cost efficiency:



Source: Fried et al. (2008)

Figure 2-2. Alternatively views to examine cost efficiency

Similarly, a maximum revenue function or revenue frontier can be defined as:

$$r(x, p) = \max_q \{p^S q : D_o(x, q) \leq 1\} \qquad (2.1.4)$$

The measure of revenue efficiency RE is defined by the ratio of maximum revenue to the actual revenue: RE (q, x, p) = r(x, p)/p^Tq.

And the measure of output-allocative efficiency AE_o can be measured by the equation: AE_o(q, x, p) = RE(q, x, p)/TE_o(x, q).

2.2. Techniques of efficiency measurement

Generally, efficiency could be estimated by two main approaches: non-parametric and parametric approach. Meanwhile the parametric involves econometric methods; non-parametric method applies Data Envelopment Analysis (DEA) methods.

The non-parametric approach was initiated by Charnes, Cooper and Rhodes (1978). This approach is related to mathematical programming method that has mainly focused on the development of DEA methods. This approach could be applied for analyzing cases with multiple-input and multiple-output production technologies. With DEA methods, the use of linear programming methods is involved to construct a non parametric piece-wise surface (frontier) over the data. Basing on this surface, efficiency is calculated (Coelli, 2005). In these methods, the functional form of the production frontier is not required; however it is necessary to studies producers' behavior to construct the efficient frontier and the distance between a production unit and the frontier. It should be also considered that since DEA approach does not include random errors, the problems related to error term distribution are released from the analysis process. Yet, this technical advantage may also lead to problem of bias result in measuring efficiency since the production process is affected by stochastic element (Pascoe and Simon, 2003). Recently, from basic models of DEA methods, certain extended models have been performed such as stochastic analysis model.

The parametric approach, on the other hand, includes identifying and estimating a stochastic production frontier or stochastic cost frontier. In this method, the output (or cost) is assumed as a function of inputs, inefficiency and random error. The important advantage of the stochastic frontier function approach (SFAF) is its incorporation of stochastic error, and therefore it permits application of hypothetical testing. The disadvantage of this approach is the requirement of an explicit functional form and assumptions about the distribution of the error term. For the stochastic frontier method, results of efficiency measure sensitively depend on the chosen parametric form (Linh, 1994).

2.3. DEA approaches to efficiency measurement

Requiring few assumptions, DEA has been a choice for use in cases that are resistant to other approaches due to the complex and unknown nature of the relationships between the used inputs and outputs of decision making units (Cooper, et al., 2004).

Efficiency measurement through applying DEA related mainly to production frontier and linear programming. Initially, Data Envelopment analysis (DEA) was proposed by Charnes, Cooper and Rhodes (CCR) in 1978. As statement of Farrell (1957), DEA is a non-parametric method that assumes that the production function is unknown. With this method, efficiency is measured by comparing each individual production unit with all other production units or possible combination of production units within its sample data (Pascoe, et. al. 2003). In practice, a linear programming (LP) problem is analyzed to describe numerically the piecewise linear production frontier. Then efficiency of each unit is calculated by comparing output and input use with points on the production frontier. As the production unit is on the frontier it will be considered as efficient firm and have the efficiency sore of 1, if it is inside the frontier the firm will be identified as inefficient firm and has efficiency score smaller than 1(Pascoe, et. al. 2003).

Additionally, as mentioned in many studies, applying DEA method can provide a best practice frontier represented by a piecewise linear empirical envelopment surface; specific targets (efficient projections) onto the frontier for each inefficient DMU; and an efficient reference set or peer group for each DMU defined by the efficient units closest to it (The peer group are DMUs that produce the same or higher level of outputs with the same or less inputs in relation to the inefficient DMU being compared.

Practically, a DEA model can be identified by many ways depending on the actual situation or problem. A DEA model often refers to a particular mathematical formulation (Pascoe, 2003). In their study, Banker, Charnes and Cooper (1984) as well as Cooper, Seiford and Tone (2000) mentioned about such formulations. Basing on the basic concepts and principles DEA have clarified into four types of DEA models including CCR ratio model, BCC returns to scale model, additive model and multiplicative model (Charnes, Cooper and Seiford (1994). Ahn, Charnes and Cooper (1988), in a comparative study, have proved theoretically that even though different DEA models are applied, the results in the form of efficiency or inefficiency of a production unit are robust.

(Charnes, Cooper and Rhodes (1978) have found the very important features of DEA. That is DEA method generates a single output/input index to characterize efficiency of a production unit that produce one or multiple outputs from a set of inputs. Though taking the ratio of total weighted output to the total weighted input relative efficiency for each DMU are calculated. The weights attached to each input and output are selected by a linear programming-code (Pascoe, et. al. 2003)

Concerning the DEA mode proposed by Charnes et al. (1978), a DMU is analyzed subject to the restrictions that it must be compared with all other DMUs using the same set of weights, and that none of the other DMUs can have an efficiency score higher than one. If it is possible to find a set of weights for which the efficiency ratio of a particular DMU is equal to one, this DMU will be regarded as efficient; otherwise it will be regarded as inefficient. In order to obtain efficiency rates for each DMU, the DEA model implements *n* optimizations for the same set of observations. i.e. one optimization for each DMU (Pascoe, et. al. 2003).

2.3.1. Basic DEA models

❖ *The Constant Return to Scale DEA model*

To express the efficiency of DMUs by mathematical formulation, suppose that there are *n* DMUs to be evaluated, each DMU use an amounts of *m* different kinds of inputs to produce *s* different outputs. Then the efficiency h_j of the j^{th} DMU, can be measured by the following ratio index.

$$h_j = \frac{\sum_{r=1}^{s} u_{rj} y_{rj}}{\sum v_{ij} x_{ij}} = \frac{\text{weighted sum of outputs}}{\text{weighted sum of inputs}} \qquad (2.3.1)$$

In which x_{ij} are observed as positive values of the i^{th} input of DMU_j (i=1, 2, ..., m) and y_{rj} are observed values of the r^{th} output of DMU_j (r=1, 2, ..., s). In the CCR DEA model, virtual weights, u_{rj} and v_{ij} are identified through the following mathematical programming model:

Maximize

$$\underset{uv}{h_o} = \frac{\sum_{r=1}^{s} u_{ro} y_{ro}}{\sum_{i=1}^{m} v_{io} x_{io}} \qquad (2.3.2)$$

Subject to

$$\frac{\sum_{r=1}^{s} u_{rj} y_{rj}}{\sum_{i=1}^{m} v_{ij} x_{ij}} \le 1;\ j = 1,2,...,j_o,...,n$$

$$u_{ro} \ge 0; r = 1,...,s,$$

$$v_{io} \ge 0; i = 1,...,m,$$

In their study, Charnes, Cooper, and Rohdes (1978) called the optimal u^*_r and v^*_i as "virtual rates of transformation" or "virtual multipliers". When they are multiplied to outputs or inputs respectively, virtual output and a virtual input will be defined.

Weights has significant roles in DEA models, it represents a relative value system for each assessed DMU which provides the highest possible rating for the DMU. With this characteristic of weights, DEA allows total flexibility in the selection of weights such that each DMU will achieve the maximum efficiency rating feasible for its input and output levels. The weights estimated by DEA can, however, prove to be inconsistent with prior knowledge or accepted views on the relative values of the inputs and outputs (Allen et al., 1997).

To be computationally easier to solve the problem[4], the above fractional linear programming problem is transformed into an ordinary linear programming problem as following:

[4] In the original form, if u*, v* is the solution, then ku*, kv* is also the solution of the problem.

Maximize $\quad \underset{u,v}{h_o} = \sum_{r=1}^{s} u_{ro} y_{ro}$ (2.3.3)

Subject to

$$\sum_{i=1}^{m} v_{io} x_{io} = 1$$

$$\sum_{r=1}^{s} u_{ro} y_{ri} - \sum_{i=1}^{m} v_{io} x_{ij} \leq 0;\ j = 1,...n$$

$$-u_{ro} \leq 0; r = 1,..., s,$$

$$-v_{io} \leq 0; i = 1,..., m,$$

Apply the dual characteristic of the linear programming problem, an equivalent envelopment form can be estimated as following:

Minimize $\quad W_0 = w_0$ (2.3.4)

Subject to

$$w_o x_{io} \geq \sum_{j=1}^{n} \lambda_j x_{ij},\ i = 1,..., m$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} \geq y_{ro},\ r = 1,..., s$$

$$\lambda_j \geq 0,\ j = 1,..., n; o \in \{1,..., n\}$$

In the envelopment form, a scalar factor w_0 represents the efficiency measure of a DMU. The minimum value of w_0 is the optimal solution since being multiplied with inputs x it tells us the maximum possible reduction in inputs when keeping at least the same output-level. The factor w_0 will always be less or equal to 1. λ_j is considered as an intensity variable that is used to make sure that it is possible to construct a virtual DMU of the investigated DMU, as a combination of other DMUs. λj must be computed for all the n DMUs in data set. For efficient units, λj will be equal to 1 because then the model cannot find any combination of other units that are more efficient (Pascoe, et. al., 2003).

❖ *The Variable Return to Scale Model and scale efficiency*

In the CCR model, the hypothesis of Constant Returns to Scale (CRS) technology is assumed. This means the size of a DMU will not be matter for the efficiency. In fact, an efficiency score obtained through the CCR-model will be affected by both scale efficiency and technical efficiency. Therefore, Banker, Charnes and Cooper (1984) (BCC) developed an input oriented DEA-model that imposes the hypothesis of Varying Returns to Scale (VRS) as following:

Maximize $W_0 = w_0$ (2.3.5)

$$w_o x_{io} \geq \sum_{j=1}^{n} \lambda_j x_{ij}, i = 1,..., m$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} \geq y_{ro}, r = 1,..., s$$

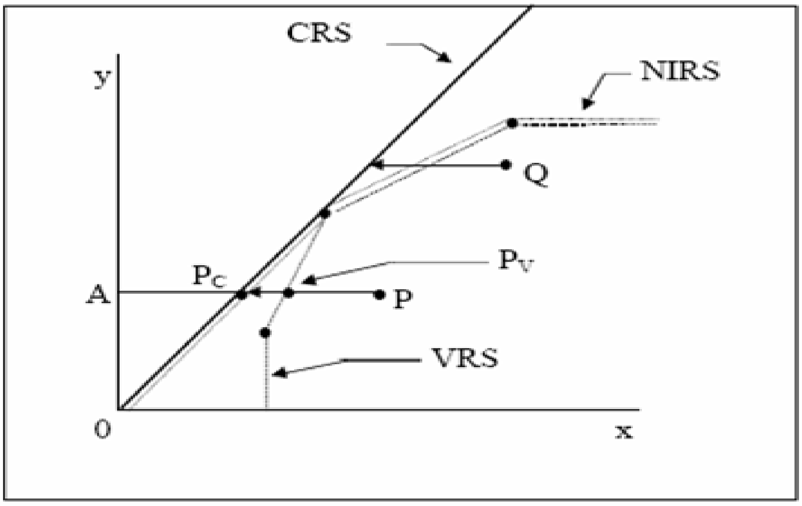
Subject to $$\sum_{j=1}^{n} \lambda_j = 1$$

$$\lambda_j \geq 0, j = 1,..., n; o \in \{1,..., n\}$$

Comparing the CCR model to the BCC model, there is a new restriction that is $\sum_{j=1}^{n} \lambda_j = 1$. This new restriction is to make sure that the reference points that DMUs are compared with are convex combinations of observed DMUs. With this additional restriction, "pure" technical efficiency is calculated.

The BCC model helps to estimate a production frontier consisting segments of increasing returns to scale, decreasing returns to scale and constant returns to scale. The nature of the scale inefficiency can be defined into two types: (1) the production unit is too small so it belongs to the increasing returns part of the production frontier; (2) Or the production unit is too large, then it belongs to the segment where the decreasing returns to scale happened. From the CCR model (unrestricted). These types of wrong scale that creates scale inefficiency for production unit can be observed. Looking at the sum of $\sum_{j=1}^{n} \lambda_j$ gained from the CCR model; the issue of weather a DMU is too large or too small scale is solved. As $\sum_{j=1}^{n} \lambda_j > 1$ this meaning that the scale for the production unit is too large. In contrast, as $\sum_{j=1}^{n} \lambda_j < 1$ meaning the scale for the production unit is too small. If $\sum_{j=1}^{n} \lambda_j = 1$, the unit is optimal scale (Banker et al., 1984).

In practice, for each DMU, scale efficiency can be estimated by running both a CRS and a VRS DEA, then dividing the TE scores obtained from the CRS DEA into two components, one from scale inefficiency and the remain is from "pure" technical efficiency. As difference in the CRS and VRS TE scores existed, the firm is defined to have scale inefficiency. Particularly, SE = TE_{CRS}/TE_{VRS} (Coelli et al., 2005).



Source: Coelli et al. (2005)

Figure 2-3 . Scale Efficiency measurement in DEA

❖ *Input versus output orientation*

In input oriented DEA model, technical efficiency is identified as a proportional reduction in input usage, with output levels are held as constant. In contrast, for oriented DEA model, technical efficiency is estimated as a proportional increase in output production, with input levels are held as constant. An output oriented DEA-models that imposes the hypothesis of Varying Returns to Scale (VRS) can be estimated as following (Coelli et al., 2005):

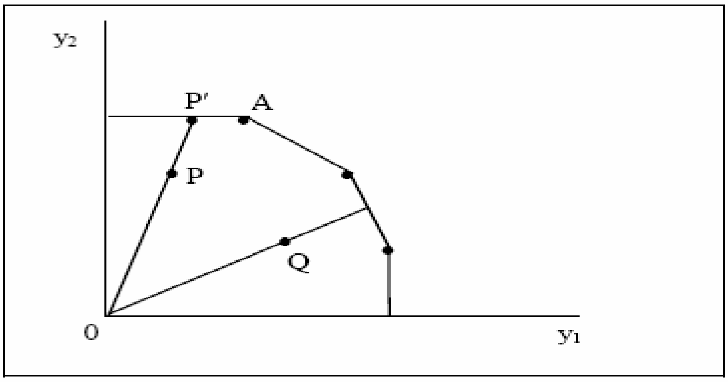
$$\text{Max } W_o = w_o \qquad (2.3.6)$$

$$\text{Subject to } w_o y_{ro} \le \sum_{j=1}^{n} \lambda_j y_{rj}, r = 1,..., s$$

$$x_{io} \ge \sum_{j=1}^{n} \lambda_j x_{ij}, i = 1,..., m$$

$$\sum \lambda = 1$$

$$\lambda, \ge 0 \quad \forall j$$



Source: Coelli et al. (2005)

Figure 2-4. Output - oriented DEA

2.3.2. Extensional DEA methods

❖ *Supper efficiency*

Super efficiency approach is one among six general approaches which were developed to rank the performance of DMUs. Besides the existing of five other approaches (including cross-efficiency matrix; benchmarking; multivariate statistical techniques; combining multiple-criteria decision methodologies with the DEA approach), super efficiency approach has been mentioned also in a number of papers (Adler et al, 2002).

Super efficiency analysis approach was first presented by Andersen and Petersen (1993) with the basic idea is “to compare the unit under evaluation with a linear combination of all other units in the sample, i.e., the DMU itself is excluded”. Then, in his paper, Yao (2003) also mentioned that as a DMU under evaluation is not included in the reference set of the original DEA models, the resulting DEA models are called super efficiency DEA models. The super efficiency methods have been used also in many ways such as sensitivity testing; identifications of outliners; and circumventing the bounded – range problem in a second stage regression method (Coelli, 2005). Formulation (2.3.9), (2.3.10) and figure 2-6 express VRS super efficiency DEA models.

$$\min \theta_o^{VRS-super}$$

Subject to

$$\sum_{\substack{j=1\\ j\neq 0}}^{n} \lambda_j x_{ij} \leq \theta_o^{VRS-super} x_{io}, i = 1,2,...,m,$$
$$\sum_{\substack{j=1\\ j\neq 0}}^{n} \lambda_j y_{rj} \geq y_{ro}, r = 1,2,...,s,$$
$$\sum_{\substack{j=1\\ j\neq 0}}^{n} \lambda_j = 1$$
$$\theta_o^{VRS-super} \geq 0$$
$$\lambda_j \geq 0, j \neq 0 \qquad (2.3.9)$$

Above is a formulation example of the input oriented VRS super-efficiency DEA model (x_{io} and y_{ro} are respectively the i^{th} input and r^{th} output for a DMUo under evaluation which is excluded from the reference set).

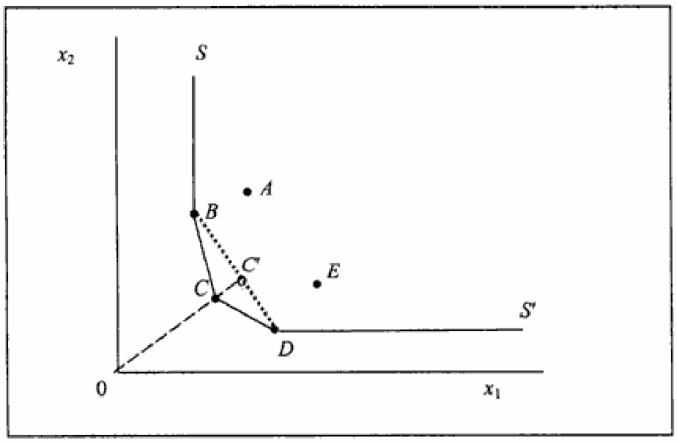
If the condition $\sum_{\substack{j=1\\ j\neq 0}}^{n} \lambda_j = 1$ is removed the above VRS super-efficiency DEA model will become CRS supper efficiency DEA model that is usually feasible [unless zero data in input existed] (Yao [b], 2003).

Alternatively, an output oriented of supper efficiency can be estimated as following.

$$\max \phi_o^{VRS-super}$$

Subject to

$$\sum_{\substack{j=1\\ j\neq 0}}^{n} \lambda_j x_{ij} \leq x_{io} 1 = 1,2,...,m,$$
$$\sum_{\substack{j=1\\ j\neq 0}}^{n} \lambda_j y_{rj} \geq \phi_o^{VRS-super} y_{ro}, r = 1,2,...,s,$$
$$\sum_{\substack{j=1\\ j\neq 0}}^{n} \lambda_j = 1$$
$$\phi_o^{VRS-super} \geq 0$$
$$\lambda_j \geq 0, j \neq 0 \qquad (2.3.10)$$



Source: Coelli et al. (2005)

Figure 2-5. Super efficiency

One short coming of the super efficiency methods is that some of the linear programs may be infeasibility. The CCR super-efficiency DEA model is developed under the condition (a) the DEA frontier exhibits constant returns to scale (CRS) and (b) all inputs (or outputs) are simultaneously changed in the same proportion. When either of the conditions is not satisfied, the issues related to infeasibility of the linear program are likely to occur. If this issue occurs, we do not have a value associated with infeasibility to represent the super-efficiency, so it is difficult to obtain a complete performance ranking of efficient units, (Yao [a], 2003). To solve this issue, a certain affords has been done. Both input- and output-oriented super-efficiency models are used to fully characterize the super-efficiency. When super-efficiency is used as an efficiency stability measure, infeasibility means the highest super-efficiency (stability). If super-efficiency is interpreted as input saving or output surplus achieved by a specific efficient DMU, infeasibility does not necessary mean the highest super-efficiency. The infeasibility then may indicate zero super-efficiency (Yao [b], 2003). Detail about input- and output-oriented super-efficiency models will be mentioned more in following paragraph. According to Yao Chen [b] (2003) meanwhile input-oriented super-efficiency DEA model defines the input super-efficiency as outputs are fixed at their current levels; Output oriented super-efficiency DEA model defines the output super-efficiency as inputs are fixed at their current levels. Due to different uses of the super-efficiency concept, super-efficiency can be explained as the degree of efficiency stability or input saving/output surplus achieved by an efficient DMU. As an input-oriented super efficiency DEA model is used and if super-efficiency is used as an efficiency stability measure, then infeasibility means that an efficient DMUs efficiency classification is stable to any input changes. Similarly in the case of an output-oriented super-efficiency DEA model is used then infeasibility means that an efficient DMUs efficiency classification is stable to any output changes.

Yao Chen [b] (2003) also stated that if an input-oriented supper efficiency DEA model is infeasible and DMU_o is CRS-inefficient, then the corresponding output oriented super efficiency DEA model must be feasible. In the same manner, if an output oriented supper efficiency DEA model is infeasible and DMU_o is CRS-inefficient, then the corresponding input-oriented super efficiency DEA model must be feasible. Both input-oriented supper efficiency DEA model and output oriented supper efficiency DEA model are infeasible if and only if DMU_o is the only VRS efficient DMU.

❖ *Weight Restriction*

Weight restriction is one of two main methods that are use to incorporate value judgments in DEA to reduce the flexibility of DMUs in value system choosing. Meanwhile in method of changing data set, the comparative set of DMUs are changed, for weight restriction, restrictions are applied into the DEA weights (Cooper et al., 2004).

Generally, DEA method focuses on physical measures of input and output variables. It does not require the exact estimation of input prices or output values. This provides advantage as collecting data on these values are often quite difficult. However, to make efficiency evaluations become closer to economic efficiency and recommendation becomes more appropriate, it is essential to incorporate restrictions on the weights attached to the inputs/outputs of DMUs (Thompson, et al.,1986, and Thompson et al., 1990).

The weights assigned in DEA can be understood to be calculated to make each DMU appear as efficient as possible when those weights were applied to all other DMUs. Any other set of weights selected would make the DMU as inefficient or more inefficient (Zhu and Sherman, 2006).

In the CCR or BCC dual, the best weigh set is identified satisfying only the condition that for the same set of weights, the efficiency rate for all the units is less than or equal to one. The assessed DMUs can freely choose the weights or value assigned to each out put or input to maximize the efficiency (This weigh or value must be feasible for all other DMUs). These DEA methods do not distinct the importance of any inputs or any outputs (Pascoe et. al, 2003). Also according to Epstein and Henderson (1989) variables in the model is considered to have equal opportunity to influence reported efficiency. Though this assumption of equal importance is sufficient for estimating determining technical efficiency and the chosen weights may appropriate with an objective manner, in some applications the analyst still want to take care the additional relevant information related to the production possibility set, not just only considering the observed inputs and outputs (Pascoe, 2003). This is due to incorporating the additional relevant information will help to avoid including extreme/abnormal valuations in the gained results.

Weight restriction has been considered widely due to it functions as following: To incorporate prior views on the value of individual inputs and outputs; To relate the values of certain inputs and/or outputs; To incorporate prior views on efficient and inefficient DMUs; The assessed efficiency needs to respect the economic notion of input/output substitution; To enable discrimination between efficient units (Allen et al. 1997).

Two main approaches are applied to weight restrictions that are (1) applying weight restrictions directly to DEA weights or (2) weight restrictions are applied to the products of the weights with the respective input or out put level [considered as virtual inputs or virtual output] (Cooper et al., 2004). More details about these two approaches are as following.

- Restrictions applied to DEA weights

Approach (1) is divided to three types of techniques: Absolute weight restrictions (Absolute WRs); assurance regions of type I (AR I); and assurance regions of type II (AR II). Assurance regions approaches suggested by Thompson, Singelton, Thrall and Smith (1986), Thompson et al. (1990) probably is the most widely applied weight restriction approaches. In these approaches, lower as well as upper bounds are identified reflected the relations between two input (or output) weights (AR I), or expressed the relation of an input and an output weight (AR II). AR I restrictions provide information about the marginal rates of substitution, while, in the case of one input existed, AR II restrictions approach reflect the relative prices of outputs in terms of the input. Cooper et al., (2004) then, also summarized formulations of those techniques as following:

$$\delta_i \le v_i \le \tau_i \qquad \kappa_i v_i + \kappa_{i+1} v_{i+1} \le v_{i+2} \qquad \alpha_i \le \frac{\upsilon_i}{\upsilon_{i+1}} \le \beta_i$$

$$\rho_r \le u_r \le \eta_r \qquad w_r u_r + w_{r+1} u_{r+1} \le u_{r+2} \qquad \theta_r \le \frac{u_r}{u_{r+1}} \le \zeta_r \qquad \gamma_i v_i \ge u_r \qquad (2.3.7)$$

Absolute WRs AR I (a) AR I (b) AR II

[$\delta_i, \tau_i, \rho_r, \eta_r, \kappa_i, w_r, \alpha_i, \beta, \theta_r, \zeta_r, \gamma_i$ are constant specified by users to reflect value judgments that the DM wishes to incorporate in the analysis]

- Restrictions on virtual inputs and outputs

Weight restrictions may be also applied to virtual inputs and virtual outputs. In this case, the virtual values are considered as normalized weight reflecting the extent to which the efficiency rating of each DMU is defined. The general form of this type of weight restriction as following

$$\phi_r \le \frac{u_r y_r}{\sum_{r=1}^{s} u_r y_{rj}} \le \psi_r \qquad r = 1, \ldots, s \qquad (2.3.8)$$

The range of weight restrictions normally is determined to reflect prior views on the relative importance of the individual outputs (Cooper, 2004). Certain modification for performing restrictions on virtual values have been suggested such as

- Estimating the parameters of weight restrictions

There are number of approaches in setting up restriction parameters, different ways may be appropriate in different contexts. According to Cooper (2004), five main approaches can be identified such as following:

- *Using information on prices and costs:* price and cost information is included in DEA model through weight restrictions. Frequently the price information is not strictly accurate so arrange of price are often used. Bounds that based on price information often appear in assurance weight restrictions.
- *Using unbounded DEA weights as reference level*: This approach, which is originally suggested by Roll et al (1991) and Roll and Golany (1993), was developed to establish bounds in absolute weight restrictions, how ever it may be adapted to be applied in other types of weight restriction. In this method, initially an unbounded DEA model is run; also matrix of weight is compiled. On the other hand, a certain percentage of the extreme weights or outlier weights are removed. Alternative optimal solutions often exits and lead to the possible exist of alternative weight's matrices that provide the choice in matrices selection for user. The mean weight for each factor then is identified based on the selected weight matrix. Then a certain amount of allowable variation of each mean is determined providing an upper and lower bound for each factor weight (Cooper, 2004).

- *Using optimal weights of model DMUs*: This approach initially due to Charnes et al. (1990) and Brockett et al. (1997) who used cone ratios to analysis firms (banks) efficiency. In this method, firms that are considered as excellent are used to set the weight restrictions. They are tested for efficiency and the weights of those that are considered DEA efficient and are use in constructing the cone ratios (Cooper, 2004).
- *Using expert opinion*: This method use different views, opinions of experts who involve in analysis process. Expert opinions can be used alone or in combination with other source of information such as price information or model DMUs' weight (Cooper, 2004).
- *Using estimated average marginal rates of transformation as reference levels*: This approach is developed by Dyson and Thanassoulis (1988). This method is applied only in the case that DMUs use a single input to produce multiple outputs or use multiple inputs to produce single output (Cooper, 2004).

❖ *Allocative Efficiency*

As price data is available and a behavior objective is identified for example cost minimization or revenue maximization or profit maximization, it is possible to measure allocative efficiency and technical efficiency.

+ *In this case of cost minimization:* two linear programs should be implemented, one used to measure technical efficiency, the other used for measuring economic efficiency. (Coelli et al., 2005).

$$\begin{aligned}
&\min \theta \\
\text{Subject to}\quad &\sum_{j=1}^{n} \lambda_j x_{ij} \le \theta x_{io}\, i = 1,2,...,m, \\
&\sum_{j=1}^{n} \lambda_j y_{rj} \ge y_{ro}, r = 1,2,...,s, \\
&\sum_{\substack{j=1 \\ j\neq 0}}^{n} \lambda_j = 1 \\
&\lambda_j \ge 0
\end{aligned}$$

VRS DEA model

$$\begin{aligned}
&\min_{\lambda, xi^*} \sum_{i=1}^{m} w_i\, x_i^* \\
\text{Subject to}\quad &\sum_{j=1}^{n} \lambda_j y_{rj} \ge y_{ro}, r = 1,2,...,s, \\
&\sum_{j=1}^{n} \lambda_j x_{ij} \le x_i^*\, i = 1,2,...,m, \qquad (2.3.11) \\
&\sum \lambda = 1 \\
&\lambda \ge 0
\end{aligned}$$

Cost minimization DEA

Where y, x are output and input used respectively, w_i is input price for the ith DMU, x_i^* is optimal value of input obtained from the cost minimization DEA. Then the total cost efficiency (CE) of the i^{th} DMU is calculated as AE = CE/TE (Coelli, 2005).

+ The case of revenue maximization:

In the same manner, for the case of VRS revenue maximization, two set of linear programs are required also, one is output oriented DEA model [as in formulation (2.3.6] and one is revenue maximization DEA as following.

$$\begin{aligned}
&\text{Max} \quad \sum_{r=1}^{s} p_r y_r^* \\
&\text{Subject to} \quad y_r^* \le \sum_{j=1}^{n} \lambda_j y_{rj}, r = 1,...s \\
&x_{io} \ge \sum_{j=1}^{n} \lambda_j x_{ij}, i = 1,...m \qquad (2.3.12) \\
&\sum \lambda = 1 \\
&\lambda \ge 0
\end{aligned}$$

Revenue maximization DEA

Where Q, X are output and input matrix respectively, p_i is output price for the i^{th} DMU, q_i^* is optimal value of output obtained from the profit maximization DEA. The total then revenue efficiency (RE) of the i^{th} DMU is identified as AE = RE/TE (Coelli, 2005).

+ The case of profit maximization:

If price data on both inputs and outputs are available then profit efficiency can be calculated by the following model (Coelli, 2005).

$$\begin{aligned}
&\text{Max} \quad \sum_{r=1}^{s} p_r y_r^* - \sum_{i=1}^{m} w_i x_i^* \\
&\text{Subject to} \quad y_r^* \le \sum_{j=1}^{n} \lambda_j y_{rj}, r = 1,...s \\
&\sum_{j=1}^{n} \lambda_j x_{ij} \le x_i^* i = 1,2,...,m, \qquad (2.3.13) \\
&\sum \lambda = 1 \\
&\lambda \ge 0
\end{aligned}$$

Profit efficiency is measured as the ratio of observed profit over potential maximum profit. Profit efficiency is not decomposed straight forward in to technical and allocative components. However, as stated by Coelli (2005) that there has been a number of possible choices for calculating them.

❖ *Categorical and fixed variables*

In basic DEA model, there has been an implicit assumption that is the investigated DMU is able to control its inputs and outputs. However, in reality this assumption is not always be satisfied. For some variables, the managers can not or difficult to fulfill. Such variables are called exogenous variables. (Controllable variables, therefore, are called endogenous variables).
An extension of CCR- and BCC-models to deal with exogenously fixed inputs and/or outputs has been developed by Banker and Morey (1986). In their models, while the exogenously fixed inputs are kept at their current level, the possible reductions in controllable inputs are estimated. On the other hand, by allowing variables appear as categorical variables, they can develop DEA models that can deal with controllable (endogenous) categorical variables or non-controllable categorical variables.

❖ *DEA model relating to Adjusting for the environment*

As stated by Coelli (2005), environmental factors such as ownership differences, local characteristic, and labor union power or government regulations could impact the DMU efficiency. These have been a number of ways in which those environmental variables can be accommodated in a DEA analysis. However, the two stage approach seem to be the most appropriate one due to its advantages such as being able to accommodate more than one variable, or accommodate both continuous and categorical variable, does not require prior assumptions regarding the direction of the influence of the environmental variable, hypothesis test can be implemented, easy to be calculated (Coelli, 2005).

❖ *Input congestion*

It has been identified that in some cases, as constrains that are not under the control of firms existed, the situation of excess input use may happen, then, input congestion issues may occurs. Some DEA model has been performed to deal with this situation by adding the assumption of weak disposability in inputs[5]. The input congestion DEA model was estimated by Färe, Grosskoft and Lovell (1985, 1994) by changing the inequalities in the input restrictions (in the input oriented VRS DEA) to equalities and by introducing a δ parameter in the input restrictions as in following model:

$$\min \theta$$

Subject to
$$\begin{aligned}
&\sum_{j=1}^{n} \lambda_j x_{ij} = \delta\theta x_{io} i = 1,2,...,m, \\
&\sum_{j=1}^{n} \lambda_j y_{rj} \geq y_{ro}, r = 1,2,...,s, \\
&\sum_{\substack{j=1 \\ j\neq 0}}^{n} \lambda_j = 1 \\
&\lambda_j \geq 0 \\
&0 < \delta \leq 1
\end{aligned} \qquad (2.3.14)$$

Input congestion efficiency (ICE) then can be estimated though solving a strong disposability[6] DEA model and a weak disposability DEA model: ICE=TE_S/TE_W. In which TE_S and TE_W are measured under strong disposability and weak disposability respectively.

It is noted that weak disposability in outputs can happen, and weak disposability in both inputs and outputs can together be imposed (Coelli, 2005)[7].

[5] Firms can abate harmful emissions by decreasing the activity level

[6] Firms can always causelessly dispose of unwanted inputs or outputs

[7] It was recognized from some studies that a debate about the model of Fare et al. compared to a competing slack-based model of Zhu and others has been existed.

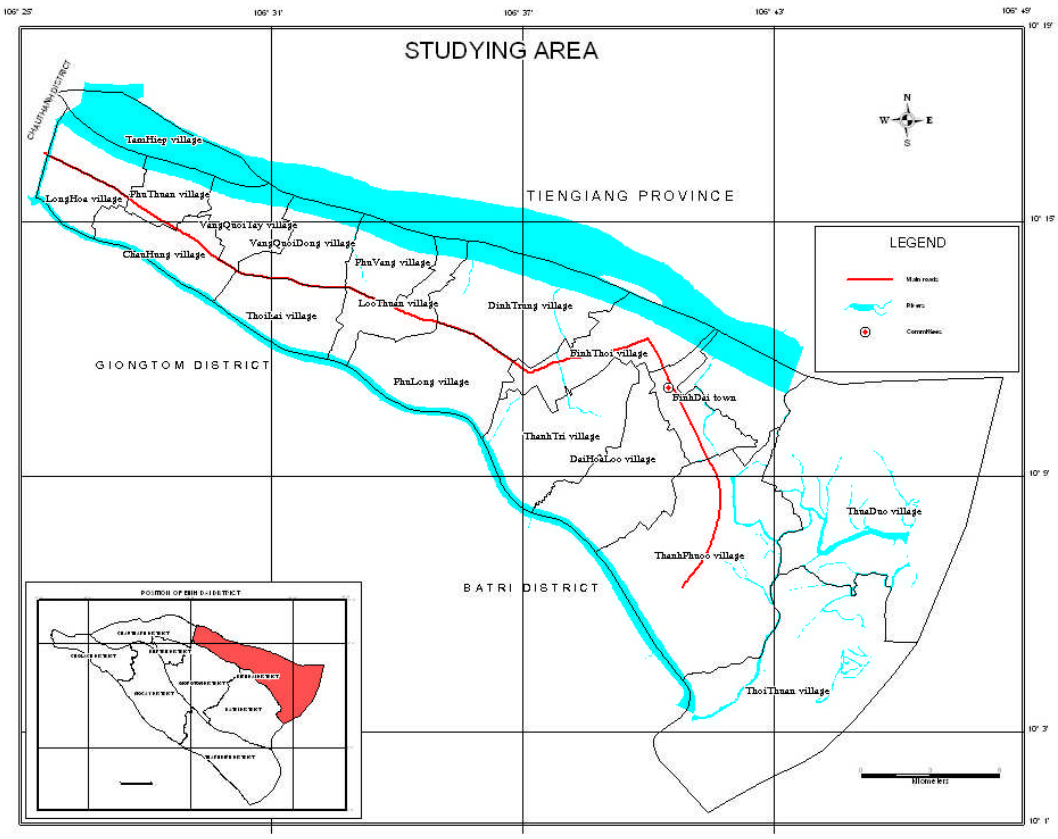
3. OVERVIEWS ON EFFICIENCY ANALYSIS IN AQUACULTURE

There have been a number of studies related to analyzing efficiency in aquaculture. Issues such as technical efficiency, cost efficiency, allocative efficiency or economic efficiency are considered to test the efficient level of many aquaculture models such as shrimp farming, fish farming. Sharma et al (1999) and Linuma et al. (1999) had focused in analyzing economic efficiency and technical efficiency respectively of fish culture. Latter on, Chiang et al. (2004) applied stochastic frontier production function to test the technical efficiency of milkfish production in Taiwan; Cinemre (2005) analyzed the cost efficiency and explored determinants of cost inefficiencies of trout farms in the Black Sea Region, Turkey. Kolawole (2006) also put affords in investigating technical efficiency and the potential productivity of aquaculture. In dealing with the hypothesis “Are small firms less efficient?”, Chih (2007) applied two efficiency methods including two-stage switching regression and metafrontier production function. Also, stochastic production frontier was applied by Poulomi (2008) in his study: “comparative study of traditional vs. scientific shrimp farming in West Bengal: a technical efficiency analysis”.

In Vietnam, however, there has been still a shortcoming in applying effectively efficiency analysis methods in analyzing the operations of aquaculture systems. Normally, efficiency analysists often focus on traditional economic factors such as net benefit; price; capital turn over, (Net benefit/revenue), (Revenue/overrating cost), (Net benefit/total capital cost). In recent time, researchers begin to consider more on efficiency analysis methods like DEA, stochastic production frontier. On this trend, Den et al (2007) has a quite interesting study that focus on analyzing technical efficiency of prawn farms in the Mekong delta.

4. GENERAL INFORMATION ABOUT THE STUDY AREA

Binh Dai is a coastal district of Ben Tre province which is located the Me Kong delta in the south area in Vietnam. The Tien Giang River flows along the district at the North West, while the sea is closed to the district in the South West. Binh Dai district locates near to districts such as Ba Tri, Giong Trom and Chau Thanh in the South Est. It comprises a total of 404 square kilometers of land and the topography is characterized by low land with many rivers located. There are 19 communes, 1 ward in the district. To 2006, the number of population is 132,523 persons which lead to the population density of 328 persons per square kilometers. (Bentre Statistical Office, 2007).



Source: VIFEP, 2005

Figure 4-1. Map of Binh Dai district[8]

[8] In electronic file, expanding zoom will help to see clearer the map

4.1. Location and physical environment

Binh Dai district is stretched between 106° 25 and 106° 49’ northern latitude and between 10° 1’ and 10°19 eastern longitude. The study area is located between 70km kilometers from Ho Chi Minh City- the developed city in the South in Vietnam.

Concerning environmental conditions, Binh Dai is characterized by the tropical climate with two main seasons, the dry season and rainy season. The rainy season is from May to October while dry season is from November to April. However, the average relative humidity in months is not much varies during a year, just around 77 to 90 percent. The average air temperature in months is around 25 – 30^0 C. The number of sunshine hours in months is from 120 – 220 hours which count to around 2000 hours per year. March, April, and May and November, December and January are periods that often have high number of sunshine hours (Bentre Statistical Office, 2007).

4.2. Social and economic conditions

Infrastructure systems (Electricity, transportations, schools and public health centers) in Binh Dai have been being developed significantly. Electricity is enough provided and telephone communication is available for use. There have been many investments on building road so the number and the quality of roads are improved. About school system, to 2006, there were 53 schools in the district in which there were 28 primary schools, 16 middle schools and 4 secondary schools. Regarding public health, there were 183 officers working as medical staffs and 12 pharmaceutical staffs (Bentre Statistical Office, 2007).

Important Economic sectors of the district include agriculture, fisheries (capture fishing and aquaculture), industries, and commerce and services. To 2008, the district could still remain the economic development rate at 13.12%, consequently the GDP was 12,070 millions VND/year. The production value from agriculture and fisheries sector in 2008 counted for 11.8 percent in which fisheries is around 77.6 percent meanwhile there was also the significant increase in industrial and commercial and service development (17.2 percent and 22.9 percent respectively). Up to 2008, Binh Dai had 1,058 large and small industrial firms providing 5,091 employments. Besides, there were 4,186 commercial and service with the investment of 213.3 billions providing 9,769 employments (Ben Tre people’ committee 2008).

4.3. Status of fishing capture and aquaculture in the study area

In 2006, production from aquaculture is 63.692 tons in which there were 4.646 tons of fish products, 12.347 tons of shrimp and 10.128 ton of other products. The fishing capture products were 36.571 tons in which there were 26.217 tons of fish, 1.023 tons of shrimp and 9.331 ton of other products. In 2006, area used for aquaculture in Binh Dai was 15.422 ha in which 265 ha were for cultivating fish, 12.948 ha were for cultivating shrimps, the remain was for rearing other species.

4.4. The intensive Tiger Shrimp farming system in the study area

Tiger shrimp was considered to be intensively cultivated widely in Binh Dai district and had contributed significantly to the economic development of the district. This aquaculture model demands highly technical requirements with many technologies used to ensure the growth of shrimp in ponds. In term of economic aspects, this model requires a high investment to build infrastructure and equipment and to operate shrimp culture activities in a crop. Farmer cultivated tiger shrimp in the study are may have high benefit but they may also experience with serious failures due to the risks in aquaculture. Appendix C contains general technical and economic indicators of the shrimp farming model.

5. METHODS AND PROCEDURES

5.1. Methods used to analyze data

DEA approaches, which are linear programming methods, are applied in analyzing data set and input orientation is applied. Methodologies which were suggested by Sherman and Zhu (2006) are used to analysis data as following:

Basic DEA models (CRS and VRS DEA) are applied to evaluate the performance of farms. Meanwhile CRS DEA models deal with the case that the assumption of constant return to scale existed, VRS DEA is applied as the assumption variant return to scale happened.

- Input oriented envelopment DEA models:

$$\begin{array}{lll} \textit{CRS} & \min \theta - \varepsilon\left(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+\right) & \\ & \text{Subject to} & \\ & \sum_{j=1}^{n} \lambda_j x_{ij} + s_i^- = \theta x_{io} & \text{i} = 1,2,...\text{m}; \\ & \sum_{j=1}^{n} \lambda_j y_{rj} - s_r^+ = y_{ro} & \text{r} = 1,2,...\text{s}; \\ & \lambda_j \geq 0 & \text{j} = 1,2,...\text{n}; \\ \text{VRS} & \text{Add } \sum_{j=1}^{n} \lambda_j = 1 & \\ \textit{NIRS} & \text{Add } \sum_{j=1}^{n} \lambda_j \leq 1 & \\ \textit{NDRS} & \text{Add } \sum_{j=1}^{n} \lambda_j \geq 1 & \end{array} \qquad (5.1.1)$$

In model (5.1.1), θ is the output-oriented efficiency score, s_i^+ and s_i^- are output and input slacks, respectively. Through dealing with such slacks, efficient target of inputs and outputs can be identified: $\hat{x}_{io} = \theta * x_{io} - s_i^{-*}$; $\hat{y}_{ro} = y_{ro} + s_r^{+*}$.

The presence of ε in the envelopment model effectively allows the maximization over θ to pre-empt the optimization involving the slacks, s_i^+ and s_i^-.

Concerning the envelopment DEA model, two-stage process will be done. Firstly, we estimate $\theta *$ and ignoring the slacks (as the following basic DEA model). Then, optimizing the slacks by fixing the $\theta *$ in an additive model as in the following linear programming problem that is the case of CRS. (Sherman and Zhu, 2006).

$$\max \sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+$$
$$\textit{subject to}$$
$$\sum_{j=1}^{n} x_{ij}\lambda_j + s_i^- = \theta^* x_{io} \quad \mathrm{i} = 1,2,...,\mathrm{m}; \qquad (5.1.2)$$
$$\sum_{j=1}^{n} y_{rj}\lambda_j - s_r^+ = y_{ro} \quad \mathrm{r} = 1,2,...,\mathrm{s};$$
$$\lambda_j \geq 0 \quad \mathrm{j} = 1,2,...,\mathrm{n}$$

- Scale efficiency then is calculated as SE = TE_{CRS}/ TEV_{RS}.

- With the purpose of having better farm ranking, super efficiency DEA models will be applied to compare farms that represented as efficient.

$$\textit{CRS} \quad \min \theta^{\sup er}$$
$$\text{Subject to}$$
$$\sum_{\substack{j=1 \\ j \neq 0}}^{n} \lambda_{\mathrm{j}} x_{ij} \leq \theta^{\sup er} x_{io} \quad \mathrm{i} = 1,2,...\mathrm{m};$$
$$\sum_{\substack{j=1 \\ j \neq 0}}^{n} \lambda_{\mathrm{j}} y_{rj} \geq y_{ro} \quad \mathrm{r} = 1,2,...\mathrm{s}; \qquad (5.1.3)$$
$$\theta^{\sup er} \geq 0$$
$$\lambda_{\mathrm{j}} \geq 0 \quad \mathrm{j} \neq 0;$$
$$\text{VRS} \quad \text{Add } \sum_{j=1}^{\mathrm{n}} \lambda_{\mathrm{j}} = 1$$

- ***Testing hypothesis:***

To further examine certain relationships, determinants, and implications related to inputs, outputs, technical efficiency, and scale efficiency, following hypothesis tests will be implemented:

- Hypothesis I: In term of capacity utilization, the larger farms the more generally technical efficient farms.

- Hypothesis II: In term of capacity utilization, the larger farms the more purely technical efficient farms.

- Hypothesis III: There is the existence of scale inefficiency in the production process of the shrimp farms

- Hypothesis IV: There are certain relationships between input used and efficiency scores of farms

Methodologies applied to test hypothesis are as following:

Testing hypothesis I, II: F-test (with null hypothesis of no differences in average efficient scores of farm size groups) is used to test the differences in the mean of efficient scores of farm size groups (less than 10,000 square meters; from 10,000 to 15,000; and larger than 15,000 square meters).

Testing hypothesis III: CRS DEA results and VRS DEA results are considered. With the assumption that the scale influences in farms are various, CRS cases (scale effects existed) and VRS cases (no scale effects existed) can be considered as independently and randomly distributed samples. Then, two (data) samples (CRS versus VRS) are performed. And F-test (with null hypothesis of no differences in the mean of efficient score of the two groups) is also applied to test the existence of scale efficiency.

Testing hypothesis IV: regression approach will be applied to identify the relationship between the input used with the four types of efficient (CRS efficiency; VRS efficiency; CRS super efficiency; and VRS super efficiency). The Cobb-Doulas type of function is proposed for use to test such relationships. In the function, efficiency scores of farms will be dependent variable, while culture area, seed, feed, labor, fuel, chemical, and furniture will be the independent variables. The significant of parameters (regression elasticities) performed and mentioned in the regression functions will be test through t-test or checking p_{value} (with the null hypothesis of parameters are equal to zero).

In summary, Procedures of analysis are illustrated as in figure 5-1:

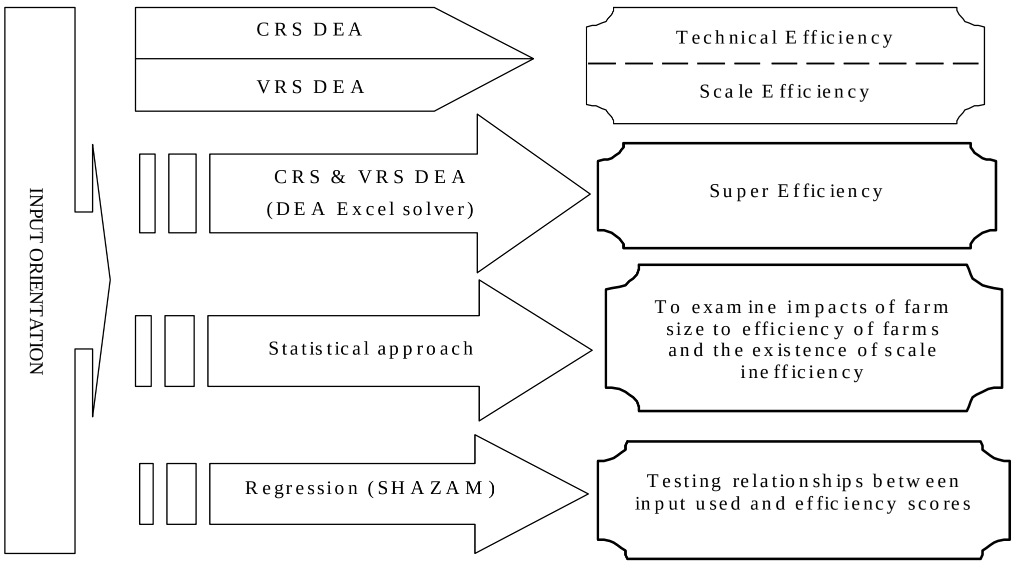


Figure 5-1. Applied analysis procedures

5.2. Data Description

Data set used in this thesis was collected in 2005 by The Vietnam Institute for Economic and Planning (VIFEP) with the cooperation of certain relevant agencies through implementing the project “Develop aquaculture system profile in Vietnam”. This project was done to provide database and tools for the development, implementation, monitoring and assessment of sustainable aquaculture plan as well as to assess existing systems in terms of techniques, economic, social and environment.

The data set was collected through a household survey implemented at certain areas in Vietnam which is biologically, topographically and economically representative for different zones in Vietnam. Originally the surveys were done to investigate many aquaculture models with different species such as fish, shrimp, and mollusk. The data set used in this thesis is related to the intensive Tiger Shrimp culture model which had been surveyed in Binh Dai district, Ben Tre province. To have better consistency, describing about data collection will focus on the intensive Tiger Shrimp culture model in Binh Dai district, which will be further analyzed in this thesis.

38 households, which operated Tiger shrimp intensive cultivation, had been surveyed in Binh Dai district in where there had been a significant development of shrimp cultivation. In the survey, households were considered as decision making unit since shrimp farms were operated by households. Households were randomly selected from the two villages with 10 households from Dai Hoa Loc village, 26 from Thach Phuoc village. The higher number of investigated households in Thach Phuoc compared with that of Dai Hoa Loc due to the larger area and having more shrimp farming of Thach Phuoc. The data collection had been implemented by using a structured questionnaire which was used to gain information about shrimp farming. On the other hand, the survey was implemented in May as the shrimp cultivation crop had just finished so the asked relevant information was still fresh to households. This would provide many advantages to interviewees as well as interviewers. There had been a selected wide content included in the questionnaire to investigate the status of farming activities. The information which was mentioned in questionnaire included real cultivation area and money for rending cultivated area; quantity, price and harvested size of production; quantity and price of feed; quantity and price of seed; money for buying chemical; money for buying fuel; number of days in a crop; percentage of failure (over 5 years); number and salary of fixed and seasonal labor; surviving rate;

money for working furniture; depreciation; money for maintaining furniture; interest; tax; Furthermore, the farm households were also drawn to describe environmental degradation and disease status that they had had, in particular the water quality in ponds and their opinion about applied technologies. The questionnaire is in Appendix A.

Selected people participated in data survey were staffs worked at VIFEP and RIA 1-3. They were believed to have good experiences and appropriate skills in gathering data in surveys. On the other hand, relevant local participants worked at local agencies were also invited to participate in the survey. They had well understanding about the status of aquaculture development as well as social-economic conditions and culture in the study area.

Questionnaire had been developed and improved during the process of data collection. The questionnaire was checked and revised carefully through workshops with the participating of many experts. Then training course on understanding and practicing interviews was implemented. This helped interviewers being acquainted with the questionnaire and understand the language, culture and tradition of the study area. The questionnaire was pre-tested in certain area to correct possible mistakes and to evaluate the relevance of a given question. After pre-testing some relevant information was added while irrelevant information was exclude. This process helped to ensure being appropriate of questionnaire to reach the objective of the project**.** During the process of collecting data, there had been improvement for fielded questionnaire. Incomplete questions would be revised to ensure to have valid responses from farmers.

Certain secondary data had been collected from Local agencies, and institute. There materials helped to have better overviews about the study area through providing supplementary information.

There were some challenges in data collection regarding to being able to gather the valid information and getting the participation of household heads. Economical information asked in questionnaire could challenge farmers to answer and even for some famers they might feel hesitate to answers economical questions related to their aquaculture activities. On the other hand, sometimes it was difficult to make an appointment with household lead who are the best to answer the questionnaire as they might busy or was absent at the time survey conducted. For above challenges, survey team had tried to solve by explain clearly about the non political purpose of the survey as well as set up alternative meeting with household head or changed to investigate the other similar farm.

It can be state that the data collection process is appropriate with using right persons for interviewing and relevant valid information was selected to be gathered. It also included monitoring and evaluation during data collection and having participations of many experts. Therefore the data set has enough confidential indicators to be chosen to analyze in this thesis. However, for some gathered information, they were not detail enough in term of technical term. With furniture and chemical variables for example, just monetary information are available, no information about quantity. This leads to alternative aggregation variables are used as these variables are analyzed in DEA which are "scale variable" methods. This can be seen as limitations of this thesis as. In further study, a detail survey should be considered to implement to have perfect data that are analyzed in DEA models.

To apply DEA model in analyzing technical efficiency of the shrimp farming model, most important variable are chosen among variables involved in production process. Shrimp production is the output variable of the model. Chosen inputs variables include: culture area; seed quantity; feed quantity; labor; fuel; money for buying Chemical and money for buying furniture.

From 38 surveyed households, after analyzing the quality of data set, just 28 shrimp farms are selected and used for analyzing technical efficiency in DEA models. Two farms were removed due to lacking of in formation about used chemical. On the other hand, when perform statistical analysis, 8 farms have presented as "outliners" as their operations are not representative production process. The used criteria in removing outliers are to remove all producers that have less than average output per input factor for all inputs. This method shows reasonable because after checking the original data profile, it was found that the 8 removed farms faced with problem of having extreme high quantity of input used, or having very small harvested size, low survival rate, low harvested product price. Two situations must be happened with these farms: first, the information about these farms was bias; second, these farms had experienced with disease situations or the bad environment in ponds. Since the purpose was to focus on comparing shrimp farms that are represent for normal production, those eight farms are removed (however, an additional calculation that includes the eight farms is also done to provide foundations for discussion; result about the additional calculation are put in appendix G). In analyzing, to easier to be followed, the 28 farms are coded from BD1 to BD28.

5.3. Variables

Intensive farming involves one output of shrimp production using several inputs such as land/water area, seed, feed, fertilize, labor, fuel, chemical, furniture and capital services.
For purpose of analysis variables are defined as following:

Table 5-1. Variables definitions

Variables	Units	Definitions
Product (y)	Kg/crop	Quantity of shrimp production
Culture area (x_1)	m^2	Real water area used to cultivate shrimp
Seed (x_2)	Individual/crop	Seed quantity used in one crop
Feed (x_3)	Kg/crop	Feed quantity used in one crop
Fuel (x_4)	Liter	Quantity of fuel used in one crop
Labor (x_5)	Working days	Working days (fixed + seasonal labor) in one crop
Chemical (x_6)	Thousand VND	Money used for buying Chemical in one crop
Furniture (x_7)	Thousand VND	Money used to buy furniture

For the furniture and chemical variables, there is no information about types and used quantity, so as a solution the money spent to by chemical and furniture are used as alternative aggregation variables. Fortunately, this is acceptable as dealing with DEA models.

Certain farm-specific factors for example experiences, age, education level of farmers are also necessary to be considered in efficiency analysis process. Unfortunately these variables are not available. This can be seen as limitation in this thesis.

Farmers' performance depends on various socio-economic factors, such as local development, and provision of infrastructure, which in turn influence the farmer's access to inputs, availability of modern technologies, and level of farmer's education and technical application (Khem et al. 1999). Collected data is focused on one district so such socio-economic factors are assumed to be similar between farms. Details about inputs and output statistic and regression are presented in appendix B (B_1, B_2).

5.4. Instrument used in thesis

The software DEA-Solver-PRO of Cooper, L.M. Seiford and K. Tone is applied to measure technical efficiency and scale efficiency. The software DEA Excel Solver written by Zhu is also used to measure supper efficiency of shrimp farms.

SHAZHAM software is used to test the hypothesis

Excel is used to restore and analyze data set.

6. RESULTS

Table 6-1 shows the statistical summary of the data set. It can be seen that there has been large variations in certain inputs. The greatest variations were seen in seed, chemical, furniture and culture area. The great variations in inputs used may be an indicator of mismanagement.

Table 6-1. Table Summary of statistics of data sample

Variables	Minimum	Maximum	Average	Std Deviation
Culture area	1,200.0	50,000.0	12,007.1	10,242.0
Seed	50,000.0	600,000.0	196,935.7	130,359.1
Feed	150.0	18,000.0	4,232.5	4,174.7
Fuel	17.9	4,081.6	891.5	1,049.2
Labor	75.0	720.0	176.8	136.4
Chemical	800.0	110,100.0	16,695.1	24,099.8
Furniture	1,700.0	97,000.0	26,110.7	24,038.1
Production	300.0	15,000.0	3,366.1	3,218.0

6.1. Technical and scale efficiency results

The overall technical efficiency of a shrimp farm includes its scale efficiency and its pure technical efficiency. Table 6-2 illustrates that the mean values of overall technical, scale and pure technical efficiency were 0.911, 0.923 and 0.984, respectively. The results suggest two important findings. Firstly, it is possible to increase efficiency levels in the shrimp farms in Binh Dai district. The average overall technical efficiency could be increased on average by around 9 percent by eliminating pure technical inefficiencies through the adoption of the best practices of efficient shrimp farms and by operating at optimal scales. Secondly, the results also indicate that scale inefficiency for shrimp farms in Binh Dai district significant impacted to overall inefficiency

Table 6-2. Frequency of technical and scale efficiency scores of shrimp farms

	Overall technical efficiency	Scale efficiency	Pure technical efficiency
1	16	16	22
0.9-1	3	3	4
0.8-0.9	5	6	2
0.7-0.8	1	1	
0.6-0.7	1	1	
0.5-0.6	1		
<0.5	1	1	
Average	0.911	0.923	0.984
Std Deviation	0.148	0.141	0.037
Minimum	0.397	0.465	0.853
No of efficient farms	16	16	22

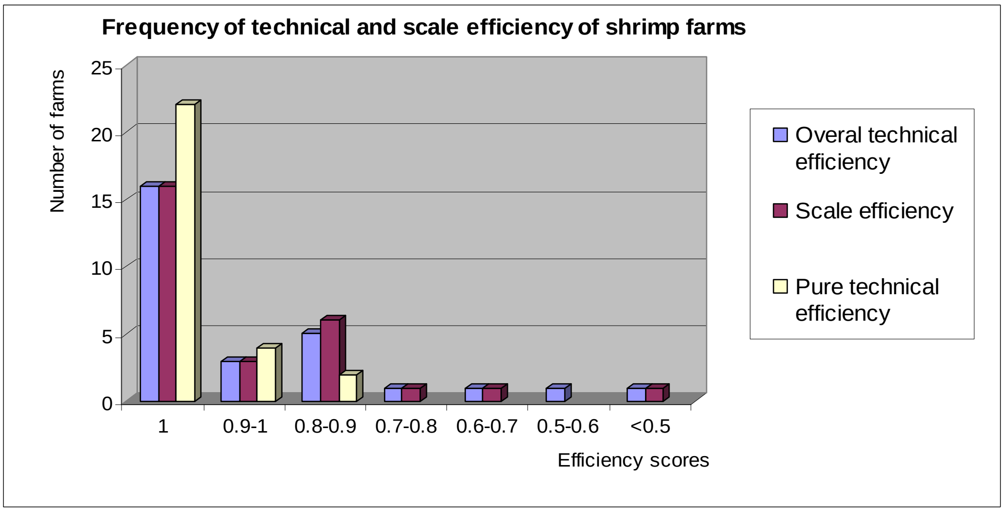


Figure 6-1. Frequency of technical and scale efficiency of shrimp farms

Figure 6-1 shows that of the 28 shrimp farms studied, 16 farms under CRS and 22 farms under VRS were fully efficient. All farms had efficient score above 0.50. CRS efficiency scores varied from 0.397 to 1 with the mean was at 0.911. Meanwhile VRS efficiency scores varied from 0.853 to 1 with the mean was at 0.984.

The VRS scale efficiency results are expressed as in Figure 6-2. The empirical DEA results suggest that, of 28 observations, 64 percent operated at their optimal scale, 36 percent operated below their optimal scale, while based on data set, there had been no farm operated above their optimal scale.

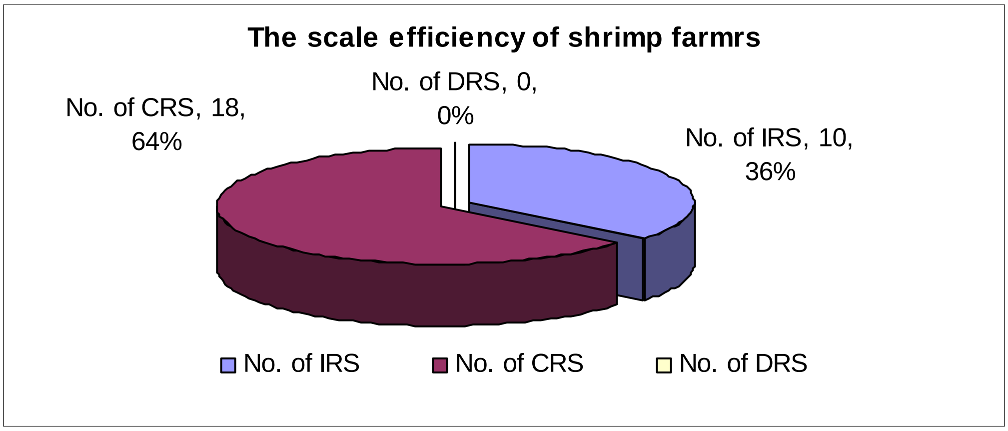


Figure 6-2. The scale efficiency of shrimp farms in Binh Dai district

The characteristics of each of the above three groups of shrimp farms are expressed in table 6-3 which indicates that the larger increase in overall technical efficiency could be achieved by solving the problem of increasing returns to scale, while eliminating the problem of constant returns to scale would lead to a lesser increase in overall technical efficiency.

Table 6-3. Overall scale efficiency of shrimp farms

Shrimp farms	**Constant Return to scale**	**Increasing return to scale**	**Decreasing return to scale**
Number	18	10	-
Area (m^2)			
Min	1,200	1,600	-
Max	50,000	20,000	-
Average	14,033	8,360	-
Average value of technical efficiency			
Overall technical efficiency	0.99	0.83	-
Pure technical efficiency	0.99	0.97	-

Efficient rating results, which are illustrated in table 6-4, are estimated though data envelopment analysis. Farms BD1, BD11, BD13, BD15, BD17, and BD20 were inefficient farms as they had efficient score less than 100 percent. Branch BD1 was less productive with a DEA productivity rating of 98 percent means that it could produce its shrimp production with only about 98 percent of the resources it actually used. Branch BD11 had a DEA productivity rating of 89 percent suggesting that it was using about 11% excess resources. Similarly, the figures for excess input use of BD13, BD15, BD17, and BD20 were 3 percent, 10 percent, 4 percent, and 15 percent respectively. The other remained farms (see appendix E), were considered as efficient farms as their efficient score equaled to 100 percent rating by DEA (then these farms become reference sets for themselves).

For the less productive farms, they have efficient score lower than unity, and are inefficient compared to particular sets of best practice farms. Particularly, Farm BD1 is inefficient specifically in comparison to Farms BD10, BD14, and BD21 (those are referred to as the best practice farm reference set for BD1 as in table 6-4. These reference sets identify the farms that are most similar to the less productive farms in their mix of services and resources. A similar interpretation can be applied to explain for less productive shrimp farms: BD11; BD13; BD15; BD17; BD20.

Table 6-4. Efficiency rating[9] of less productive shrimp farms (VRS DEA)

Less productive Firm	**Efficiency rating**	**Reference sets**						
BD1	0.98	BD10	BD14	BD21				
BD11	0.89	BD6	BD7					
BD13	0.97	BD7	BD12	BD14	BD19	BD21	BD22	BD23
BD15	0.90	BD7	BD12	BD19	BD21	BD23	BD24	
BD17	0.96	BD7	BD12	BD14	BD19	BD21	BD23	BD27
BD20	0.85	BD12	BD19	BD21	BD24			

Table 6-5. Shrimp farming efficiency rating (CRS DEA)

Less productive Firm	**Efficiency rating**	**Reference sets**				
BD1	0.93	BD5	BD7	BD10	BD14	BD21
BD2	0.98	BD5	BD10	BD14		
BD11	0.88	BD6	BD7			
BD12	0.56	BD14	BD26			
BD13	0.92	BD10	BD14	BD21	BD23	
BD15	0.77	BD9	BD10	BD14	BD21	BD23
BD16	0.80	BD10	BD14	BD21	BD27	
BD17	0.89	BD9	BD10	BD14	BD21	BD23
BD19	0.81	BD5	BD10	BD14	BD21	BD23
BD20	0.40	BD9	BD10	BD14	BD21	BD23
BD24	0.69	BD18	BD21			
BD28	0.85	BD5	BD10	BD14		

As showed in table 6-5, compared with the case of VRS DEA, the number of inefficient farms in CRS DEA will be larger. This is due to the existing of additive farms which were efficient in VRS yet were not in optimal scale so they were still considered to be inefficient in CRS DEA. Such farms were BD16, BD19, BD24, and BD28. More detail results about efficient rating of both less productive farms and productive farms can be seen at appendix E and F.

[9] DEA productivity rating is based on comparing each farm with every other farm. A rating of 100 percent indicates a best practice farm while a rating of less than 100 percent indicates a less productive farm. The reference set for a less productive farm is the set of best practice farms identified with DEA that provide their volume and mix of services with fewer resources than such less productive farm (Zhu and Sherman, 2006)

Table 6-6. Potential resource saving of shrimp farms in Binh Dai district

Potential resource saving (Constant return to scale)							
Less productive shrimp farms	**Culture area (m^2)**	**Seed (individuals)**	**Feed (kg)**	**Fuel (Liters)**	**Labor (Working days)**	**Chemical(Thousand VND)**	**Furniture (Thousand VND)**
BD1	1,153	78,234	475	57	16	1,017	48,003
BD2	93	23,706	74	769	38	186	7,943
BD11	806	74,258	806	470	188	18,214	12,399
BD12	3,360	26,315	96	85	54	1,414	9,839
BD13	811	32,228	268	16	18	3,680	1,817
BD15	3,352	34,727	579	32	49	662	3,936
BD16	1,178	17,675	295	115	67	393	10,136
BD17	1,824	16,322	272	22	13	2,040	1,741
BD19	747	24,080	262	28	91	280	729
BD20	7,324	120,629	1,809	62	74	4,679	16,243
BD24	18,188	29,526	190	5	56	823	5,682
BD28	235	13,138	220	1,025	86	294	2,180
Total saving	**39,071**	**490,839**	**5,345**	**2,687**	**750**	**33,681**	**120,648**
Total resource used by all farms	**107,600**	**1,937,000**	**34,510**	**8,717**	**1,764**	**101,834**	**310,630**
Saving as % of total resource	**36%**	**25%**	**15%**	**31%**	**43%**	**33%**	**39%**

The quantity of excess resources used by inefficient farms is illustrated in table 6-6. The excess used resources refer the amount of resource savings that inefficient shrimp farms could achieve if they increased their productivity to the efficient level achieved by best practice farms. Particularly, branch BD1 could be able to produce its current shrimp product level with 1,153 m^2 of culture area, 78,234 seed individuals fewer, 475 kilograms fewer of feed, 57 liters fewer of fuel, 16 fewer of working days, 1,017 thousand VND less in finance used for buying chemical, and 48,003 thousand VND less in finance used for buying furniture. The similar interpretation is applied to other less productive shrimp farms.

Totally, the 12 inefficient shrimp farms mentioned in table 6-6 should be able to reduce culture area, seed, feed, fuel, labor, chemical, and furniture by 39,071 m^2, 490,839 individuals, 5,345 kilograms, 2,687 liters, 750 working days, 33,681 thousand VND and 120,648 thousand VND respectively. These figures correspond to the percentage of input saving of such less productive farms as following: 36%, 25%, 15%, 31%, 43%, 33%, and 39%.

6.2. Super efficiency results

Results of super efficiency analysis are described in table 6-7. Applying super efficiency analysis, not only less productive farms are ranked but also for efficient farms; The efficient score of productive farms can be larger than unity.

Table 6-7. Input oriented constant return to scale super efficiency

DMU Name	Input-Oriented CRS Super Efficiency	Reference sets				
BD20	0.40	BD9	BD10	BD14	BD21	BD23
BD12	0.56	BD14	BD26			
BD24	0.69	BD18	BD21			
BD15	0.77	BD9	BD10	BD14	BD21	BD23
BD16	0.80	BD10	BD14	BD21	BD27	
BD19	0.81	BD5	BD10	BD14	BD21	BD23
BD28	0.85	BD5	BD10	BD14		
BD11	0.88	BD6	BD7			
BD17	0.89	BD9	BD10	BD14	BD21	BD23
BD13	0.92	BD10	BD14	BD21	BD23	
BD1	0.93	BD5	BD7	BD10	BD14	BD21
BD2	0.98	BD5	BD10	BD14		
BD8	1.02	BD5	BD7			
BD27	1.03	BD9	BD10	BD14	BD26	
BD6	1.04	BD7				
BD25	1.10	BD7	BD10	BD23		
BD26	1.11	BD10	BD14	BD27		
BD3	1.13	BD5	BD7			
BD22	1.18	BD10	BD21	BD23		
BD14	1.31	BD6	BD10	BD18		
BD10	1.32	BD7	BD21	BD22		
BD4	1.60	BD5	BD23			
BD18	1.71	BD14				
BD5	1.74	BD3	BD10	BD21		
BD7	1.79	BD8	BD10	BD23		
BD9	2.49	BD23				
BD23	2.58	BD4	BD9	BD22		
BD21	3.95	BD5	BD23			

For the inefficient farms, their score and reference sets are the same compared with that of them in the case of constant return to scale DEA. In contrast, for the CRS DEA inefficient farms, as examined in super efficiency analysis their scores as well as their reference sets have been changed. This is due to the characteristic of super efficiency approach; these that efficient farms are excluded out of their reference sets. By this way, shrimp farms are clearly ranked. Of the 28 shrimp farms, in super efficiency analysis, BD1 was the least efficient as its efficient score was 0.4 meanwhile BD21 was identified as the best in term of efficiency in production process as it reached efficient score to 3.95. CRS Efficient farms, which all have the efficient score of unity in the case of constant return to scale, are distinctly clarified through super efficiency analysis.

To examine the pure technical efficiency for farms which were considered as efficient in CRS DEA, VRS super efficiency analysis has been implemented. The results are expressed in table 6-8.

Table 6-8. Input oriented variant return to scale super efficiency

DMU Name	**Input-Oriented VRS Super Efficiency**	**Reference sets**							
BD20	0.85348	BD12	BD19	BD21	BD24				
BD11	0.88980	BD6	BD7						
BD15	0.90313	BD7	BD12	BD19	BD21	BD23	BD24		
BD17	0.95720	BD7	BD12	BD14	BD19	BD21	BD23	BD27	
BD13	0.97308	BD7	BD12	BD14	BD19	BD21	BD22	BD23	
BD1	0.97607	BD10	BD14	BD21					
BD2	1.02334	BD3	BD5	BD6	BD7	BD10	BD14		
BD8	1.02464	BD5	BD7	BD10					
BD16	1.03264	BD5	BD12	BD19	BD21	BD24	BD27		
BD25	1.10462	BD7	BD10	BD23					
BD26	1.12271	BD7	BD10	BD21	BD27				
BD27	1.19984	BD5	BD9	BD12	BD14	BD19	BD24	BD26	BD28
BD22	1.27043	BD10	BD19	BD21	BD23				
BD6	1.31944	BD3	BD28						
BD28	1.36691	BD3	BD12	BD19					
BD3	1.39404	BD5	BD19	BD28					
BD4	1.61285	BD3	BD5	BD23					
BD7	1.78799	BD5	BD8	BD10	BD23				
BD5	1.81578	BD3	BD10	BD21					
BD14	1.89620	BD10	BD18						
BD18	2.04444	BD12	BD14						
BD12	2.18336	BD6	BD18	BD19	BD24				
BD19	2.41931	BD3	BD12	BD23					
BD23	3.01798	BD4	BD9	BD10	BD22				
BD9	3.06728	BD4	BD19	BD23					
BD21	4.08427	BD5	BD23	BD24					
BD24	4.38117	BD12	BD21						
BD10	infeasible								

Considering only pure efficiency, compared to CRS super efficiency, the efficient score and reference sets have been changed also. BD20 was still the least pure efficiency, at 0.85, Yet BD24 become the most pure efficient farms as its score was 4.38. It should be noted that it is infeasible to rank BD10VRS super efficiency analysis as there has no value system to evaluate this farms as itself is excluded out off its reference sets.

6.3. Hypothesis testing

Hypothesis will be tested to examine further certain relationships, factors related to inputs, outputs, technical efficiency, and scale efficiency.

- **Testing hypothesis I: In term of capacity utilization, the larger farms the more technically efficient farms**

  The statistic result used for testing hypothesis I is illustrated as in table 6-9.

  Table 6-9. Statistically examining the impacts of farm size to farms' general technical efficiency[10]

Farm size		General technical efficiency
< 10,000 m^2	(12 farms)	0.91
10,000 m^2 - 15,000 m^2	(9 farms)	0.89
> 15,000 m^2	(7 farms)	0.95
$F_{statistic}$		0.303
F_{value}		3.39

As $F_{statistic} < F_{value}$ at $\alpha = 0.05$, statistically there had been no differences in the mean of general technical efficient scores of the three farm size groups (do not reject null hypothesis). Therefore, it can be stated that the size of farms had no statistically impacts on the general technical efficient level of shrimp farms. This result, however, should also be interpreted with cautions as the size of observations was rather small, a further research is suggested.

- **Testing hypothesis II: In term of capacity utilization, the larger farms, the more purely efficient farms**

  Table 6-10. Statistically examining the impacts of farm size to farms' purely technical efficiency[11]

Farm size		Purely technical efficiency
< 10,000 m^2	(12 farms)	0.99
10,000 m^2 - 15,000 m^2	(9 farms)	0.97
> 15,000 m^2	(7 farms)	1.00
$F_{statistic}$		1.77
F_{value}		3.39

[10] The null hypothesis is that there are no differences in the average general technical efficiency between farm size groups.

[11] Null hypothesis: there are no differences in the average purely technical efficiency between farm size groups

As in table 6-10, $F_{statistic} < F_{value}$ at $\alpha = 0.05$. Again, statistically, differences in the mean of purely technical efficient scores of the three farm-size groups had not been existed. So, it can be also stated that statistically the impacts of farm-size on purely technical efficient level of shrimp farms had not be seen. However, due to the small size of observations, this result should be also studied further in future.

- **Testing hypothesis III: There is the existence of scale inefficiency in the production process of the shrimp farming**

Table 6-11. Statistically examining the existence of scale inefficiency[12]

		Efficiency score
CRS (Scale effects existed)	(28 farms)	0.91
VRS (No Scale effects existed)	(28 farms)	0.98
$F_{statistic}$		4,175
F_{value}		4

The test for the existing of return to scale is illustrated in table 6-11. Interestingly, in this test, $F_{statistic} > F_{value}$ at $\alpha = 0.05$. This means that statistically there had been differences in the mean of scale efficient score of the two samples (reject the null hypothesis). Therefore, it can be stated that, statistically there had been an existing of scale inefficiency in the shrimp farms as the efficiency scores of the CRS sample were significant lower than that of the VRS sample.

- **Testing hypothesis IV: There are certain relationships between input used and technical efficiency of farms**

- Testing relationships between general technical (CRS) efficiency and inputs used in production process.

To examine the relationships between inputs used and CRS efficiency of farms, natural logarithm (ln)-transformed observations of super efficiency was regressed by OLS against

[12] Null hypothesis: there are no differences in the average efficiency between CRS group and VRS group

farm size_area,seed, feed, labor, fuel, chemical, and furniture. The relationships represented by parameters (regression elasticities) will be test through checking t-test of p_{value}.

Proposed general function form is as following:

$$\ln E_{(CRS\ efficiency)} = a + c_1 \ln(\text{farm size\_area}) + c_2.\ln(\text{seed}) + c_3 \ln(\text{feed}) + c_4 \ln(\text{labor}) + c_5 \ln(\text{fuel}) + c_6 \text{Ln}(\text{chemical}) + c_7 \ln(\text{furniture}) \quad (6.3.1)$$

Running the SHAZAM software, following results are given:

Table 6-12. Elasticity regression results used for examining relationships between inputs used and general technical efficiency[13]

VARIABLE NAME	ESTIMATED COEFFICIENT	STANDARD ERROR	T-RATIO 20 DF	P-VALUE	PARTIAL CORR.	STANDARDIZED COEFFICIENT	ELASTICITY AT MEANS
LNA	-0.71532E-01	0.7072E-01	-1.011	0.324	-0.221	-0.3246	-0.0715
LNS	0.16359	0.1212	1.349	0.192	0.289	0.5296	0.1636
LNFE	-0.53627E-02	0.2633E-01	-0.2037	0.841	-0.045	-0.0459	-0.0054
LNFUE	0.12579E-02	0.1984E-01	0.6340E-01	0.950	0.014	0.0147	0.0013
LNL	-0.43920E-02	0.1240	-0.3541E-01	0.972	-0.008	-0.0108	-0.0044
LNC	0.45818E-01	0.4808E-01	0.9530	0.352	0.208	0.2865	0.0458
LNFUR	-0.71279E-01	0.6691E-01	-1.065	0.299	-0.232	-0.3447	-0.0713
CONSTANT	-0.96815	0.5258	-1.841	0.080	-0.381	0.0000	-0.9682

Notation: A - Area; S - Seed; FE - Feed; FUE - Fuel; L - Labor; C - Chemical; FUR – Furniture

It should be noticed from table 6-12 that P_{value} of all coefficients in the function are greater than 0.05. This means that statistically each input used has no significant effects to the CRS super efficient level of such farms.

[13] Null hypothesis: coefficients are different from zero

- Testing the relationships between pure technical (VRS) efficient scores and inputs used in production process.

Proposed general function form for this case is:

$$\ln E_{(VRS\ efficiency)} = a + v_1 \ln(\text{farm size\_area}) + v_2.\ln(\text{seed}) + v_3 \ln(\text{feed}) + v_4 \ln(\text{labor}) + v_5 \ln(\text{fuel}) + v_6 \ln(\text{chemical}) + v_7 \ln(\text{furniture}) \quad (6.3.2)$$

Table 6-13. Elasticity regression results used for examining relationships between inputs used and VRS efficiency[14]

VARIABLE NAME	ESTIMATED COEFFICIENT	STANDARD ERROR	T-RATIO 20 DF	P-VALUE	PARTIAL CORR.	STANDARDIZED COEFFICIENT	ELASTICITY AT MEANS
LNA	-0.98250E-03	0.1437E-01	-0.6838E-01	0.946	-0.015	-0.0231	-0.0010
LNS	-0.16619E-03	0.2505E-01	-0.6634E-02	0.995	-0.001	-0.0028	-0.0002
LNFE	0.40808E-02	0.5495E-02	0.7426	0.466	0.164	0.1806	0.0041
LNFUE	-0.16932E-02	0.4099E-02	-0.4131	0.684	-0.092	-0.1022	-0.0017
LNL	-0.52914E-02	0.2190E-01	-0.2416	0.812	-0.054	-0.0673	-0.0053
LNC	-0.13909E-02	0.5745E-02	-0.2421	0.811	-0.054	-0.0536	-0.0014
LNFUR	-0.96629E-02	0.1259E-01	-0.7672	0.452	-0.169	-0.2417	-0.0097
CONSTANT	0.50755E-01	0.1161	0.4370	0.667	0.097	0.0000	0.0508

Again, in table 6-13, P_{value} of all coefficients are greater than 0.05. This testing result leads to a statement that there are also no significant affects of each input used to the pure technical efficiency of farms.

- Testing the relationships between CRS super efficient scores and inputs used in production process.

Due to farms can be better ranked in super efficiency measures, relationships between input used with the CRS super efficiency (or with the VRS super efficiency as will be mentioned in next test) are considered to be tested.

For the case related to CRS super efficiency, proposed general function form is:

$$\ln E_{(CRS\ super\ efficiency)} = a + k_1 \ln(\text{farm size\_area}) + k_2.\ln(\text{seed}) + k_3 \ln(\text{feed}) + k_4 \ln(\text{labor}) + k_5 \ln(\text{fuel}) + k_6 \ln(\text{chemical}) + k_7 \ln(\text{furniture}) \quad (6.3.3)$$

[14] Null hypothesis: coefficients are different from zero

Table 6-14. Elasticity regression results used for examining relationships between inputs used and CRS super efficiency[15]

VARIABLE NAME	ESTIMATED COEFFICIENT	STANDARD ERROR	T-RATIO 20 DF	P-VALUE	PARTIAL CORR.	STANDARDIZED COEFFICIENT	ELASTICITY AT MEANS
LNA	0.17070E-01	0.1486	0.1149	0.910	0.026	0.0342	0.0171
LNS	0.48681	0.2546	1.912	0.070	0.393	0.6948	0.4868
LNFE	-0.10360E-01	0.5530E-01	-0.1873	0.853	-0.042	-0.0391	-0.0104
LNFUE	-0.26682E-01	0.4168E-01	-0.6402	0.529	-0.142	-0.1372	-0.0267
LNL	0.54079E-01	0.2605	0.2076	0.838	0.046	0.0587	0.0541
LNC	-0.76666E-01	0.1010	-0.7592	0.457	-0.167	-0.2114	-0.0767
LNFUR	-0.24554	0.1406	-1.747	0.096	-0.364	-0.5235	-0.2455
CONSTANT	-1.1622	1.105	-1.052	0.305	-0.229	0.0000	-1.1622

Testing result about relationships between input used and CRS super efficiency is presented in table 6-14. In this case, P_{value} of all coefficients occurred in the regression function are also greater than 0.05. Therefore it can be also stated that statistically the impacts of inputs used to CRS super efficiency are also not significant.

- Testing the relationships between VRS super efficiency and inputs used in production process:

Proposed general function form for this test is as following:

$$\ln E_{\text{(VRS super efficiency)}} = a + d_1 \ln(\text{farm size\_area}) + d_2.\ln(\text{seed}) + d_3 \ln(\text{feed}) + d_4 \ln(\text{labor}) + d_5 \ln(\text{fuel}) + d_6 \ln(\text{chemical}) + d_7 \ln(\text{furniture}) \quad (6.3.4)$$

Table 6-15. Elasticity regression results used for examining relationships between inputs used and VRS super efficiency[16]

VARIABLE NAME	ESTIMATED COEFFICIENT	STANDARD ERROR	T-RATIO 19 DF	P-VALUE	PARTIAL CORR.	STANDARDIZED COEFFICIENT	ELASTICITY AT MEANS
LNA	0.17162	0.1096	1.566	0.134	0.338	0.3443	0.1716
LNS	0.68991E-02	0.1880	0.3670E-01	0.971	0.008	0.0093	0.0069
LNFE	0.96585E-01	0.4102E-01	2.355	0.029	0.475	0.3688	0.0966
LNFUE	-0.43165E-01	0.3106E-01	-1.390	0.181	-0.304	-0.2195	-0.0432
LNL	0.47565E-02	0.2139	0.2224E-01	0.982	0.005	0.0047	0.0048
LNC	-0.14866	0.7598E-01	-1.956	0.065	-0.409	-0.4005	-0.1487
LNFUR	-0.23969	0.1095	-2.188	0.041	-0.449	-0.4920	-0.2397
CONSTANT	1.9546	0.8912	2.193	0.041	0.449	0.0000	1.9546

[15] Null hypothesis: coefficients are different from zero
[16] Null hypothesis: coefficients are different from zero

Table 6-15 shows results from testing the relationships of input used and pure technical efficiency. It is interesting that while the impact of remain inputs are not significant, Feed and Furniture statistically represent a significant impacts on pure technical efficiency of farms (their $p_{value} < 0.05$). In this test, feed is found to increase pure technical efficiency, meanwhile, surprisingly, furniture is found to decline pure technical efficiency. However, correlation of feed and furniture with efficiency are rather low (0.4 and -0.4 respectively), the result seems do not provide much significant implication for management

7. DISCUSSIONS, IMPLICATIONS AND CONCLUSIONS

7.1. Discussions and limitations

The results show that technical efficiency level of farms in Binh Dai district is rather high, on average above 90 percent. This efficiency level reflects that if without existing of "risks"[17], the intensive shrimp farming technology can control quite well the production process. The results reflect performance of farms in normal production process (certain "risk" farms are removed as discussed in the data description part); as "risk" farms are added into calculation, the average overall technical efficiency then was reduced to 82 percent (an added analyzing including "risk" farms are presented in appendix G). As the number of observations in analysis is quite small, to be able to represent absolutely the performance of shrimp farming in Binh Dai, it may be necessary also to carry out further studying.

The scale efficiency level is also quite high, this express that farms were operated at quite optimal scale. However, the experimental results also imply that, compared with farms that are increasing return to scale, certain advantages may exist in farms that are constant return to sale as they have higher average efficiency. More comprehensive discussions about relationships between farm scale and efficiency, however, are limited as there is no existing of decreasing return to scale farms in data set. This issue can be solved as having larger number of data.

Statistical test for the impacts of farm size to the generally technical efficiency and the pure technical efficiency of farms showed that statistically there have been no impacts between them. These might be surprising results as economists often expect that there are relationships between efficiency and farm size, and also technical experts frequently propose that to be easier for management, farm size should be limited at certain level. However, the results from the statistic tests are not unexplained. Since the technology of intensive shrimp farming is applied in Binh Dai district, inputs used in the production process could had been controlled and utilized well, this could lead to the situation that the impacts of farm size to technical efficiency is not significant. For other type of shrimp farming such as extensive or semi-intensive farming, the impact of scale may become more significant. The test results, as mentioned, should be interpreted with cautions due to the quite small observations were analyzed.

[17] "Risk" term reflect disease happened or an accident environment existed

The test for the existence of scale inefficiency showed that there was still the existing of scale inefficiency in the shrimp farms. This result corresponds to the DEA results and also reflects the reality in the production process in shrimp farming in Binh Dai district. This test again leads to a reminding that the above test about impacts of farm size should be tested more by a more comprehensive study.

According to the hypothesis tests related to the regression approach, in almost cases there have no significantly relationships between each input factor to the technical efficiency of farms. (Except for feed and furniture in the test related to VRS super efficiency; however, their coefficients are very small and their correlation to efficiency are also rather low). These results again remind one thing that without the existing of substitute inputs, efficiency level of a farm should be impacted by the way of using all necessary inputs to produce certain outputs. Changes in only one input may not help to significantly change the technical efficiency of farms (base on efficiency definition in the context of DEA).

This thesis proposed an input oriented as farmers are normally limited in finance and resources used. Specially, in term of environmental carrying, this oriented seems to be appropriate as the farmers can not use as much input as possible. If technical and price information are both available, a profit maximization oriented DEA analysis is a good alternative approach that can eliminate the wonder of deciding weather input oriented or output oriented should be applied.

The studying area in this thesis is not so large, if an investigation is implemented in large area a certain environmental variables should be identified and put into DEA process.

As more information about inputs, outputs are available, more hypothesis statistical tests could be implemented to test the determinants of efficiency as well as other related issues.

As can be seen from the studying case, applying DEA approach, chances to improve shrimp farms' operations can be identified. DEA methods, with their own advantages in comparing the relative efficiency, have been being interesting and useful tools to be used. A correct application in management, however, requires certain efforts as it requires knowledge and understanding about mathematic and linear programming, and also requires a good data set.

During reviewing DEA methods, it is recognized that, in investigating relationships between efficiency and inputs used, there has been also other useful approaches such as stochastic frontier analysis can be applied also. This leads to a further suggested study about applying such approaches to examine the performance of farms.

Chemical, furniture variables used in analysis are measured in monetary unit; they have been used in analysis as aggregation variable. Although this is allowed in DEA, it will be better to have both technical and price information available. With having both technical and price information of inputs, and outputs, allocative, revenue or profit then can be estimated.

7.2. Applications in shrimp farming management

An important concern can be implied that, if risk factors such as disease out-breaking or accident environment were controlled, the technology applied in intensive shrimp farming in Binh Dai was quite good. This model can provide high efficiency in term of technical as well as scale concerns. Therefore, it can be encouraged to be applied.

In order to reduce "risk", farmers should follow instructions of extensional experts of aquaculture experts. Successful applying the shrimp farming technology in the context of natural, social and economic conditions in local area is the key to avoid the risk.

Although the result implied that impacts of farm size to efficiency are not significant, in reality managers should still consider to farm size used, an appropriate farm size should appropriate with management ability and capital capacity of farmers

7.3. Conclusions and recommendations

DEA with its own advantages can be useful tools that can be used to relatively measure the performance of shrimp farms. These have been a number of DEA methods available for use and application should appropriate with the availability of data, the purpose and ability of managers.

Through the case study, it can be indicated that, even though the intensive shrimp farming was quite efficient with the overall technical efficiency (to 91 percent), there are still significant possibilities to increase efficiency levels in the tiger shrimp farms in Binh Dai district. The average overall technical efficiency could be increased by around 9 percent by eliminating pure technical inefficiencies by operating at optimal scales and by adapting to best practices of efficient shrimp farms.

High scale and pure technical efficiency of the shrimp farms are indicators that indicate that if risks factors such as diseases, accident environment are controlled, the technology applied in Binh Dai district was quite efficient. This model of shrimp farming, therefore, can be encouraged to develop.

The result of investigating the technical efficiency of shrimp farms in Binh Dai district also showed that, in the context of intensive shrimp farming technology was applied, at normal production process; there was still an existence of scale inefficiency. About the impact of farm size to efficiency of farms, the relationships between them has not statistical showed clearly and it should be further studied.

Due to the limitation in time and finance, this thesis is implemented with certain limited number of observations and focus at specific issues. Comprehensively further researches can be continuously carried out such as: examining capacity utilization of farms, comparing the performance of farms at varied situations (in normal production process and in cases that risk factors existed); implementing and comparing result gained through applying stochastic and DEA frontier analysis.

8. REFERENCES

Adler, N., Friedman, L., & Sinuany-Stern, Z. (2002). *Review of ranking methods in the Data Envelopment Analysis context*. European Journal of Operational Research, 140, 249-265

Allen, R., A. Athanassopoulos, R. G. Dyson, and E. Thanassoulis (1997). Weights restrictions and value judgments in data envelopment analysis: Evolution, development and future directions. *Annals of Operations Research* 73, 13-34.

Andersen, P., & Petersen, N. C. (1993). *A procedure for Ranking Efficient Units in Data Envelopment Analysis*. Management Science, 39(10), 1261-1264.

Banker, R. D., A. Charnes, and W. W. Cooper (1984). Some models for estimating technical and scale inefficiencies in data envelopment analysis. *Management Science* 30(No 9), 1078-1092.

Ben Tre people' committee (2008). http://www.bentre.gov.vn/index.php?option=com_content&task=view&id=4366&Itemid=178

Bentre Statistical Office (2007) *Statistical yearbook 2006.*

Brocket, P. L., A. Charnes, W. W. Cooper, Z. M Huang, D. B. Sun (1997), Data transformations in DEA cone ratio envelopment approaches for monitoring bank performances, *European Journal of Operational research 98*, 250-268

Charnes, A., and W. W. Cooper (1985). Preface to topics in Data Envelopment Analysis. *Annals of Operations research* 2, 59-94.

Charnes, A., W. Cooper, and L. M. Seiford (1994). *Data envelopment analysis: Theory, methodology, and application*. Dordrecht; Boston and London: Kluwer Academic.

Charnes, A., W. W. Cooper, and E. Rohdes (1978). Measuring the Efficiency of Decision Making Units, *European Journal of Operational Research, 2*(6): 429 – 444.

Charnes, A., W. W. Cooper, Z. M. Huang, and D. B. Sun, (1990), Polyhedral Cone-Ratio DEA models with an illustrative application to large industrial Banks, *Journal of Econometrics* 46, 73-91

Chiang FuSung, Sun ChinHwa, Yu JinMey (2004). Technical efficiency analysis of milkfish (Chanos chanos) production in Taiwan - an application of the stochastic frontier production function. *Aquaculture ISSN 0044-8486 . vol. 230, no1-4, pp. 99-116*

Chih-Hai Yang and Ku-Hsieh Chen (2007). Are small firms less efficient?. *Small Business Economics. Volume 32, Number 4, pp. 375-395*

Cinemre H.A. , Bozoğlu M., Demiryürek K. and Kılıç O. (2005). *The cost efficiency of trout farms in the Black Sea Region, Turkey*. Department of Agricultural Economics, University of Ondokuz Mayıs, 55139, Samsun, Turkey

Coelli, T. J., D.S.P. Rao, C. J. O'Donnell and G. E. Battese (2005). *An introduction to Efficiency and Productivity Analysis*. Second edition, Springer Science + Business Media, Inc.

Coelli, T.J., and D.S.P. Rao (2005). Total factor productivity Growth in Agriculture: A Malmquist Index Analysis of 93 Countries, 1980 – 2000. *Agricultural Economics, 32, 115-134.*

Cooper, W.W., K.S. Park, and J.T.Pastor (1999). RAM: A Range Adjusted Measure of inefficiency for use with Additive Models, and Relations to other Models and Measures in DEA. *Journal of Productivity Analysis* 11:1 (February), 5 – 42.

Cooper. W.W., L.M. Seiford and K. Tone (1999). *Data Envelopment Analysis - A Comprehensive Text with Models, Applications, References, and DEA-Solver Software.* Kluwer Academic Publishers,

Cooper. W.W., Seiford L. M., Zhu J., (2004) *Hand book on data envelopment analysis*. Kluwer Academic publicshers. Lon don.

Den Do Thi, Tihomir Ancev and Michael Harris (2007). *Technical Efficiency of Prawn Farms in the Mekong Delta, Vietnam*. Contributed Paper to 51st AARES Annual Conference, Queenstown, NZ, February

Epstein, M. K., and J. C. Henderson (1989). Data envelopment analysis for managerial control and diagnosis. *Decision Sciences* 20(1), 90-119.

Färe, R and C.A.K. Lovell (1978). Measuring the technical Efficiency of Production. *Journal of Economic theory, 19,150-162.*

Färe, R., S. Grosskopf, C.A.K. Lovell (1985), *The measurement of Efficiency of Production*, Kluwer Academic Publicshers, Boston.

Färe, R., S. Grosskopf, C.A.K. Lovell (1994), *Production Frontier*, Cambridge University Press, Cambrige.

Fried, H.O., Lovell, C.A.K. and Schmidt, S. (2008). *The Measurement of Productive Efficiency and Productivity Growth*. Oxford University Press US, 2008.

Http://en.wikipedia.org/wiki/Capacity_utilization

Khem R. Sharma, PingSun Leung), Hailiang Chen, Aaron Peterson (1999) Economic efficiency and optimum stocking densities in fish polyculture: an application of data envelopment analysis_DEA/to Chinese fish farms. *Aquaculture 180_1999.207–221*

Kolawole, S.O.Ojo and Bernhard Brummer (2006). Productivity Potential and Technical Efficiency of Aquaculture Production in Alleviating Poverty: Empirical Evidence from Nigeria. *Journal of Fisheries international 1(1-2) : 21-26, 2006*

Lawrence R. K. and et.al. (2008). Capacity Utilization: Concept, Measurement, and Recent Estimates. *Brookings Papers on Economic Activity, Vol. 1973, No. 3 (1973), pp. 743-763*

Linh H. Vu (1994). *Efficiency of Rice Farming Households in Vietnam: A DEA with Bootstrap and Stochastic Frontier Application*. Department of Applied Economics, University of Minnesota.

Linuma M., Sharma K. R., Leung P. S. (1999). *Technical efficiency of carp pond culture in peninsula Malaysia: an application of stochastic production frontier and technical inefficiency model*. Aquaculture;175 (3–4):199–213.

Lovell, C.A.K. (1993). Production Frontiers and Productive Efficiency, in H.O. Fried, C. A.K Lovell, S. S. Schmidt (eds) *The Measurement of Productive Efficiency*. New York: Oxford University Press.

Pascoe, Sean, Simon. Mardle. et. al. (2003). *Efficiency analysis in EU fisheries: Stochastic Production Frontiers and Data Envelopment Analysis*. Second edition, Univer.

Roll, Y. and B. Golany (1993). Alternative methods of treating factor weights in DEA, *Omega, The international Journal of management Science 21/1*, 99-109.

Roll, Y., W. D. Cook, and B. Golany (1991). Controlling factor weights in data envelopment analysis, *IIE Transactions 23/1, 2-9.*

Sharma K. R., Leung P. S., Chen H., Peterson A. (1999). *Economic efficiency and optimum stocking densities in fish polyculture: an application of data envelopment analysis (DEA) to Chinese fish farms*. Aquaculture;180 (3–4):207–21.

Tewodros A. K. (2001) *Farm Household Technical Efficiency: A Stochastic Frontier Analysis - A Study of Rice Producers in Mardi Watershed in the Western Development Region of Nepal* (Master thesis submitted to Department of Economics and Social Sciences, Agricultural University of Norway).

Tewodros. A. K. (2001). *Farm household technical Efficiency: A Stochastic Frontier Analysis – A Study of Rice Producers in Mardi Watershed in the Western Development Region of Nepal*. Department of Economics and social Sciences. Agriculture University of Norway.

Thompson, R. G., Langmeier, L. N., Lee, C.-T., Lee, E., & Thrall, R. M. (1990). *The Role of multiplier bounds in effciency analysis with application to Kansas farmin*g. Journal of Econometrics, 46, 93-108.

Thompson, R. G., Singelton, F. D., Thrall, R. M., & Smith, B. A. (1986). *Comparative Site Evaluations for Locating a High-Energy Physics Lab in Texas*. Interfaces, 16(6), 35-49

VIFEP. (2005). *National aquaculture profile*. Vietnam Institute for Fisheries economic and Planning, SUFA and SUMA components.

Yao Chen [a] (2003). Ranking efficient units in DEA. *International Journal of Management Science. Omega 32 (2004) 213 – 219.*

Yao Chen [b] (2003). Measuring super-efficiency in DEA in the presence of feasibility. *European Journal of Operational Research 161 (2005) 545–551*

Zhu J. H. Sherman D. (2006). *Service Productivity management improving Service performance using data envelopment analysis (DEA)*. Springer Science-i-Business Media, LLC.

9. APPENDICES

Appendix A. Questionnaire used to collect data

Vietnam Institute for Fisheries Economics and Planning

QUESTIONARE

TO DEVELOP AQUACULTURE PROFILE

(SHRIMP FARMING)

Name of households:

Address:

Date:

1. Water area (m^2):
2. Real culture area (m^2):
3. Production quantity (kg/crop):
4. Price of products (VND/kg):
5. Harvested size (individuals /kg):
6. Feed (kg/crop):

Content	Protein proportions	Phosphor proportion	Price	Quantity of feed
Type 1				
Type 2				
Type 3				

7. Quantity of Seed (individuals/crop):
8. Price of seed:

9. Number of crops per year:

10. Number of days per crop:

11. Failure (counted in 5 years):

12. Size of products as failure happed

13. fix labors Salary (millions VND/month):

14. seasonal labors Salary (per working day):

15. Money for renting land (or buying land):

16. Money for buying fuel:

17. Money for buying chemical:

18. Money for buying Furniture (pumping machine, air machine…):

19. Interest:

20. Depreciations:

21. Furniture maintaining cost:

22. Environmental protection fee:

23. Tax:

24. Other cost:

25. Environmental degradation

Source: VIFEP, 2005

***Appendix B_1*. Inputs and output statistic (with farm-codes)**

DEU Name	Code	(1) Culture area	(2) Seed	(3) Feed	(4) Fuel	(5) Labor	(6) Chemical	(7) Furniture	(8) Production
Ngô Văn Thụ	BD1	17,000	430,000	7,000	840	240	15000	97,000	6,200
Huỳnh Văn Hà	BD2	5,000	165,000	3,970	1,329	150	10000	28,900	3,300
Nguyễn Văn Đức	BD3	1,500	70,000	2,000	930	150	3000	7,700	1,300
Võ Thanh Hùng	BD4	7,400	207,200	4,800	1,347	260	5500	5,500	3,100
Bùi Văn Nghiệp	BD5	4,700	130,000	4,500	1,386	120	3000	17,500	3,400
Đỗ Nhật Trung	BD6	1,200	50,000	1,200	2,381	120	10500	10,000	1,000
Nguyễn Mạnh	BD7	10,000	350,000	10,000	1,954	120	31000	46,200	8,000
Ngô Văn Bình	BD8	16,000	420,000	15,000	3,464	240	110100	66,000	10,300
Nguyễn Thanh Hùng	BD9	36,000	120,000	3,000	198	720	29000	1,700	2,500
Đỗ Nhựt Sỹ	BD10	20,000	600,000	18,000	2,143	480	48200	93,000	15,000
Đỗ Nhựt Tài	BD11	7,000	300,000	7,000	4,082	380	45000	46,000	5,000
Lê Quốc Nam	BD12	5,000	60,000	220	143	75	3000	13,800	300
Pham Văn Phụ	BD13	10,000	200,000	3,300	201	121	7460	22,400	2,800
Nguyễn Văn Hùng	BD14	9,000	200,000	350	305	120	3840	21,000	1,500
Nguyễn Văn Mưa	BD15	10,000	150,000	2,500	137	120	2860	17,000	1,800
Nguyễn Văn Bụ	BD16	6,000	90,000	1,500	171	120	2000	21,000	1,200
Nguyễn Văn Nghĩa`	BD17	10,000	150,000	2,500	206	120	6700	16,000	2,100
Nguyễn Thị Quýt	BD18	10,000	180,000	150	171	120	3310	15,000	1,100
Nguyễn Văn Chung	BD19	4,000	80,000	1,400	149	121	1500	3,900	900
Lê Văn Hoá	BD20	12,000	200,000	3,000	103	122	5314	26,930	1,200
Phạm Văn Phụ	BD21	12,000	200,000	3,200	66	124	800	30,000	3,200
Nguyễn Văn	BD22	7,800	220,000	3,800	137	121	3370	14,090	2,700
Bùi Văn Phong	BD23	20,000	300,000	5,200	130	122	4010	6,780	4,000
Pham van Tung	BD24	20,000	60,000	620	18	75	1000	10,000	450
Tran van Bong	BD25	50,000	300,000	8,000	857	120	50000	37,000	6,000
Pham van Tien	BD26	13,000	150,000	3,500	549	130	50000	37,000	3,500
Phan van Hien	BD27	10,000	80,000	1,300	225	120	10000	12,000	1,400
Pham tri Dung	BD28	1,600	52,000	1,500	1,339	120	2000	7,700	1,000
Min		**1,200**	**50,000**	**150**	**18**	**75**	**800**	**1,700**	**300**
Max		**50,000**	**600,000**	**18,000**	**4,082**	**720**	**110,100**	**97,000**	**15,000**
Average		**12,007**	**196,936**	**4,233**	**891**	**177**	**16,695**	**26,111**	**3,366**
Std dev		**10,430**	**132,751**	**4,251**	**1,069**	**139**	**24,542**	**24,479**	**3,277**

Source: VIFEP, 2005

Appendix B_2. Correlations between output/inputs and inputs

Correlation all observations	(1) Real culture area (m2)	(2) Seed quantity (individu al/crop)	(3) Feed quantity (kg/crop)	(4) Fuel (l)	(5) Total working days (fixed and variable labor)	(6) Money for buying Chemical (VND)	(7) Money for buying furniture 1000 VND	(8) Produc-tion (kg/crop)
(I) Real cuture area (m2)	1							
(I) Seed quantity (individual/crop)	0.41	1						
(I) Feed quantity (kg/crop)	0.10	0.21	1					
(I) Fuel (l)	0.00	0.43	0.34	1				
(I) Total working days (fixed and variable labor)	0.36	0.34	0.05	0.30	1			
(I) Money for buying Chemical (VND)	0.38	0.56	0.13	0.59	0.46	1		
(I) Money for buying furniture 1000 VD	0.26	0.86	0.17	0.44	0.28	0.57	1	
(O) Production (kg/crop)	0.39	0.85	0.14	0.56	0.40	0.66	0.76	1

Appendix B_3. Regression results from analyzing data set

Regression Statistics	
Multiple R	0.972096
R Square	0.944971
Adjusted R Square	0.92571
Standard Error	0.246873
Observations	28

	df	SS	MS	F	Significance F
Regression	7	20.93151	2.990215	49.06307	3.18E-11
Residual	20	1.218927	0.060946		
Total	27	22.15043			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%
Intercept	-4.0835	0.951923	-4.28973	0.000357	-6.06917	-2.09782	-6.06917	-2.09782
ln(1)	0.16435	0.138566	1.186077	0.249492	-0.12469	0.453393	-0.12469	0.453393
ln(2)	0.584288	0.156453	3.734603	0.001307	0.257934	0.910643	0.257934	0.910643
ln(3)	0.316179	0.063849	4.951967	7.68E-05	0.182992	0.449365	0.182992	0.449365
ln(4)	0.20559	0.094979	2.164582	0.042692	0.007467	0.403714	0.007467	0.403714
ln(5)	0.012862	0.140488	0.09155	0.927966	-0.28019	0.305915	-0.28019	0.305915
ln(6)	-0.03849	0.085407	-0.45066	0.657082	-0.21665	0.139667	-0.21665	0.139667
ln(7)	-0.01098	0.082733	-0.13274	0.895726	-0.18356	0.161596	-0.18356	0.161596

Appendix C. General technical and economic indicators of the shrimp farming model

Technical indicators	**Mean**	**SD**	**Min**	**Max**	**Unit**
Culture area	10,997.4	8,507.1	1,200.0	36,000.0	m3
Productivity (kg/ha)	3,124.0	3,039.1	500.0	8,666.7	kg/crop/ha
Converse Feed Rate (CFR)	7.9	0.4	0.7	2.9	kg feed/ kg shrimp
Harvested size	57.0	39.9	35.0	150.0	kg
Number of crops per year	1.1				crop/year
Length of a crop	116.9	24.8	60.0	150.0	days/crop
Fail rate					%
Shrimp size when fail happen					Individuals/kg
Survival rate	66%	0.3	0.3	1.7	%
Density	22.3	10.2	3.3	46.7	Individuals/m2
Number of seed					
Economic analysis					
Capital cost	77,854,563	51,124,657	8,013,889	251,000,000	đ/ha
Fix cost	17,159,301	14,319,501	4,355,814	61,015,525	đ/ha/crop
Variable cost	107,275,323	104,311,777	20,700,100	297,083,792	đ/ha/crop
Operating cost	124,434,624	113,703,361	29,633,606	358,099,317	đ/ha/crop
Revenue	228,518,993	269,936,195	18,000,000	736,666,667	đ/ha/crop
Benefit	104,084,369	187,868,661	(182,834,187)	453,069,155	đ/ha/crop
Total labor cost	4,222,459	9,186,544	65,753	32,876,712	đ/ha/crop
Added value (including labor contribution)	108,306,829	190,814,500	(161,345,206)	458,944,993	đ/ha/crop
Investment efficiency (benefit/operating cost)	1	1	(1)	2	%
Capital cost +Variable cost	185,129,885	122,458,786	33,291,681	457,357,221	đ/ha
Fix labor	8	10	2	33	months/ha/crop
Seasonal labor	9	50	-	200	Days/ha/crop
Price of hiring fix labor	317,031	363,051	35,000	1,200,000	đ/ha/month
Price of hiring seasonal labor					
Price of shrimp products	68,632	21,528	30,000	92,000	đ/kg
Price of feeds	16,203	712	15,000	18,000	đ/kg
Price of seeds	53	7	45	65	đ/individual

Source: VIFEP, 2005

Appendix E. Shrimp farming efficiency rating (VRS DEA)

Firm	Efficiency rating	Reference set						
BD1	0.98	BD10	BD14	BD21				
BD2	1	BD2						
BD3	1	BD3						
BD4	1	BD4						
BD5	1	BD5						
BD6	1	BD6						
BD7	1	BD7						
BD8	1	BD8						
BD9	1	BD9						
BD10	1	BD10						
BD11	0.89	BD6	BD7					
BD12	1	BD12						
BD13	0.97	BD7	BD12	BD14	BD19	BD21	BD22	BD23
BD14	1	BD14						
BD15	0.90	BD7	BD12	BD19	BD21	BD23	BD24	
BD16	1	BD16						
BD17	0.96	BD7	BD12	BD14	BD19	BD21	BD23	BD27
BD18	1	BD18						
BD19	1	BD19						
BD20	0.85	BD12	BD19	BD21	BD24			
BD21	1	BD21						
BD22	1	BD22						
BD23	1	BD23						
BD24	1	BD24						
BD25	1	BD25						
BD26	1	BD26						
BD27	1	BD27						
BD28	1	BD28						

***Apendix F*. Shrimp farming efficiency rating (CRS DEA)**

DMU	Score	Reference set (lambda)				
BD1	0.93	BD5	BD7	BD10	BD14	BD21
BD2	0.98	BD5	BD10	BD14		
BD3	1	BD3				
BD4	1	BD4				
BD5	1	BD5				
BD6	1	BD6				
BD7	1	BD7				
BD8	1	BD8				
BD9	1	BD9				
BD10	1	BD10				
BD11	0.88	BD6	BD7			
BD12	0.56	BD14	BD26			
BD13	0.92	BD10	BD14	BD21	BD23	
BD14	1	BD14				
BD15	0.77	BD9	BD10	BD14	BD21	BD23
BD16	0.80	BD10	BD14	BD21	BD27	
BD17	0.89	BD9	BD10	BD14	BD21	BD23
BD18	1	BD18				
BD19	0.81	BD5	BD10	BD14	BD21	BD23
BD20	0.40	BD9	BD10	BD14	BD21	BD23
BD21	1	BD21				
BD22	1	BD22				
BD23	1	BD23				
BD24	0.69	BD18	BD21			
BD25	1	BD25				
BD26	1	BD26				
BD27	1	BD27				
BD28	0.85	BD5	BD10	BD14		

Appendix G. Frequency of technical and scale efficiency scores of shrimp farms (36 farms)

	Overall technical efficiency	**Scale efficiency**	**Pure technical efficiency**
1	16	16	24
0.9-1	3	6	5
0.8-0.9	6	6	3
0.7-0.8	2	1	1
0.6-0.7	3	2	3
0.5-0.6	2	2	
<0.5	4	3	
Average	0.825	0.858	0.946
Std Deviation	0.236	0.212	0.105
Minimum	0.082	0.130	0.630
No of efficient farms	16	16	24